

# Up-to-Date Progress, Future Challenges and Future of Artificial Intelligence in Dermatology: From Diagnosis, Drug Discovery and Clinical Pathway

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## Abstract

The advent of artificial intelligence (AI) heralds a transformative era in healthcare, with dermatology emerging as a frontier for innovation. AI has demonstrated remarkable potential in enhancing diagnostic accuracy, therapeutic decision-making, and personalized management of skin diseases, particularly through image-based analysis. This review aims to summarize the evolution of AI algorithms in adapting to the progress of dermatological practices, assess the integration of AI-driven diagnostic and therapeutic interventions in clinical settings, and discuss the potential of AI in enhancing personalized and precise management of dermatological conditions. We evaluate the integration of AI-driven tools in clinical practice, highlighting their role in reducing diagnostic errors, while addressing persistent challenges such as demographic bias in training data. Further, we discuss the promise of generative AI in medical education, where synthetic clinical vignettes generated by models such as Generative Pre-trained Transformer 4 (GPT-4) have achieved high expert ratings for scientific accuracy. By critically analyzing current research and applications, this review outlines a roadmap for overcoming barriers including data diversity limitations and real-world validation and calls for interdisciplinary collaboration to advance intelligent, equitable dermatological care.

**Keywords:** dermatology; artificial intelligence; machine learning; precision medicine; clinical applications

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## Introduction

Artificial intelligence (AI), rooted in Turing's seminal question "Can machines think?", has evolved into a transformative discipline integrating theories, methods, and applications to simulate human intelligence<sup>[1,2]</sup>. Since AlphaGo's 2016 victory over Lee Sedol, AI has advanced across text-speech recognition, image analysis, generative models, and large language models (LLMs), increasingly matching or exceeding human performance<sup>[3]</sup>. Improved computing power and algorithms have driven AI from laboratory concepts to multi-field deployment, spanning neural networks to protein structure prediction<sup>[4]</sup>, contributing to the Nobel Prize in Physics and Chemistry in 2024. In medicine, a data-intensive field, AI's precision and processing speed address the high demands of diagnostic imaging and clinical decision support, ensuring efficient and accurate data extraction and analysis<sup>[5,6]</sup>.

Skin diseases rank as the fourth most prevalent global health issue, often underestimated due to inadequate health education and resources<sup>[6]</sup>. The 2019 Global Burden of Disease Study highlights a persistent rise in their prevalence, affecting millions worldwide<sup>[7]</sup>. In China, 30,000 dermatologists serve 360 million patients, revealing a substantial shortage domestically<sup>[8]</sup>. Meanwhile, sub-Saharan Africa has 3 dermatologists for every million individuals, compared with 100 for every million in the U.S. and as few as 2 for every million in certain South American regions. These shortages impede timely diagnosis and treatment, notably in underserved and remote areas<sup>[9,10]</sup>. To address these global inequities, AI-driven solutions, such as teledermatology platforms and automated diagnostic systems, present scalable strategies to improve accessibility, precision, and mitigate healthcare obstacles, thereby advancing equitable dermatologic care.

Dermatology traditionally relies on visual assessment, pathological interpretation, and dermoscopic image evaluation for diagnosis, making it conducive to medical imaging AI applications<sup>[11,12]</sup>. The training of AI models benefits from extensive datasets such as the 129,000-lesion archive curated by Esteva et al.<sup>[13]</sup>. Google Inception v3, a skin cancer detection system, exhibited diagnostic accuracy on par with expert dermatologists. AI contributes to objectivity by quantitatively analyzing lesion boundaries, pigmentation patterns, and textural features<sup>[14,15]</sup>. Moreover,

AI-powered telemedicine platforms have enhanced diagnostic accessibility in underserved regions<sup>[16]</sup>. To ensure consistent clinical application, the Checklist for Evaluation of Image-Based Artificial Intelligence Reports in Dermatology (CLEAR Derm) Consensus Guidelines underscores essential principles such as fairness, robustness, and patient safety in AI<sup>[17,18]</sup>. This places greater demands on clinicians when using AI in clinical practice.

AI research has evolved from analyzing images to integrating electronic health records (EHRs), laboratory data, and multi-omics information to establish comprehensive diagnostic frameworks. Including machine learning (ML), these techniques have been instrumental in identifying metabolomic biomarkers for early detection of systemic lupus erythematosus (SLE), delineating DNA methylation networks in psoriasis, and constructing personalized models for atopic dermatitis based on mitochondrial gene profiles<sup>[19–22]</sup>. AI-driven tools, such as random forest models for predicting drug responses, have significantly enhanced personalized therapy optimization<sup>[21,23,24]</sup>. Autonomous surgical robots have demonstrated remarkable precision levels, facilitating precise resections of skin tumors<sup>[25–27]</sup>. Natural language processing (NLP) systems such as Generative Pretrained Transformer 4 (GPT-4) analyze EHRs and patient narratives to offer tailored clinical recommendations, thereby augmenting diagnostic and treatment procedures<sup>[27–33]</sup>.

AI comprises five key technical domains driven by functional requirements: (1) pattern recognition for feature-based classification<sup>[34]</sup>; (2) ML to mimic human learning and improve algorithmic performance<sup>[35]</sup>; (3) data mining for extracting diagnostic and decision-support insights<sup>[36]</sup>; (4) intelligent algorithms designed for specialized computational tasks; and (5) human–computer interaction facilitated by LLMs to integrate clinical data<sup>[37]</sup>.

This review synthesizes advances across four AI paradigms: image recognition, large language models, multi-omics, and multimodal integration, within a unified dermatological framework. It examines the translational pathway from algorithm development to clinical deployment, addressing regulatory, ethical, and implementation challenges. By bridging these domains, this review provides a practical roadmap for clinicians, researchers, and

polymakers to advance intelligent, equitable, and precision dermatological care.

## The AI development and the core algorithmic foundation

### ML and DL of AI in dermatology

Dermatological AI relies on two key components: data engineering and data structuring, with ML and its deep learning (DL) subset serving as the foundation of

diagnostic frameworks (Fig. 1). ML enables autonomous learning and adaptive optimization by iteratively improving algorithms using training data to enhance predictive accuracy and decision-making<sup>[38,39]</sup>. In dermatology, ML assists in pattern recognition, image classification, lesion segmentation, and personalized treatment, while DL excels in complex image analysis and automated feature extraction.

ML comprises four primary paradigms: supervised, unsupervised, semi-supervised, and reinforcement learning

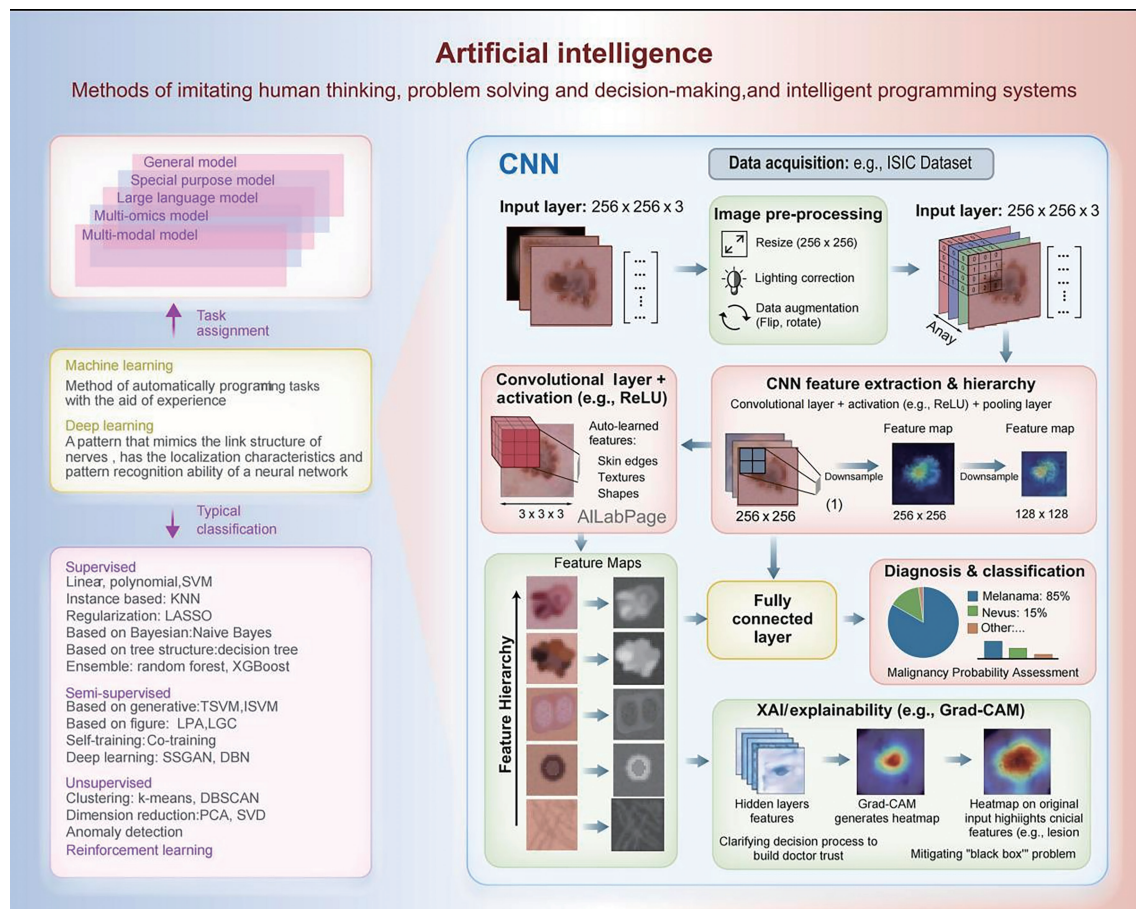


**Figure 1:** Schematic of artificial intelligence functional modules and convolutional neural network architecture in dermatology.

The figure outlines core AI methodologies, including ML, DL and RL, with representative algorithms spanning supervised, semi-supervised, and unsupervised paradigms. A typical CNN workflow for skin lesion analysis starts from data acquisition, where images undergo preprocessing. The input layer feeds into convolutional + activation (ReLU) and pooling layers, generating feature maps that automatically learn skin edges, textures, and shapes. After hierarchical feature extraction, a fully connected layer outputs malignancy probability for diagnostic classification (e.g., psoriasis, atopic dermatitis). To mitigate the black box problem, Grad-CAM produces a heatmap overlaid on the original input, highlighting critical lesion features and thereby enhancing interpretability and supporting clinician validation.

Abbreviations: CNN, convolutional neural network; DBN, deep belief network; Grad-CAM, gradient-weighted class activation mapping; ISIC, International Skin Imaging Collaboration; ISVM, inductive support vector machine; KNN, k-nearest neighbours; LASSO, least absolute shrinkage and selection operator; LGC, local and global consistency; LPA, label propagation algorithm; PCA, principal component analysis; ReLU, rectified linear unit; SSGAN, semi-supervised generative adversarial network; SVD, singular value decomposition; SVM, support vector machine; TSVM, transductive support vector machine; XAI, explainable artificial intelligence. DBSCAN, density-based spatial clustering of applications with noise.

(RL)<sup>[40]</sup>. In supervised learning, lesions are classified using labeled images, such as distinguishing between benign and malignant skin lesions with pathologically annotated data<sup>[41]</sup>. Unsupervised learning involves handling unlabeled data through clustering and pattern recognition techniques, aiding tasks such as segmentation and anomaly detection<sup>[38]</sup>. Semi-supervised learning seeks to minimize annotation costs by utilizing a blend of limited labeled data and extensive unlabeled datasets, thereby improving diagnostic accuracy<sup>[42]</sup>. Reinforcement learning optimizes diagnostic decisions through a trial-and-error iterative process guided by feedback from clinicians. Its effective application can increase the sensitivity of melanoma detection from 61.4% to 79.5%<sup>[43]</sup>. Despite its effectiveness, RL encounters challenges due to its substantial computational demands and requires further optimization for personalized clinical applications<sup>[43–45]</sup>.

DL is a subset of ML (Table 1) that utilizes artificial neural networks (ANNs), particularly convolutional neural networks (CNNs), to analyze medical images. ANNs enhance regression and classification tasks by capturing nonlinear relationships within data, while the multilayer convolutional architecture of CNNs enables automatic extraction of dermatological lesion features for classification, detection, and segmentation<sup>[42,46]</sup>. Each neural network layer captures distinct features (Fig. 2), and model performance is closely related to network depth, architecture, and data quality<sup>[47]</sup>. Training CNNs for dermatological diagnosis typically begins with acquiring high-resolution images of skin lesions, which are often

sourced from datasets provided by the International Skin Imaging Consortium (ISIC), one of the most representative open-access dermatology databases, which has accumulated over 540,000 publicly available images<sup>[48]</sup>. Image preprocessing generally includes resizing images to a standardized resolution (e.g.,  $256 \times 256$  pixels), adjusting illumination, and applying data augmentation techniques such as flipping and rotation to improve generalization performance. A typical CNN architecture consists of six layers: an input layer, convolutional layers, activation functions, pooling layers, fully connected layers, and an output layer (Fig. 2). Preprocessed dermoscopic images are fed into the input layer and are typically represented as a three-dimensional array: height  $\times$  width  $\times$  number of channels. For instance, a dermoscopic color image with a resolution of  $256 \times 256$  pixels is represented as a  $256 \times 256 \times 3$  array. The convolutional layer is the core component of CNNs and is responsible for automatically learning features from the input image, such as edges, textures, and shapes of skin lesions. A convolutional kernel, often with a small spatial size (e.g.,  $3 \times 3 \times 3$ ), contains learnable parameters—weights corresponding to the input channels. The dot product between the kernel and the local receptive fields of the input image produces a two-dimensional matrix known as a feature map. A convolutional layer typically contains multiple kernels, each generating a distinct feature map, which are then stacked to form the output feature representation. Following convolution, a nonlinear activation function is applied to enable the network to learn complex nonlinear patterns. Pooling layers perform downsampling to reduce the spatial dimensions of feature maps, thereby

**Table 1: Comparison of machine learning and deep learning**

|                      | Machine learning (ML)                                                                         | Deep learning (DL)                                                                                      |
|----------------------|-----------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------|
| Definition           | Based on manual feature extraction, utilizing statistical algorithms for pattern recognition. | Automatically learns features from data, leveraging multi-layer neural networks for complex learning.   |
| Data requirement     | Requires smaller datasets but depends on high-quality feature extraction.                     | Highly dependent on large-scale datasets and does not require manual feature extraction.                |
| Applicable scenarios | Suitable for structured data (e.g., numerical and categorical data).                          | Suitable for unstructured data (e.g., images, audio, and text).                                         |
| Model complexity     | Simpler models with high training efficiency and strong interpretability.                     | More complex models with longer training times, but highly effective in handling high-dimensional data. |
| Applications         | Gene analysis, simple image classification, drug efficacy prediction.                         | Medical imaging analysis, dermatological diagnosis, lesion segmentation.                                |

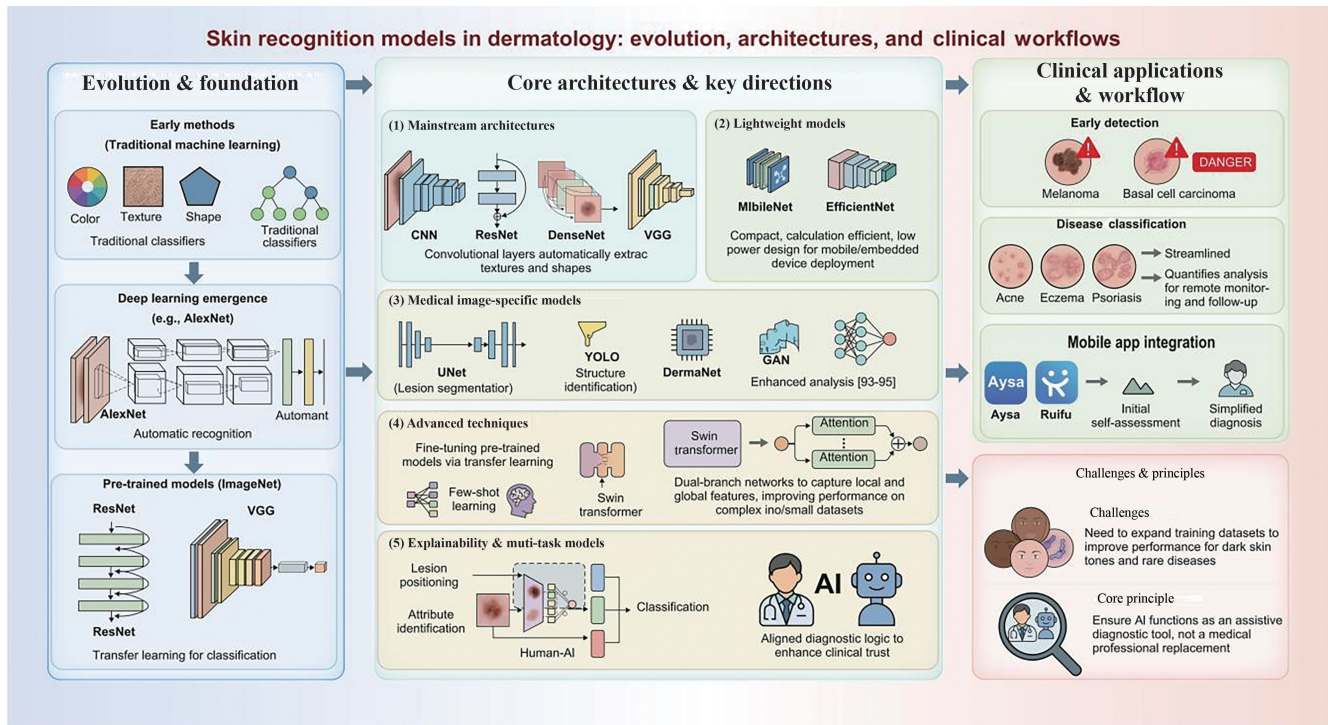


**Figure 2:** Evolution of skin recognition models from traditional machine learning to deep learning and transfer learning.

Skin recognition models in dermatology have evolved from traditional ML based on color, texture, and shape features to DL with AlexNet and subsequently to pretrained ImageNet models (ResNet, VGG) via transfer learning. Mainstream architectures include CNN, ResNet, DenseNet, and VGG for automatic extraction of textures and shapes, while lightweight models (MobileNet, EfficientNet) enable deployment on mobile or embedded devices. Medical image specific models such as UNet and DermaNet further enhance structural analysis, and advanced techniques, including finetuning, few shot learning, Swin Transformer, and dual branch networks improve performance on complex or small datasets. Explainability and multi-task models support lesion positioning, attribute identification, and human–AI interaction. Clinically, these models facilitate early detection of melanoma and basal cell carcinoma, disease classification, remote monitoring, and mobile applications (e.g., Aysa, Ruifu) for initial self-assessment. Challenges remain in expanding training datasets for dark skin tones and rare diseases, with the core principle that AI serves as an assistive diagnostic tool rather than a replacement for medical professionals.

Abbreviations: CNN, convolutional neural network; DenseNet, densely connected convolutional network; EfficientNet, efficient network; MobileNet, mobile network; ResNet, residual network; Swin, shifted window transformer; U-Net, U-shaped network; VGG, Visual Geometry Group; YOLO, you only look once (an object detection algorithm), AlexNet, Alex Network; GAN, generative adversarial network; DermaNet, Dermatological Network.

decreasing computational cost and improving translation invariance, meaning that minor positional variations do not significantly affect recognition performance. Through successive convolutional layers, the network extracts hierarchical features, progressing from basic elements (e.g., colors and edges) to increasingly complex textures and patterns. These features are subsequently used to classify skin lesions and estimate the likelihood of skin disease (e.g., 85% melanoma vs. 15% nevus). Despite their high diagnostic accuracy, CNN models often face challenges in interpretability, commonly referred to as the “black-box” problem. To address this limitation, explainable artificial intelligence (XAI) techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM), are used to generate heatmaps

highlighting critical regions (e.g., lesion boundaries), thereby enhancing clinicians’ trust and clarifying the decision-making process.

Several prominent CNN architectures widely applied in dermatology—including GoogleNet, Inception-V3/V4, ResNet, Inception-ResNet V2, and DenseNet—have demonstrated outstanding performance in large-scale image classification tasks by overcoming challenges such as vanishing gradients and improving the recognition of complex features<sup>[39,42]</sup>. These models are typically trained on diverse and reliable datasets, such as the ISIC archive, DermNet, synthetic dermatological datasets, and collections that include samples from multiple skin tones<sup>[48–53]</sup>.

## ***Evaluation in AI diagnosis for dermatology***

The assessment of AI-driven diagnostic and therapeutic systems frequently utilizes statistical parameters well-known to dermatologists, such as sensitivity, specificity, and accuracy<sup>[54,55]</sup>. Nevertheless, the advent of AI has brought forth supplementary statistical methods commonly employed in evaluating AI algorithms, such as the area under the receiver operating characteristic curve (AUROC), cross-validation, and the F1 score.

The AUROC assesses a model's capacity to differentiate between normal and diseased states across various thresholds, with a value of 1 indicating flawless classification and 0.5 representing random chance<sup>[56]</sup>. The F1 score, which merges precision and recall, proves particularly beneficial in imbalanced datasets, offering a balanced metric ranging from 0 (complete error) to 1 (perfect classification) when precision and recall exhibit notable discrepancies<sup>[57,58]</sup>. Cross-validation, a pivotal technique for evaluating the generalizability of models, entails the iterative training and testing on distinct data subsets<sup>[59]</sup>. In dermatology, characterized by limited data availability, cross-validation enhances efficiency and diminishes bias compared to single-split evaluations<sup>[60]</sup>. For instance, in 5-fold cross-validation with 100 dermatological images, the dataset is divided into five subsets, each used once as the test set, providing a mean F1 score (e.g., 0.77) to indicate model stability across diverse samples.

## ***The transferable application of AI technology from other diseases to dermatology***

Beyond skin disease identification and assistance, AI possesses cross-disease expertise in the fields of retinal pathology, tumor detection, and image-assisted diagnosis. Gulshan et al.'s diabetic retinopathy system achieved an F1 score of 0.95 in diabetic retinopathy detection using DL (compared to 0.91 for ophthalmologists), earning U.S. Food and Drug Administration (FDA) approval<sup>[61]</sup>. Trained on hundreds of thousands of annotated images, the system learned complex pathological features, enhancing its generalization ability to enable automated initial screening of fundus images. This reduces physician workload while offering scalability for deployment across different regions and devices. AI models consistently achieve area under the curve (AUC) values exceeding 90%

in applications such as lung cancer screening<sup>[62]</sup>, breast cancer detection<sup>[63]</sup>, prostate segmentation<sup>[64]</sup>, pediatric disease diagnosis<sup>[65]</sup>, and liver cancer detection<sup>[66]</sup>. Notably, in real-time multimodal fusion for liver cancer diagnosis and antimicrobial susceptibility testing, Sturm et al. validated ML-based nanomotion technology achieving an astonishing 98.9% accuracy in antibiotic sensitivity detection. This technology is transferable to pathogen identification and treatment monitoring in dermatology<sup>[67]</sup>. The key points for transferring these AI systems are: (1) massive standardized datasets, highlighting the importance of strengthening multi-center data sharing and standardization; (2) comprehensive integration of diagnosis, treatment, and management through advanced modeling techniques (e.g., reinforcement learning/multi-task learning); (3) seamless integration of AI with EHRs to advance intelligent diagnostic consultations and risk/prognosis assessment tools; (4) establishment of robust multi-center validation frameworks to ensure clinical relevance, interpretability, and data consistency in dermatological AI applications.

## ***Research, development and application of AI algorithm in dermatological diagnosis***

### ***Feature focused image recognition model***

Image recognition models are computer vision systems that utilize ML and DL algorithms to analyze image content, classify, and locate specific features within images. In dermatology, initial approaches relied on conventional ML techniques incorporating manually engineered features (e.g., color, texture, and shape). The emergence of DL, as demonstrated by AlexNet, facilitated the automatic identification of conditions such as melanoma. Subsequently, models pretrained on extensive datasets (e.g., ImageNet), such as ResNet and VGG, have been widely employed for the classification of skin diseases<sup>[68,69]</sup>.

Current dermatological image recognition models (Fig. 2) focus on several key directions: (1) Mainstream architectures such as CNN, ResNet, DenseNet, and VGG enable automated extraction of texture and shape features through convolutional layers<sup>[70]</sup>. (2) Lightweight models such as MobileNet and EfficientNet prioritize compact design, computational efficiency, and low power consumption, supporting mobile and embedded device

deployment<sup>[69,70]</sup>. (3) Medical-specific models, including DermaNet, U-shaped convolutional network (UNet), you only look once (YOLO), and generative adversarial network (GAN), are optimized for medical imaging tasks such as lesion segmentation and structural recognition, enhancing dermatological image analysis<sup>[71–73]</sup>. (4) Techniques such as transfer learning and few-shot learning fine-tune pre-trained models to mitigate data scarcity. Advanced architectures (e.g., Swin Transformer, two-branch networks) incorporate attention mechanisms to capture both local and global features, improving performance on complex and small-sample datasets<sup>[74,75]</sup>. (5) Interpretability-focused and multitask models integrate lesion localization, attribute recognition, and classification to align AI decision-making with dermatologists' diagnostic logic, advancing clinical trust and adoption<sup>[76,77]</sup>.

Image recognition models are extensively utilized in the early detection of skin cancer, particularly in identifying melanoma and basal cell carcinoma. These models also aid in the automated categorization of common skin conditions such as acne, eczema, and psoriasis, thereby enhancing the efficiency of outpatient workflows. Furthermore, they facilitate the quantification of disease progression for remote monitoring and follow-up purposes. Mobile applications (e.g., Aysa, Ruifu) have been integrated into outpatient services, enabling patients to conduct preliminary self-assessment via image uploads, thus streamlining pre-hospital diagnosis<sup>[78,79]</sup>. Ongoing challenges include the need to improve model performance for darker skin tones and rare diseases through the diversification of training datasets<sup>[80]</sup>. The current mainstream dermatological public datasets, such as ISIC, HAM10000, and SCIN, still show significant imbalances in terms of skin color representation. The widely used ISIC database and its derivative dataset HAM10000 mainly consist of dermoscopy images from Europe and Australia, thus overall featuring a majority of individuals with light skin tones<sup>[48]</sup>. HAM10000 contains a total of 10,015 dermoscopy images, but this dataset does not provide clear Fitzpatrick skin type labels, making it difficult to directly conduct performance evaluations between different skin tone subgroups<sup>[48,81]</sup>. In the ISIC 2018 dataset, the individual typology angles of most images are mainly concentrated in the 34.5°–48° range, which mainly corresponds to lighter skin tones, while the proportion of dark skin samples is significantly insufficient<sup>[82]</sup>.

In contrast, the Skin Condition Image Network (SCIN) dataset, designed at the outset with a clear emphasis on skin color diversity, includes over 5,000 volunteers who contributed more than 10,000 images<sup>[83]</sup>. It also provides self-reported and expert estimated skin color labels in the Fitzpatrick III–VI types, offering a wider coverage. Moreover, SCIN not only includes neoplastic lesions but also incorporates inflammatory, infectious, and allergic skin diseases, which are typically underrepresented in traditional dermoscopy datasets focused mainly on skin cancer<sup>[84]</sup>.

To overcome the inherent deficiency of current mainstream dermatology datasets in terms of skin color representation and prevent AI from exacerbating health inequalities in clinical deployment, future research should focus on data source expansion and targeted collection for minority ethnic groups, and conduct multi-center collaborations across countries or regions. For instance, a prospective image acquisition cohort specifically targeting Fitzpatrick IV–VI types could be established, or active collection of images of common skin diseases (such as inflammation and infection) among non-white ethnic groups could be carried out in grassroots community clinics, thereby filling the representational gap in the absolute quantity of data distribution<sup>[85,86]</sup>. However, merely expanding the data may not solve the problem; fairness considerations should be introduced in the algorithm design through loss functions to correct model bias. In conventional training, the standard cross-entropy loss is prone to driving the model into the trap of “majority class optimality”, masking the misdiagnosis rate of dark skin. To address this issue, dynamic intervention mechanisms can be introduced during the training phase. For example, sample reweighting or focal loss can be used to assign higher error penalty weights to the less frequent dark skin samples in the training set; or adversarial debiasing networks can be utilized to force the extraction of lesion features independent of skin color features, thereby mathematically compelling the model to achieve performance balance across different skin color subgroups<sup>[87]</sup>. Before clinical deployment, the AI model must undergo external multi-ethnic validation tests. The AI model cannot merely be internally evaluated on a homogeneously divided test set but must undergo rigorous double-blind tests in an independent external cohort that is completely separate from the training environment and has a different demographic distribution (for example, an independent

validation set collected in front-line medical institutions in Asia or Africa). Only when its generalization ability and diagnostic fairness are proven in diverse populations can the AI system be regarded as a safe and reliable universal medical tool<sup>[88]</sup>.

### ***LLMs based on inquiry-analysis-feedback***

ML and DL models have facilitated the automated classification and diagnosis of various skin conditions such as skin cancer, pigmented lesions, eczema, acne, and psoriasis<sup>[13,48,89]</sup>. Nevertheless, current models are constrained to specific classification tasks and necessitate validation by dermatologists. They do not possess the ability to generate natural language reports or engage with patients autonomously, thereby limiting symptom description and feedback. The incorporation of LLMs into dermatological workflows presents a novel opportunity to improve doctor-patient communication, provide diagnostic support, and enhance health education.

LLMs, a type of DL-based NLP technology, are trained on extensive datasets (e.g., books, articles, online content) to perform various tasks including text generation, translation, question answering, and code composition<sup>[90]</sup>. Built on the Transformer architecture, LLMs utilize multi-layer encoder-decoder structures to capture contextual dependencies and produce coherent natural language output. These models tokenize input text into words or sub-words, convert them into vector representations, and leverage attention mechanisms to predict and construct coherent sentences or paragraphs. In the field of dermatology, LLMs analyze patient histories and symptoms to propose diagnoses and referrals, demonstrating proficiency in natural language reasoning and context-aware recommendations as opposed to traditional algorithms focused on image analysis (Fig. 3). SkinGPT-4 combines a visual Transformer with an LLM to generate diagnostic reports with accuracy comparable to that of dermatologists<sup>[33]</sup>. LLMs are also employed to automate pathology reports, aid in complex case reviews, and provide guidance in image analysis and immunohistochemistry<sup>[91]</sup>. In dermatology certification examinations involving image-text cases, GPT-4 achieved a 90% accuracy, meeting clinical standards<sup>[92]</sup>. LLMs designed for patient interaction translate symptom descriptions, such as “red and itchy skin”, into easily

understandable health information, offering personalized advice.

LLMs are instrumental in advancing equitable healthcare. GPT-4 Vision, mitigates skin color bias by accurately identifying melanoma across diverse skin tones, enhancing diagnostic fairness<sup>[93]</sup>. The SkinGEN framework combines an LLM with an image-generation model and GAN to explain diagnoses, boosting patient trust in AI<sup>[94]</sup>.

### ***Multi-omics models based on molecular typing***

The integration of multi-omics technologies with AI has advanced the field of dermatology by transitioning from single-modality to comprehensive data analysis. Through the amalgamation of genomic, epigenomic, transcriptomic, and proteomic data, these models facilitate precise subtyping. A multi-omics model based on gene co-expression networks (GCN) that combines RNA expression and DNA methylation has demonstrated a substantial enhancement in the accuracy of tumor classification<sup>[95]</sup>. Comparable methodologies are being utilized in the study of skin conditions such as psoriasis and melanoma to achieve more nuanced subtype distinctions.

Recent DL advances, including sparse matrix factorization and self-supervised learning, have improved dimensionality reduction and feature extraction for high-dimensional multi-omics data, retaining key molecular signatures while reducing computational demands. These methods facilitate biomarker discovery, precise diagnosis, and personalized treatment of skin disease subtypes. The PathME model, leveraging pathway-based features, enhances molecular subtyping accuracy for inflammatory skin diseases such as psoriasis<sup>[96]</sup>. Moreover, to enhance clinician confidence, multi-omics approaches are increasingly incorporating XAI by integrating protein-protein interaction and ceRNA networks with causal inference models<sup>[97]</sup>. This integration enables the generation of diagnostically relevant outputs that are both biologically meaningful and interpretable.

Multi-omics models offer significant advantages in the clinical diagnosis and basic research of skin diseases: (1) integrating diverse omics layers to uncover disease pathways and therapeutic targets<sup>[98]</sup>; (2) leveraging

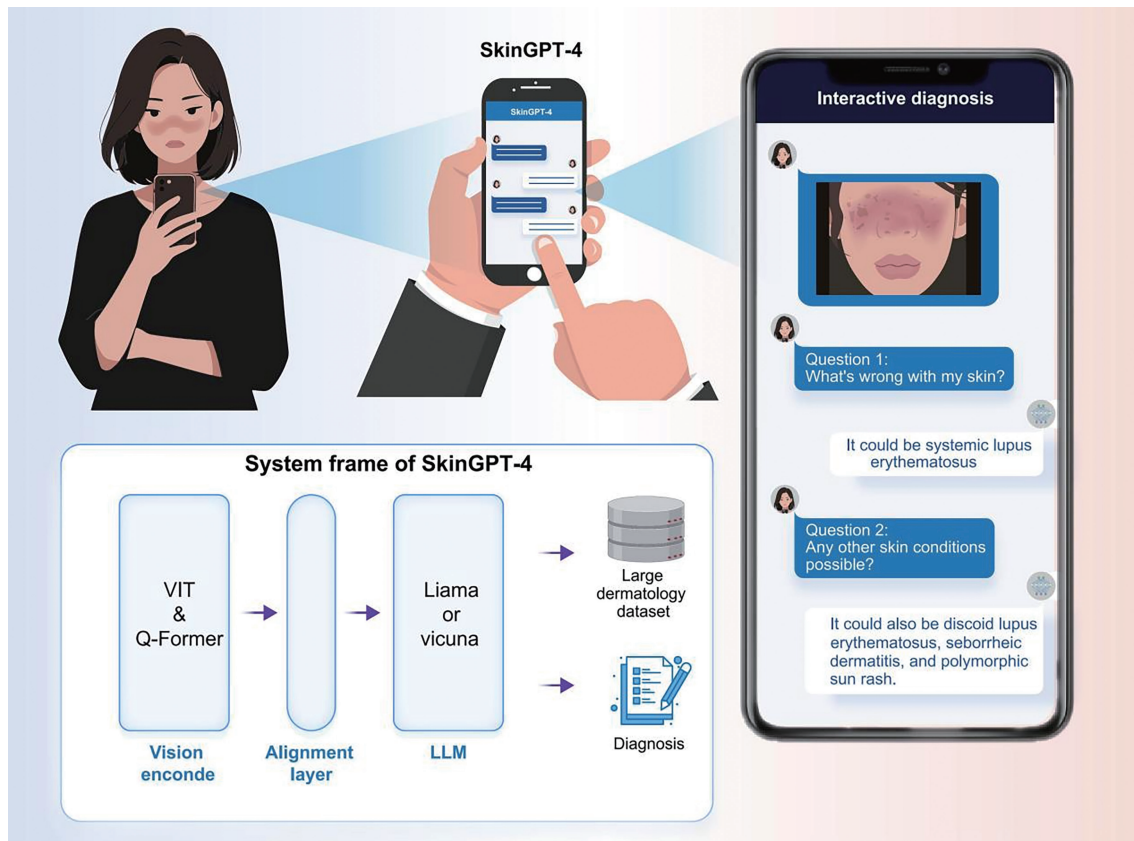


**Figure 3:** Typical large language model based framework for dermatological artificial intelligence diagnosis.

Schematic illustrating a multimodal framework that integrates vision transformers, alignment layers, and LLMs to process skin images and patient text inputs. The system outputs interactive diagnostic suggestions, demonstrating human–AI dialogue for dermatological decision support.

Abbreviations: GPT, generative pre-trained transformer; Q-Former, querying transformer; VIT, vision transformer; LLM, large language model.

single-cell and spatial transcriptomics for precise inflammatory cell profiling in conditions such as psoriasis and atopic dermatitis; (3) analyzing skin microbiota dynamics via combined metagenomic and proteomic data, offering new perspectives on host-microbe interactions<sup>[99]</sup>; (4) predicting personalized drug responses by evaluating skin barrier integrity, metabolic pathways, and immune status, advancing precision dermatology and cosmetology<sup>[100]</sup>. These models also refine immunotherapy strategies by dissecting gene expression patterns across tumor and stromal compartments in cancers such as melanoma, enabling targeted modulation of immune cells<sup>[98]</sup>. The interdisciplinary nature of multi-omics fosters collaboration across dermatology, microbiology, and immunology, accelerating comprehensive exploration of skin health and disease<sup>[101]</sup>.

AI-driven multi-omics models have made significant

strides in accurately classifying skin diseases, yet encounter challenges including data heterogeneity, noise interference, limited biological interpretability, and high computational demands<sup>[97,102]</sup>. To enhance interpretability, integrating causal inference with biological networks such as protein–protein interactions and pathways is crucial. Additionally, the analysis of high-dimensional omics data necessitates substantial computing resources and cost of sequencing, thereby restricting accessibility in resource-limited settings. Data scarcity, particularly concerning rare subtypes of skin diseases, further compromises the robustness of models. Federated learning presents a promising solution by facilitating the sharing of data across multiple institutions to enhance the generalizability of models. Future endeavors should prioritize the development of interpretable, scalable, and globally inclusive AI systems that integrate multi-omics data for dermatological applications.

## **Multimodal model for multidimensional information integration**

Integrating cross-modal data, such as medical images, clinical records, omics, and dynamic monitoring, into multimodal models enhances diagnostic precision and treatment decisions, beyond the molecular emphasis of multi-omics and the linguistic capabilities of LLMs (Table 2)<sup>[103]</sup>. Skin conditions such as SLE, psoriasis, autoimmune bullous disorders (e.g., bullous pemphigoid, linear IgA disease), and melanoma are characterized by intricate interactions among immune responses, genetic predispositions, and environmental influences. Therefore, a comprehensive integration of data is essential to improve clinical outcomes in managing these conditions<sup>[104–107]</sup>.

In dermatology, multimodal data fusion spans: (1) images (dermoscopic, clinical, pathological); (2) text (medical histories, diagnostics, lab reports); (3) multi-omics data; (4) dynamic monitoring (wearables); and (5) other formats (videos, audio). Traditionally analyzed in isolation, these diverse data sources are now being integrated using AI techniques to enhance both diagnostic processes and treatment outcomes. Hao et al. proposed a multimodal framework combining RNA and chromatin data to refine cell identity mapping and elucidate immune responses to vaccination<sup>[108]</sup>. Similarly, multimodal image fusion (CT, MRI, and PET) has improved diagnostic accuracy<sup>[109]</sup>, while Medical Contrastive Language-Image Pre-training (MedCLIP) and Medical Generative Pre-trained Transformer (Med-GPT) integrate images, text, time-series, and omics data, advancing medical knowledge retrieval and clinical decision-making<sup>[103,110,111]</sup>.

The clinical application of multimodal AI models typically follows five steps: (1) data acquisition and preprocessing (cleaning, standardization, noise reduction); (2) feature extraction to refine modality-specific data; (3) modality alignment and algorithmic fusion; (4) model training and optimization; and (5) deployment prioritizing practicality and interpretability<sup>[112]</sup>. Each modality requires tailored preprocessing: for example, U-Net segments dermatological lesions<sup>[113]</sup>; omics data undergo noise reduction and key feature selection to identify biomarkers<sup>[114–118]</sup>; support vector machine (SVM) detects hyphal features in fungal infections<sup>[119]</sup>; and NLP extracts disease-relevant information from EHRs<sup>[120]</sup>.

Data fusion methods are categorized into early, mid, and late fusion. Early fusion combines features at the input level, which is beneficial for highly correlated modalities. For instance, merging dermoscopic images with medical history can enhance the assessment of severity<sup>[117]</sup>. Mid fusion involves extracting features independently and integrating them through joint learning, making it suitable for intricate analyses such as combining RNA sequencing with imaging data using co-attention mechanisms<sup>[121]</sup>. Late fusion merges final predictions through weighted voting or averaging, particularly effective when modalities are weakly correlated, as seen in integrating DNA methylation data with clinical scoring models in SLE<sup>[114]</sup>. Training models that incorporate multiple modalities poses challenges related to data heterogeneity, noise, and redundancy<sup>[118]</sup>. Dermatological images, for example, may be affected by lighting conditions, skin oils, or hair, while text data could suffer from semantic mismatches. A fundamental challenge lies in establishing connections between visual features (e.g., lesion texture) and symptoms (e.g., itching severity)<sup>[118]</sup>. Recent strategies to address these challenges include optimizing loss functions, such as cross-entropy, to enhance classification robustness<sup>[122]</sup>, integrating ResNet with attention mechanisms for precise lesion detection<sup>[119]</sup>, and utilizing Transformers to dynamically assign weights to modalities for improved alignment<sup>[123]</sup>.

The potential of multimodal AI in dermatological diagnosis is significant, yet it encounters challenges such as data inconsistency, high computational costs, and limited interpretability<sup>[122,123]</sup>. Variability among institutions impedes model generalization, while the complexity of high-dimensional data increases training requirements.

## **AI promotes systematic innovation in skin disease drug development**

AI accelerates drug development by enhancing target identification, lead optimization, molecule design, and trial simulation. This transformation, traditionally a decade or more, is now expedited through AI technologies such as omics analysis, DL, and NLP. Insilico Medicine's PandaOmics identified TRAF2- and NCK-interacting kinase (TNIK) as a fibrosis target and completed preclinical candidate screening within 18 months using Pharma.AI. GENTRL algorithm designed six discoidin domain

**Table 2: Comparison of four artificial intelligence models in dermatology**

| Dimension                   | Multi-omics model                                                                                                                                                                          | Multimodal model                                                                                                                                                                                                                         | LLM                                                                                                                                                                                           | Image recognition model                                                                                                                                                |
|-----------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Data sources                | Genomics (DNA mutations, copy number variations), Epigenomics (DNA methylation), Transcriptomics (RNA expression), Proteomics, Metabolomics                                                | Image data (dermoscopy, pathology slides, CT, MRI), Text data (medical history, physician notes, lab reports), Omics data (genomics, epigenomics, transcriptomics, proteomics, metabolomics), Dynamic monitoring data (wearable devices) | Text-based data, including patient descriptions, physician notes, and scientific literature; Can integrate patient history, lab results, symptom descriptions, and multimodal inputs          | Image data (clinical photos, dermoscopy, pathology slides); Focuses solely on visual inputs without integrating textual or molecular data                              |
| Technical framework         | Feature extraction and dimensionality reduction: sparse matrix decomposition, variational autoencoders (VAEs); Graph convolutional networks (GCNs) leveraging biological networks          | Early fusion: integration of image and text at data input stage; Mid-level fusion: cross-attention mechanisms to enhance intermodal associations; Late fusion: independent training followed by results integration                      | Pretrained language models (e.g., Transformer-based architectures such as GPT, BERT); Fine-tuning or embedding domain-specific medical data for clinical tasks                                | Convolutional Neural Networks (CNNs) such as ResNet, EfficientNet; Vision Transformers (Swin Transformer); Lightweight models such as MobileNet; UNet for segmentation |
| Applicable scenarios        | Molecular subtyping and biomarker discovery; Understanding disease mechanisms at the molecular level; Supporting personalized treatment strategies                                         | Integrated diagnosis and dynamic monitoring; Real-time decision support (e.g., image recognition combined with text-based diagnostics)                                                                                                   | Multimodal question-answering: extracting insights from patient descriptions and medical literature; Assisting in the interpretation of complex model predictions                             | Skin disease classification (e.g., melanoma detection); Lesion segmentation and boundary delineation; Image-only AI diagnostic tools                                   |
| Advantages                  | Precisely elucidates disease mechanisms at the molecular level; Provides detailed molecular subtyping for drug development and target discovery                                            | Integrates multimodal data, covering both macroscopic phenotypes and microscopic molecular features; Supports holistic analysis, improving diagnostic and predictive accuracy                                                            | Understands and generates natural language; Supports complex medical queries; Dynamically synthesizes medical knowledge and processes unstructured data, such as patient symptom descriptions | High accuracy in visual pattern recognition; Mature DL architectures; Strong performance in classifying skin conditions purely from images                             |
| Limitations                 | Limited to molecular-level analysis; Difficult to integrate macroscopic data (e.g., imaging and dynamic patient monitoring); High computational costs for processing high-dimensional data | Challenges in aligning cross-modal data, particularly in spatial and temporal synchronization; Model performance may be affected by noise and variability in data quality                                                                | Accuracy depends on training data quality; Lacks direct modeling of multimodal data (e.g., extracting image features); Limited interpretability in clinical decision-making                   | Cannot interpret non-visual data (e.g., patient history); Struggles with rare diseases without sufficient visual samples; Sensitive to image quality                   |
| Representative applications | GCN-based multi-omics classification in dermatology; PathME model for pathway-based molecular subtyping                                                                                    | MedCLIP integrating imaging and text for dermatological diagnosis; Vision Transformer enhancing classification accuracy with multimodal inputs                                                                                           | SkinGPT-4 integrating clinical text and images for dermatological diagnosis and treatment recommendation, achieving 89% diagnostic accuracy                                                   | MobileNet/EfficientNet for mobile skin apps; UNet for lesion segmentation; Swin Transformer for precise classification                                                 |
| Future trends               | Efficient feature extraction using self-supervised learning to reduce data noise; Causality-driven modeling using biological networks to improve interpretability                          | Optimizing cross-modal alignment and deep multimodal fusion algorithms; Expanding clinical scenario support (e.g., real-time monitoring and prediction)                                                                                  | Expanding multimodal integration with imaging and omics data; Enhancing medical dialogue systems and decision-support explainability                                                          | Hybrid architectures combining CNN + Transformers; Improved robustness to diverse skin types and image quality; Lightweight models for real-time clinical use          |

Abbreviations: BERT, bidirectional encoder representations from transformers; CNN, convolutional neural network; DL, deep learning; EfficientNet, efficient network; GCN, graph convolutional network; GPT, generative pre-trained transformer; LLM, large language model; MobileNet, mobile network; ResNet, residual network; UNet, U-shaped network; VAE, variational autoencoder; MedCLIP, Medical Contrastive Language-Image Pre-training. Swin Transformer, shifted window transformer.

receptor 1 (DDR1) inhibitors in 21 days, resulting in four active compounds and one with promising *in vivo* outcomes<sup>[124–126]</sup>. In China, DeepBlock improved ligand design, increasing synthesizability by 6% and achieving a 0.54 drug-like score<sup>[127]</sup>. Stanford’s TrialPathfinder simulated lung cancer trials, suggesting that relaxed eligibility criteria could double enrollment and reduce mortality risk, benefiting more patients<sup>[128]</sup>. In dermatology, AI advances precision therapy by integrating omics, imaging, and clinical expertise for novel drug discovery, regimen optimization, and drug repurposing (Table 3).

### **AI-assisted new drug discovery: cross-disease, high-throughput, targeted precision**

AI accelerates target discovery and candidate compound generation by advancing drug development from “single-target” to “multi-target network” paradigms. Through the integration of transcriptomics, protein interactions, and structural data, AI constructs intricate drug–target–pathway–disease maps. Graph neural networks (GNNs) uncover critical regulatory modules, such as the IL-23/Th17 and JAK-STAT pathways’ interaction in

**Table 3: Typical case studies of artificial intelligence in dermatology for drug discovery and development**

| Type of research                          | Applicable disease types    | Research methodology or model                          | Reference                                  |
|-------------------------------------------|-----------------------------|--------------------------------------------------------|--------------------------------------------|
| AI molecular design platform              | Multiple diseases           | Chemistry42 molecular design and optimization platform | Ivanenkov <i>et al.</i> <sup>[126]</sup>   |
| AI target and biomarker discovery         | Multiple diseases           | PandaOmics target prediction platform                  | Kamya <i>et al.</i> <sup>[125]</sup>       |
| Generative model                          | Broad adaptability          | Toxicity-controlled small molecule generation          | Li <i>et al.</i> <sup>[127]</sup>          |
| Generalization to real-world data         | Oncology                    | ML-based clinical trial simulation                     | Orcutt <i>et al.</i> <sup>[128]</sup>      |
| Personalized transdermal drug delivery    | Dermatological diseases     | Transdermal drug delivery strategy                     | Zhao <i>et al.</i> <sup>[129]</sup>        |
| Multi-graph neural network modeling       | Psoriasis, skin cancer      | Drug-target prediction model                           | Zhang <i>et al.</i> <sup>[130]</sup>       |
| Multimodal foundation model               | 28 Skin diseases            | PanDerm universal multimodal large model               | Yan <i>et al.</i> <sup>[131]</sup>         |
| Machine learning prediction               | Atopic dermatitis           | Multi-algorithm model ensemble prediction              | Maulana <i>et al.</i> <sup>[132]</sup>     |
| Explainable GNN                           | Drug response               | DRExplainer graph convolutional network                | Shi <i>et al.</i> <sup>[133]</sup>         |
| Single-cell drug repositioning            | Multiple diseases           | ASGARD drug repositioning pipeline                     | He & Garmire <sup>[134]</sup>              |
| Deep simulated clinical trials            | Precision medicine          | RWD-based subgroup model                               | Lee <i>et al.</i> <sup>[135]</sup>         |
| Transfer learning for response prediction | Oncology                    | Perturbation-specific gene network transfer learning   | Bang <i>et al.</i> <sup>[136]</sup>        |
| Clinical trial data mining                | Multiple diseases           | Lab result-driven drug-disease mapping                 | Wen <i>et al.</i> <sup>[138]</sup>         |
| Causal inference + deep learning          | Multiple diseases           | Causal inference + RWD drug repositioning framework    | Liu <i>et al.</i> <sup>[139]</sup>         |
| LLM drug recommendation                   | Multiple diseases           | DrugAgent language model reasoning                     | Inoue <i>et al.</i> <sup>[140]</sup>       |
| Microbial community modeling              | Atopic dermatitis, acne     | ODE dynamics + pathway stability analysis              | Greugny <i>et al.</i> <sup>[141]</sup>     |
| Transfer learning                         | Skin disease classification | CNN model transfer learning                            | Velasco <i>et al.</i> <sup>[142]</sup>     |
| Knowledge distillation                    | Melanoma                    | Compressed model for melanoma detection                | Khan <i>et al.</i> <sup>[143]</sup>        |
| Microneedle technology                    | Dermatological diseases     | Microneedle formulation treatment strategy             | Han <i>et al.</i> <sup>[144]</sup>         |
| Deep learning drug screening              | Cancer, etc.                | DDR1 inhibitor identification                          | Zhavoronkov <i>et al.</i> <sup>[145]</sup> |

Abbreviations: CNN, convolutional neural network; DL, deep learning; GCN, graph convolutional network; GNN, graph neural network; LLM, large language model; ML, machine learning; ODE, ordinary differential equation; RWD, real-world data. DDR1, discoidin domain receptor 1; DRExplainer, drug response explainer; ASGARD, a single-cell guided drug repositioning pipeline; PanDerm, a universal multimodal large model for dermatology.

psoriasis<sup>[129]</sup>. Yu et al. introduced DrugMAN, a multi-graph attention model that merges protein and chemical networks to pinpoint targets for psoriasis, surpassing graph attention network (GAT) and GCN benchmarks<sup>[130]</sup>. Fang et al. devised the DGMM model, which merges D-VAE encoding with a genetic algorithm to generate drug-like, synthesizable small molecules<sup>[131]</sup>. By simulating the evolution of drugs, the model achieves human-level performance in molecular optimization. DGMM establishes a comprehensive AI framework from mechanism discovery to compound generation, particularly suitable for intricate, multi-mechanism skin diseases.

### ***Personalized treatment: prediction of efficacy, and population typing***

In the realm of limited clinical drug trial data, the utilization of AI to tailor treatment approaches through the prediction of drug responses and the provision of interpretable guidance is a prominent area of research. Maulana et al. introduced a framework that integrates extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), and Random Forest, incorporating various features such as skin inflammation scores, serum markers, and family history to categorize the severity of atopic dermatitis and optimize dosage<sup>[132]</sup>. The DRExplainer model merges dynamic graph convolutional networks with interpretable subgraph mining to forecast psoriasis outcomes and identify JAK/ILs-related gene subnetworks<sup>[133]</sup>. Additionally, ASGARD employs single-cell expression data to delineate drug response landscapes, initially focusing on tumors and subsequently adapting for inflammatory skin conditions such as vitiligo<sup>[134]</sup>. STEDR, on the other hand, simulates treatment trajectories based on EHRs, offering personalized classification and risk assessment strategies<sup>[135]</sup>.

### ***Drug repurposing***

AI facilitates identifying drugs capable of reversing disease-specific gene expression patterns, by comparing differentially expressed genes (DEGs) in lesional tissues with drug-induced transcriptional profiles, leveraging the inverse expression principle. Databases such as the Library of Integrated Network-Based Cellular Signatures (LINCS) L1000 enable large-scale matching between disease perturbation signatures and pharmacologic effects,

supporting candidate prioritization through network-based and pathway co-modulation analyses<sup>[136,137]</sup>.

Wen et al. integrated clinical feature vectors with CMap data to reverse-match drugs for off-label indications, improving screening accuracy<sup>[138]</sup>. Liu et al. applied counterfactual simulations to reconstruct hypothetical patient responses, enabling personalized efficacy comparisons<sup>[139]</sup>. DrugAgent combined multi-agent models (e.g., Deep-Purpose drug-target interaction [DTI]) with knowledge graphs (DGIdb, DrugBank, CTD, STITCH) to map drug–pathway–literature networks and validate candidates for atopic dermatitis<sup>[140]</sup>. Greugny et al. employed an ordinary differential equation (ODE)-based kinetic model to simulate skin flora recovery, identifying a therapeutic window for microecological interventions in acne and eczema<sup>[141]</sup>.

### ***Drug development to clinical implementation: model compression, system integration, and treatment closed-loop control***

AI integration is accelerating innovation in dermatological drug development, with early efforts centered on image recognition. Current advancements emphasize model compression, system integration, and closed-loop treatment control. Velasco et al. showed that MobileNet achieved 94.1% accuracy for psoriasis, acne, and ringworm, making it suitable for mobile deployment<sup>[142]</sup>. A distilled melanoma model was reduced to 0.26 million (M) parameters, enabling wearable applications for efficacy monitoring<sup>[143]</sup>. Han et al. further combined AI risk scoring with microneedle delivery to create a closed-loop drug release system for psoriasis treatment<sup>[144]</sup>. These developments highlight AI's transition from a diagnostic tool to an active participant in therapeutic modulation.

### ***Development of dermatological AI clinical deployment and related standards and consensus***

Effective implementation of AI in dermatology requires seamless integration of ML, DL, LLMs, and multimodal models with clinical tools such as dermatoscopes and EHRs to ensure data interoperability. AI should augment, not replace, clinician decision-making. Compliance with regulations such as General Data Protection Regulation (GDPR) and Health Insurance Portability and Accounta-

bility Act (HIPAA) is essential to protect patient privacy and ensure secure clinical deployment. In clinical practice, AI systems must adapt to real-time feedback and maintain strong interpretability and user-centered design to gain clinician and patient trust (Fig. 4). Promoting data sharing via standardized formats such as Fast Healthcare Interoperability Resources (FHIR) and Health Level Seven (HL7) is essential for cross-institutional collaboration and the large-scale implementation of dermatology AI.

### ***Trends in AI model deployment for dermatology: from traditional algorithms to hybrid and specialized models***

AI applications in dermatology have evolved from classical

ML to multimodal models. Early algorithms such as traditional ML models such as least absolute shrinkage and selection operator (LASSO), SVM, and naive Bayes (NB) have supported gene marker identification<sup>[146]</sup>, personalized treatment planning<sup>[147]</sup>, and infectious disease screening<sup>[148,149]</sup>. Yet, their dependence on manual feature extraction limits performance in high-dimensional tasks. DL overcomes this via end-to-end processing, with CNN models achieving 96%–97% accuracy on HAM10000 and surpassing conventional methods in tumor classification (e.g., VGG16, ResNet50: 88% vs. 72%)<sup>[150]</sup>. Transformer-based LLMs such as GPT-4 and BERT also enhance text-driven diagnostic support<sup>[151]</sup>. As diagnostic needs grow, specialized and hybrid models are gaining traction. Tailored DL networks for skin cancer improve efficiency

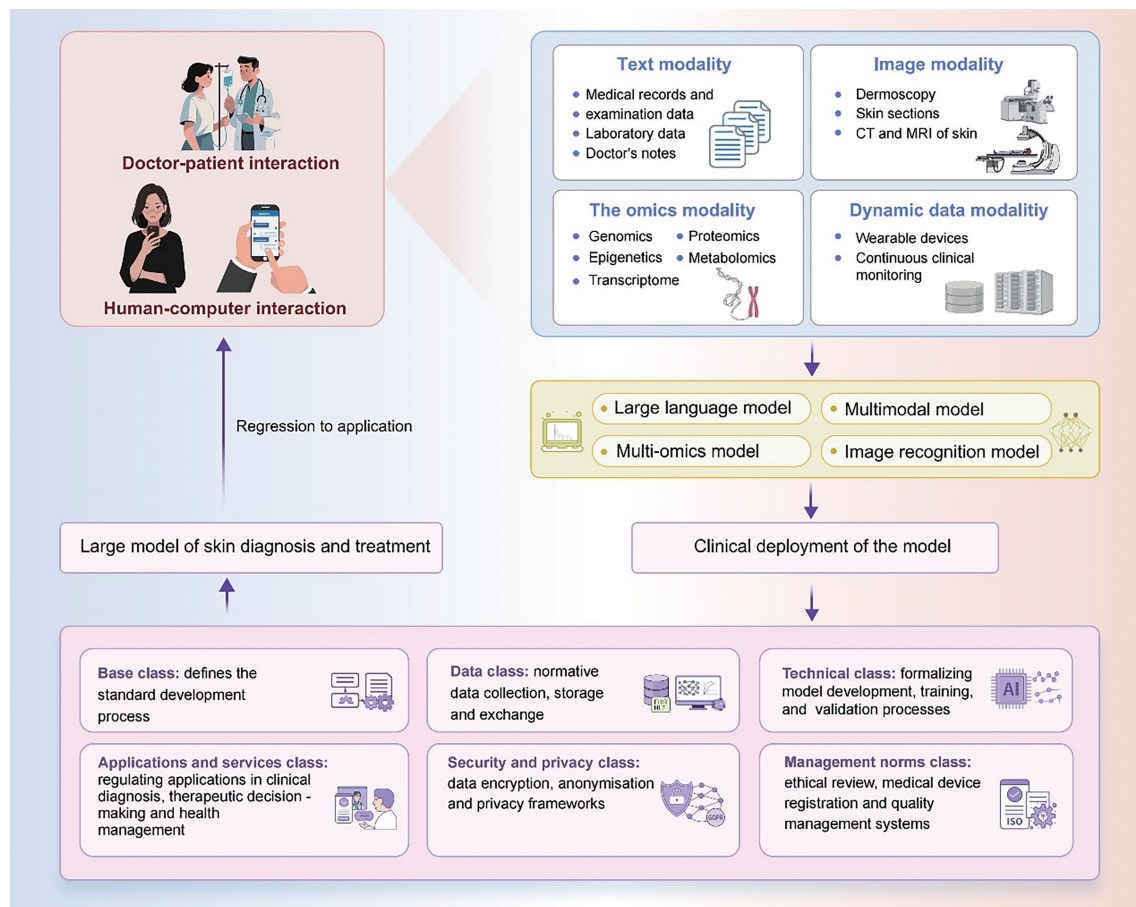


**Figure 4:** An ideal standardized artificial intelligence framework for personalized skin care.

Multimodal data from doctor-patient and human-computer interactions, encompassing text, image, omics, and dynamic signals, form the input for large-scale AI models, including large language models, multimodal architectures, and image recognition systems. These models are trained and deployed within a structured framework comprising base, data, technical, application, security, and governance standards. This facilitates closed-loop implementation in clinical settings, advancing precision diagnosis, therapy optimization, and individualized skin care.

Abbreviations: CT, computed tomography; MRI, magnetic resonance imaging.

and suit mobile deployment through parameter simplification<sup>[152]</sup>. Models adapted for diverse skin types enhance diagnostic fairness<sup>[153]</sup>. Hybrid approaches that combine CNN feature extraction with SVM classification improve accuracy, especially in small datasets<sup>[154,155]</sup>. These models are advancing personalized care and decision support in dermatology.

### **Research standards and application specifications**

A robust standardization framework is essential for clinical deployment, including: (1) foundational standards: defining AI concepts, model structures, and evaluation metrics; (2) data standards: such as HL7 and FHIR for cross-platform data exchange; (3) technical standards: detailing model training and validation protocols; (4) application standards: outlining clinical decision-making criteria; and (5) safety and ethical standards: ensuring patient data protection under GDPR and HIPAA regulations<sup>[156–158]</sup>.

Effective deployment of AI in dermatology relies on the complementary roles of FHIR and the Common Data Model (e.g., Observational Medical Outcomes Partnership [OMOP]). FHIR functions as a communication protocol facilitating standardized exchange of clinical, imaging, and omics data through modular APIs and structured formats such as JSON/XML<sup>[159–161]</sup>. It enables genomic-clinical integration in conditions such as psoriasis and SLE<sup>[162]</sup>, enhancing data interoperability across hospital networks<sup>[163]</sup>. OMOP offers a unified schema for multi-center AI research, aiding in integrating EHRs, imaging, and omics data for disease modeling and personalized treatment<sup>[164–166]</sup>. However, OMOP encounters challenges in handling unstructured inputs such as dermoscopic images and physician notes. Improving OMOP's flexibility and enhancing FHIR's data granularity are crucial for developing robust AI models in dermatology.

To advance AI-driven dermatology, existing frameworks should be extended to accommodate dermoscopic imaging, genomics, and clinical history. Integration tools such as OHDSI's ATLAS can support data mapping and quality control. Establishing dermatology-specific databases and fostering multi-center, cross-national data exchange will strengthen diagnostic precision and

individualized care through standardized, interoperable data infrastructures.

## **Real-world translational applications of AI in dermatology**

### **Telemedicine and mobile health**

Telemedicine and mobile health technologies have revolutionized the provision of care for skin diseases, effectively tackling the worldwide impact of dermatological conditions. In Europe, an estimated annual affliction of over 185 million adults underscores the significant burden<sup>[167]</sup>. Scarce dermatological resources pose challenges to prompt care delivery, especially in marginalized regions. The incorporation of AI in diagnostic processes, monitoring strategies, and teleconsultation services enhances accessibility and operational effectiveness. Research indicates that the implementation of smartphone-enabled remote management leads to a substantial 70% decrease in physical consultations, thereby optimizing results and resource distribution<sup>[168,169]</sup>.

AI-powered telemedicine enables patients to capture high-resolution skin images via mobile devices, allowing physicians to remotely assess lesion characteristics, such as morphology, color, and texture, for faster, more accurate diagnosis<sup>[170,171]</sup>. This is especially beneficial for managing chronic conditions such as eczema and psoriasis. Wearables and health apps transmit data on skin moisture, inflammation, and erythema, supporting real-time monitoring and treatment adjustment<sup>[172,173]</sup>. Integrated platforms provide clinicians with medical history, symptom evolution, and family history, enhancing diagnostic precision for complex autoimmune skin diseases<sup>[174,175]</sup>. EHR systems further assist in tracking treatment responses and refining personalized care. Additionally, telehealth tools empower patients with educational content and self-monitoring functions. Surveys show over 90% acceptance of online consultations and e-prescriptions<sup>[176]</sup>.

The success of AI-driven telemedicine relies on the integration of diverse data modalities. Although the use of omics data in telehealth is nascent, home genetic testing enables early identification of hereditary skin disorders including keratosis and congenital pigmentation abnormalities<sup>[162,177]</sup>. Wearable devices capture dynamic

parameters such as skin temperature and humidity, which can indicate inflammatory activity in real time<sup>[172,173]</sup>. The fusion of these inputs requires advanced AI processing capabilities and underscores the importance of training clinicians in intelligent diagnostic workflows.

Diagnostic accuracy of telemedicine applications depends heavily on reliable, timely data transmission, and any delays or data loss can impair outcomes. Inconsistent data formats, such as variations in EHR systems across institutions, further hinder integration efforts<sup>[178]</sup>. Ensuring patient privacy remains critical, requiring strict adherence to GDPR, HIPAA, and best practices for data encryption and anonymization. Current AI tools are limited by data quality and user proficiency among clinicians and patients. Strengthening multimodal modeling is essential to improve adaptability and performance<sup>[179]</sup>. With continued technological progress, telemedicine is expected to play a growing role in delivering dermatological care and expanding global access.

### **Typical tool applications of dermatological AI**

We summarized major AI tools currently applied in this field, covering diagnosis, image classification, subtype identification, inflammation quantification, clinical integration, and drug development. Table 4 presents an overview of each system's functions, target conditions, implementation status, and supporting studies, offering a reference framework for advancing intelligent dermatological diagnostics and therapies.

### **Practical AI considerations for dermatologists: data, algorithms, and computational resources**

As shown in Figure 5, the clinical utilization of AI in dermatology is underpinned by three fundamental components: data, algorithms, and computational infrastructure. Among these, the quality of the training data, which encompasses skin lesion images, pathology slides, EHRs and clinical documentation, plays a pivotal role in determining model efficacy<sup>[206]</sup>. Nonetheless, raw data frequently exhibit imperfections such as noise, redundancy, and gaps in annotation, necessitating systematic preprocessing procedures such as error rectification, standardization, and outlier elimination to enhance training

resilience<sup>[207]</sup>. In supervised learning, precise expert annotation of diagnostic labels and lesion delineations is indispensable for enhancing model training and predictive accuracy.

Early dermatological AI heavily relied on traditional models for their interpretability, but they faced challenges with high-dimensional, heterogeneous data and lacked the scalability of DL models<sup>[208–210]</sup>. DL addresses these limitations by enabling end-to-end learning to automatically extract intricate features from raw data. CNNs excel in skin image classification and lesion detection, while Long Short-Term Memory networks (LSTMs) handle time-series data for dynamic disease monitoring. GANs enhance and synthesize medical images<sup>[39,211–213]</sup>. Despite their effectiveness, DL models require significant computational resources, such as GPUs and TPUs, and are often opaque, complicating result interpretation and potentially undermining clinical trust. In the realm of medical AI research, there is a growing interest in specialized and hybrid models for their task-specific adaptability. Lightweight CNNs, designed for dermatological image analysis on mobile devices, optimize computational efficiency in resource-constrained environments<sup>[214]</sup>. Hybrid models frequently merge CNN-based feature extraction with classifiers such as SVM or random forests to enhance diagnostic versatility<sup>[215]</sup>. An innovative hybrid quantum computing model proposed by Vijayasri Iyer et al., leverages quantum systems to encode dermatological image features and achieves high classification accuracy on the HAM10000 dataset, showcasing the promising integration of quantum computation in dermatological diagnostics<sup>[216]</sup>. However, these models may impose substantial computational requirements, particularly in real-time and multimodal scenarios, necessitating distributed computing or multi-GPU systems for practical implementation.

For clinicians, the clinical deployment of AI modules in dermatology requires comprehensive planning across multiple dimensions: (1) data preparation: Identify relevant data types (e.g., clinical images, omics data, medical records, pathology slides, teleconsultation transcripts, and follow-up records); determine whether preprocessing (e.g., noise reduction, standardization) is necessary; consider patient stratification based on clinical features; and evaluate the need for optimization

**Table 4: Examples of typical artificial intelligence systems for dermatology in clinical deployment.**

| Tool name  | Intended use                                                                                                                                                                                                   | Validation type                                                      | Study design                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       | Sample size                                                                                                                                                                                                                                                                 | AUROC/Sensitivity/<br>Specificity                                                                                                            | Regulatory status                                                                                                                                                                                                                                                                                  | Deployment status                                 | Reference or link                                                                  |
|------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------|------------------------------------------------------------------------------------|
| SkinVision | The SkinVision app uses AI combined with a panel of expert dermatologists to assess suspicious skin lesion and provides a risk indication that helps users make informed decisions about seeking medical care. | Involving multi-center data training and prospective clinical trials | Prospective, cross-sectional, multicentre diagnostic accuracy study, conducted at two dermatology outpatient clinics in the Netherlands (Erasmus MC Cancer Institute & Albert Schweitzer Hospital), each lesion was first examined by a clinician, then assessed using the SkinVision app (iOS or Android), app risk outcomes were compared to histopathology (when indicated) or dermatologist diagnosis, reporting followed Standards for Reporting Diagnostic Accuracy (STARD) 2015 guidelines. | Adults $\geq 18$ years with $\geq 1$ suspicious skin lesion, excluded: prior biopsy, unclear diagnosis, technical failures, or inability to consent, 785 lesions (from 372 patients), Median age: 71 years, Gender: 50.8% women, Fitzpatrick skin type: $> 80\%$ type I–II. | Sensitivity: 86.9% (90% CI, 82.3–90.7), Specificity: 80.1% (95% CI, 75.7–84.1)                                                               | This is a class IIa medical device under the EU Medical Devices Regulation (MDR). It was the first AI-powered medical device to achieve CE registration under the EU Medical Device Directive (MDD) and currently has achieved the higher Class IIa certification under the MDR (EU MDR 2017/745)  | Mobile deployment, CE certified                   | Habgood E et al. <sup>[180]</sup> and Smak Gregoor AM et al. <sup>[181]</sup>      |
| VisualDx   | Give APPs and generalists support to identify and manage skin conditions quickly and accurately, making better use of referrals, and improving care delivery                                                   | labeled by board-certified dermatologists                            | Study on the diagnostic accuracy of multiple film viewers                                                                                                                                                                                                                                                                                                                                                                                                                                          | The Fitzpatrick skin type for all 222 images was recorded as one of two groups: Fitzpatrick types I–III ( $n = 169$ ) or Fitzpatrick types IV–VI ( $n = 53$ )                                                                                                               | achieved an overall accuracy of 70% in the Fitzpatrick I–III skin type group and 68% in the Fitzpatrick IV–VI skin type group ( $P = 0.79$ ) | It is a commercial regulatory product that has received 510(k) approval from the US FDA. Additionally, it complies with the CE/MDR standards of the European Union and the ONC certification requirements of the United States, and has been deployed for use in over 2,300 hospitals and clinics. | Globally adopted in clinics, integrated with EHRs | David Rebedew et al. <sup>[182]</sup> and Md. Kamrul Hasan et al. <sup>[183]</sup> |

(continued)

**Table 4**

(continued)

| Tool name                    | Intended use                                                                                                                                                                                                                                                                                                    | Validation type     | Study design                                                                                                                                                                                | Sample size                                                                                                                                                                                                                                                | AUROC/Sensitivity/<br>Specificity                                                                                                                                                                                                                                                          | Regulatory<br>status                                              | Deployment status                                              | Reference or link                 |
|------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|----------------------------------------------------------------|-----------------------------------|
| Xy-SkinNet                   | Carry out AI-assisted classification of the clinical images of six common skin diseases, laying the foundation for subsequent product research and clinical applications                                                                                                                                        | Internal validation | Research on the performance of AI algorithms and a comparative study was conducted with 31 dermatologists                                                                                   | Training sample size: More than 150,000 clinical images<br>Validation sample size: 899 images                                                                                                                                                              | Sensitivity (accuracy): 77.4%<br>Specificity: 98.6%                                                                                                                                                                                                                                        | –                                                                 | Web-based and API diagnostic tools available                   | Kai Huang et al. <sup>[184]</sup> |
| SCIN                         | Mainly serving as an open-source academic research resource, it is specifically designed for AI model training and enhancing the diversity of dermatology datasets.                                                                                                                                             | Not applicable      | A prospective observational study was conducted through Google search advertising crowdsourcing, collecting skin image data from users in the United States from March to November 2023.    | Out of the 5,749 submissions, 5,631 (i.e. 97.9%) of the images were confirmed as genuine images of skin conditions, which could be used for subsequent research and analysis.                                                                              | Not applicable                                                                                                                                                                                                                                                                             | Not applicable                                                    | Public dataset supporting DermAssist training                  | Abbi Ward et al. <sup>[185]</sup> |
| Google health AI skin system | By analyzing photos of skin, hair or nail problems, this tool helps users gain an initial understanding of the possible conditions, enabling them to make informed decisions based on the information and take self-care actions. It is an information reference tool rather than a clinical diagnostic device. | Internal validation | A retrospective diagnostic accuracy study, based on de-identified case data from 1,777 patients from 17 primary care clinics, was conducted for internal division, training and validation. | Development and training set: Over 65,000 labeled images of skin diseases and non-mal skin, covering 288 types of skin, hair and nail conditions.<br>Validation test set: A key study used 963 cases of remote dermatological consultation for evaluation. | Top-1 accuracy rate: 71%, Top-3 accuracy rate: 93%. Compared with doctors: The system's Top-3 accuracy rate is 90%. This single performance is comparable to that of dermatologists (75%) and significantly better than that of primary care physicians (60%) and registered nurses (55%). | EU: has obtained the CE certification as a Class I medical device | Multi-center testing with real-world clinical images completed | Yuan Liu et al. <sup>[186]</sup>  |

(continued)

**Table 4**  
(continued)

| Tool name        | Intended use                                                                                                                                                                                                                  | Validation type                                                                                                                                                                                                                           | Study design                                                                                                                                                                                                         | Sample size                                                                                                                                                                                                      | AUROC/Sensitivity/<br>Specificity                                                                                                                                                                                                                                  | Regulatory status                                                                                                                                                                                          | Deployment status                                                                                                                                                                                               | Reference or link                                                                                                                |
|------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------|
| DermoNet         | For the automatic classification and diagnosis of skin cancers (including basal cell carcinoma, benign keratosis-like lesions, skin fibroma, melanoma, and melanocytic nevus), to assist doctors in identifying skin diseases | Internal validation                                                                                                                                                                                                                       | Retrospective model performance study. Based on the historical public dataset (HAM10000), the SqueezeNet architecture was used for training and evaluation, and comparisons were made with various existing methods. | Total dataset: 10,015 dermoscopy images (HAM10000 dataset), Training set: approximately 8,012 (80%), Test set: approximately 2,003 (20%), Validation set: an additional 10% from the training set was set aside. | Overall accuracy rate: 92.25%, precision rate: 85%, sensitivity: 84%, F1 score: 83%                                                                                                                                                                                | Unregulated approval (pure academic model)                                                                                                                                                                 | Research model, no large-scale clinical deployment yet                                                                                                                                                          | Poonam Dhiman et al. <sup>[187]</sup>                                                                                            |
| SkinIO           | Used for routine skin self-examination and risk monitoring. Its image recognition algorithm is mainly used to assist in locating and marking potential risks.                                                                 | Clinical application feasibility/observational study                                                                                                                                                                                      | Single-arm, prospective, observational feasibility study                                                                                                                                                             | 27 participants. Among them, 21 were female (77%), with an average age of 87 years (ranging from 79 to 99 years), and 26 were white (96%).                                                                       | Sensitivity: 92%                                                                                                                                                                                                                                                   | Unregulated approval (only as an auxiliary tool for image acquisition and triage)                                                                                                                          | Deployed in multiple US hospitals                                                                                                                                                                               | Pavin Trinh et al. <sup>[188]</sup> and Nicholas Guido et al. <sup>[189]</sup>                                                   |
| Moleanalyzer Pro | As an AI-assisted decision-making tool for dermatologists, it classifies skin biopsy images into two categories (benign/malignant) and provides a risk score for malignancy.                                                  | It includes internal validation (retrospective image analysis based on a single dataset), time validation/cross-validation (external validation using multiple datasets), as well as a prospective multicenter diagnostic accuracy study. | 13 independent studies: 2 prospective, cross-sectional diagnostic accuracy cohort studies, 11 retrospective image dataset analyses                                                                                   | A total of over 3,500 dermoscopy images have been published in multiple studies, covering various diagnostic categories such as melanoma, non-melanoma skin cancer, and benign lesions.                          | Haenssle 2020: AUROC: 0.918 (95% CI 0.866–0.970), sensitivity: 95.0% (95% CI 83.5%–98.6%), specificity: 76.7% (95% CI 64.6%–85.6%); Sies 2020: AUROC: 0.945 (95% CI 0.930–0.961), sensitivity: 77.6% (95% CI 72.4%–82.1%), specificity: 95.3% (95% CI 94.2%–96.2%) | CE certification: Moleanalyzer pro (version 3.4) has obtained CE Class I certification (in accordance with Annex VIII of the EU Medical Device Regulation, and in compliance with Annex IX (EU) 2017/745). | CE certification: Moleanalyzer Pro (version 3.4) has obtained CE Class I certification (in accordance with the Annex VIII of the EU Medical Devices Regulation, and in compliance with Annex IX (EU) 2017/745). | Katharina S. Kommoss et al. <sup>[190]</sup> , Katharina Sies et al. <sup>[191]</sup> and H. A. Haenssle et al. <sup>[192]</sup> |

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Table 4

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| Tool name                                                  | Intended use                                                                                                                                                                                                                                                                                                             | Validation type                                                                                                                                                                                                                                                                                                          | Study design                                                                                                                                                                                                                   | Sample size                                                                                                                                                                                | AUROC/Sensitivity/<br>Specificity                    | Regulatory<br>status                                                                                                                               | Deployment status                                                                                                                                                                                                                                                                                                                                                             | Reference or link                                                            |
|------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| DIET-AI                                                    | Diagnose 31 common skin diseases and it can be used to assist doctors in diagnosis and treatment.                                                                                                                                                                                                                        | Multicenter clinical validation                                                                                                                                                                                                                                                                                          | A prospective, multicenter clinical study. The diagnostic results of DIET-AI were directly compared with those of six dermatologists of different qualifications (including all levels of qualifications).                     | Training phase: 200,000 images and 220,000 medical records. Clinical validation phase: 6,043 cases from 15 hospitals                                                                       | Average accuracy: 75.98%<br>Kappa coefficient: 0.752 | –                                                                                                                                                  | Deployed in Chinese community health centers                                                                                                                                                                                                                                                                                                                                  | Huanyu Li et al. <sup>[193]</sup>                                            |
| National Health Service (NHS) AI Dermatology Triage (DERM) | As an AI triage tool, within the “Emergency Suspected Cancer” pathway of the NHS, it is used to assess and route the skin lesions of adult patients. It analyzes dermoscopic images, classifies the lesions as benign, precancerous or cancerous, and prioritizes suspected cancer cases for referral to dermatologists. | As an AI triage tool, within the “Emergency Suspected Cancer” pathway of the NHS, it is used to assess and route the skin lesions of adult patients. It analyzes dermoscopic images, classifies the lesions as benign, precancerous or cancerous, and prioritizes suspected cancer cases for referral to dermatologists. | Post-marketing studies in the real world. The assessment is based on performance data obtained in the actual NHS clinical environment. Additionally, it includes a prospective, multi-center evaluation covering 12 NHS sites. | Non-randomized controlled trial. Its performance was evaluated based on post-market monitoring data and compared with the assessment made by remote dermatologists during the same period. | A total of over 165,000 patients have been served.   | Sensitivity: 97.3% for “all skin cancers”, 98.6% for “all high-risk cancers”, and 98.1% for “melanoma”.<br>Specificity: 74.0% for “benign lesions” | MHRA: UKCA Class IIa certification for the UK; EU CE Class III certification (highest risk level), National Institute for Health and Care Excellence (NICE); received “Early Value Assessment (EVA)” recommendation, allowing conditional use in the NHS for 3 years to collect further evidence, DTAC: passed the “Digital Technology Assessment Criteria (DTAC)” assessment | Colin Morton et al. <sup>[194]</sup> , Helen Marsden et al. <sup>[195]</sup> |
| NETSKIN-MODELS-AI                                          | Academic research network, aiming to develop AI-driven computational skin models to replace animal experiments                                                                                                                                                                                                           | Not applicable                                                                                                                                                                                                                                                                                                           | Academic network/framework                                                                                                                                                                                                     | Nearly 450 participating institutions                                                                                                                                                      | Not applicable                                       | –                                                                                                                                                  | Platform validated, project ongoing                                                                                                                                                                                                                                                                                                                                           | Hristijan Goreski et al. <sup>[196]</sup>                                    |

(continued)

Table 4

(continued)

| Tool name      | Intended use                                                                                                                                                                                                                              | Validation type                                                                                                                                                                   | Study design                                                                                                                                                                                                                                                            | Sample size                                                                                                                                                                                                              | AUROC/Sensitivity/<br>Specificity | Regulatory<br>status | Deployment status                                      | Reference or link                   |
|----------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------|----------------------|--------------------------------------------------------|-------------------------------------|
| DrugRepo       | Research-oriented network tools are designed to quickly calculate the potential new uses of existing drugs for hundreds of diseases by analyzing chemical structures and genomic data, thereby accelerating the drug development process. | Research on the performance of AI and bioinformatics algorithms, rather than the verification of clinical diagnostic performance                                                  | By integrating multiple large databases such as those related to chemical structures and drug-target interactions, a set of scoring algorithms was designed. These algorithms predict the matching degree by comparing the correlation data between drugs and diseases. | Disease coverage: Includes 669 diseases, belonging to 22 major disease categories. Drug coverage: From 788,078 compounds, 1,091 approved drugs were selected.                                                            | Not applicable                    | Not applicable       | Method validated with application demonstrations       | Yinyin Wang et al. <sup>[197]</sup> |
| DeepPurpose    | Predicting the interactions between drugs and their targets can be applied to drug repositioning (using old drugs for new purposes), virtual screening (identifying candidate drugs from a large number of molecules).                    | Algorithm performance verification                                                                                                                                                | A rich set of preprocessed datasets (such as DAVIS, KIBA, etc.) was provided. Through model screening, compounds highly overlapping with the candidate drugs for clinical trials were identified, thereby proving their effectiveness.                                  | It is equipped with multiple large-scale public datasets, such as BindingDB, DAVIS, KIBA, etc., which contain millions of records of drug-target interactions and are used for the training and evaluation of the model. | Not applicable                    | Not applicable       | Open-source deep learning toolkit with published cases | Yuyan Pan et al. <sup>[198]</sup>   |
| DRP-AI Toolkit | A development toolkit for embedded AI engineers, designed to convert and optimize trained AI models (such as those in ONNX format) for efficient operation on Renesas Electronics' RZ/V series MPUs (micro-processors).                   | Verify the correctness of the model's functionality after conversion, its operational efficiency (such as inference speed and memory usage), and its compatibility with hardware. | Deploy AI models (such as YOLOv5) onto development boards and conduct comparison tests on numerical results and operational performance.                                                                                                                                | Not applicable                                                                                                                                                                                                           | Not applicable                    | Not applicable       | Method proposed and validated in published studies     | Shuwei Chen et al. <sup>[199]</sup> |

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**Table 4**  
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| Tool name    | Intended use                                                                                                                                                                                                                                                     | Validation type                                                                                                       | Study design                                                                                                                                                                                 | Sample size                                                                                                                                                                                                         | AUROC/Sensitivity/<br>Specificity                                                 | Regulatory<br>status | Deployment status                         | Reference or link                              |
|--------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|----------------------|-------------------------------------------|------------------------------------------------|
| DeepSkin-Net | For the automatic classification and detection of dermatological images, it can distinguish seven types of skin lesions (vascular lesions, actinic keratosis/Bowen's disease, basal cell carcinoma, benign keratosis, skin fibroma, melanoma, melanocytic nevus) | Internal validation: the model was trained and tested using a single publicly available dataset (HAM10000)            | Retrospective algorithm performance study                                                                                                                                                    | The HAM10000 dataset contains a total of 10,015 dermoscopy images.                                                                                                                                                  | Training accuracy rate: 90.08%, validation accuracy rate: 83.48%                  | —                    | Research phase (IEEE published)           | Rajkumar Pandiarajan et al. <sup>[200]</sup> . |
| iSPInception | Automatically distinguish between benign and malignant tumors in dermoscopy images, thereby assisting in the classification of skin cancer                                                                                                                       | Internal verification                                                                                                 | Retrospective algorithm performance study                                                                                                                                                    | Used the ISIC 2019 and HAM10000 datasets                                                                                                                                                                            | Accuracy: 95.82%, precision: 96.85%, recall: 96.52%, F1 score: 95%                | —                    | Research model published                  | R. Josphineleela et al. <sup>[201]</sup> .     |
| CR-Conformer | A classification algorithm designed for clinical skin lesion images. By integrating a deep CNN branch capable of extracting local features and a Transformer branch for extracting global features, it has the potential to be applied to mobile devices.        | Internal validation: The research was entirely based on a dedicated private dataset, XJUSL, for training and testing. | Retrospective algorithm performance study. Comparing the classification accuracy, parameter quantity, and other indicators of CR-Conformer with other baseline models on the private dataset | XJUSL contains a total of 3,131 clinical skin lesion images, covering 10 types of skin lesions. The training set consists of 2,511 images, the validation set has 156 images, and the test set contains 464 images. | Accuracy: 79.96%, precision: 80.06%, recall/Sensitivity: 70.44%, F1-Score: 74.02% | —                    | Research model tested on private datasets | Dezhi Zhang et al. <sup>[202]</sup> .          |

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Table 4

(continued)

| Tool name | Intended use                                                                                                                                                                                                                                                        | Validation type                                                                                                                                                                                                                         | Study design                                                                                                                                                                                                                                                                                                                                                                                                        | Sample size                                                                                                                                | AUROC/Sensitivity/<br>Specificity                                                                                                                                           | Regulatory<br>status                                                                             | Deployment status             | Reference or link                                                                                       |
|-----------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|-------------------------------|---------------------------------------------------------------------------------------------------------|
| Ruifu     | Provide diagnostic references for doctors, support the intelligent identification of over 100 types of skin diseases, and assist in the comprehensive disease management of over 1,600 types of skin diseases, including follow-up assessment and research support. | Hybrid validation. This includes five-fold cross-validation based on the internal dataset, as well as randomized controlled trials (RCTs) involving primary care physicians and practical validations in external medical institutions. | Algorithm prototype research: conducted five-fold cross-validation using 4,740 images; randomized controlled trial: conducted a prospective RCT in community health centers, where the AI group of 10 primary care physicians used Ruifu as an aid, while the control group of 9 physicians provided conventional treatment; real-world application research: covered 19 doctors and 90 patients with skin diseases | The current collection includes over 4,740 images; external validation: 6,043 samples                                                      | AUROC: 0.987, sensitivity: 94.4%, specificity: 97.2%, accuracy: 95.8%, effect on assisting doctors: the accuracy rate of doctors' diagnosis increased from 66.88% to 81.25% | National Medical Products Administration (NMPA) Class II medical device registration certificate | Deployed in Chinese hospitals | Haijing Wu et al <sup>[203]</sup> , Qianwen Li et al <sup>[204]</sup> , Heng Yin et al <sup>[205]</sup> |
|           |                                                                                                                                                                                                                                                                     |                                                                                                                                                                                                                                         |                                                                                                                                                                                                                                                                                                                                                                                                                     |                                                                                                                                            |                                                                                                                                                                             |                                                                                                  |                               |                                                                                                         |
| Lingmou   | An AI-assisted diagnostic tool for pathologists. It can accurately identify skin tumor subtypes, make cancer determination, segment the lesion area, and provide protein expression prediction and tumor quantification analysis.                                   | Mainly for internal verification (model performance testing)                                                                                                                                                                            | Retrospective model development and performance evaluation based on large-scale datasets. The research team constructed a knowledge base by integrating over 10 years of medical literature, 36 international authoritative pathology journals, and more than 100 classic textbooks.                                                                                                                                | Relying on a high-quality pathological image resource of over 1 million cases, which includes cytology, histology and immunohistochemistry | Histopathological aspect: sensitivity: 99.6%, specificity: 83.5%, accuracy of lesion identification: 95.8%                                                                  | Has obtained the Class II medical device registration certificate from the NMPA                  | Live on App                   | Lingmou pathology large model                                                                           |
|           |                                                                                                                                                                                                                                                                     |                                                                                                                                                                                                                                         |                                                                                                                                                                                                                                                                                                                                                                                                                     |                                                                                                                                            |                                                                                                                                                                             |                                                                                                  |                               |                                                                                                         |

(continued)

**Table 4**  
(continued)

| Tool name | Intended use                                                                                                                             | Validation type                                                                                                                                                                                        | Study design                                                                                                      | Sample size                                                                                                                                                                                                                                      | AUROC/Sensitivity/<br>Specificity                                                                                                                                                                                                            | Regulatory<br>status                                                                                                                                                                                                                                                                                                                                                                                                                                                     | Deployment status                         | Reference or link |
|-----------|------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------|-------------------|
| FirstDerm | Provide a preliminary risk assessment of the patient's skin condition based on the provided images, as well as referral recommendations. | Hybrid validation. This includes algorithm evaluations in different populations (such as Uganda, China), post-market clinical follow-up studies, and comparative studies between AI and human doctors. | Retrospective (Uganda study) and prospective clinical studies (Chinese study), as well as real-world PMCF studies | Using over 300,000 anonymous smartphone skin images (covering 248 types of skin problems) for training.                                                                                                                                          | Prospective performance evaluation in the Chinese population (2023)                                                                                                                                                                          | AI tool (Skin Image Search™): Recognized as a "legacy Class I medical device" and has obtained the CE mark, it is currently transitioning to MDR Class IIa. AI system (autoderm): Also obtained the CE mark and registered with MHRA (UK Medicines and healthcare products regulatory agency). US status: autoderm has received the FDA's "Breakthrough Device" designation, but is still awaiting regulatory approval and has not yet been commercially sold in the US. | Global coverage via App and web platforms | First Derm APP    |
|           |                                                                                                                                          |                                                                                                                                                                                                        |                                                                                                                   | mance evaluation (proactive): 920 patients with diagnosed skin diseases. Post-market clinical follow-up of autoderm: analyzed 18,359 skin problems, and found 80 possible melanomas, 95 squamous cell carcinomas, and 202 basal cell carcinomas. | Top-1 diagnosis: sensitivity 41.8%, specificity 96.8%, Top-3 diagnosis: sensitivity 65.8%, specificity 91.5%. Comparative research data from the company blog (2025): AI Top-1 accuracy: 53%, AI Top-3 accuracy: 84%, AI Top-5 accuracy: 93% |                                                                                                                                                                                                                                                                                                                                                                                                                                                                          |                                           |                   |

Abbreviations: API, Application Programming Interface; AUROC, Area Under the Receiver Operating Characteristic Curve; CI, Confidence Interval; CNN, Convolutional Neural Network; DTAC, Digital Technology Assessment Criteria; EHR, Electronic Health Record; EVA, Early Value Assessment; FDA, Food and Drug Administration; MDR, Medical Device Regulation; MHRA, Medicines and Healthcare products Regulatory Agency; MPU, Microprocessor Unit; NHS, National Health Service; NICE, National Institute for Health and Care Excellence; NMPPA, National Medical Products Administration; ONNX, Open Neural Network Exchange; PMCF, PostMarket Clinical Followup; RCT, Randomized Controlled Trial; STARD, Standards for Reporting Diagnostic Accuracy; UKCA, United Kingdom Conformity Assessed; YOLO, You Only Look Once; CE, Conformance Européenne (European Conformity) .

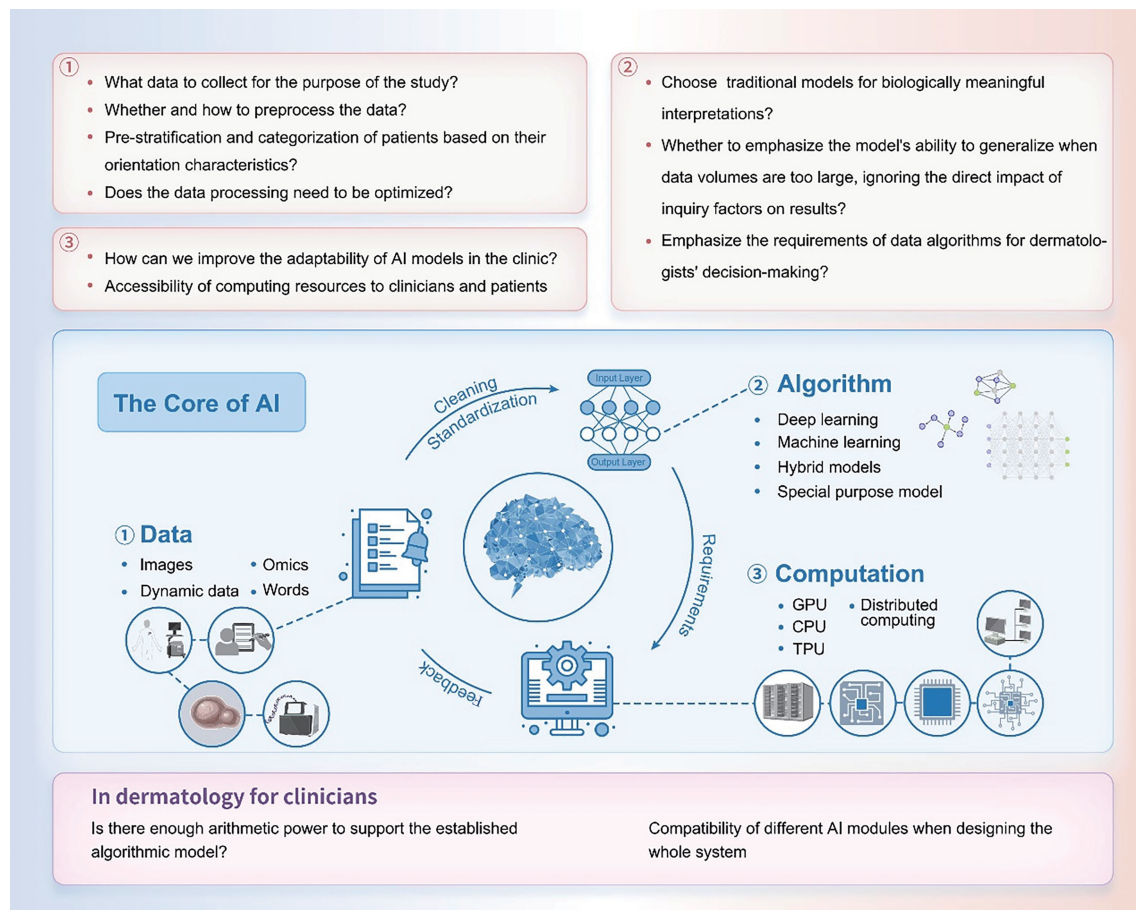


**Figure 5:** Core elements and practical considerations for artificial intelligence deployment in dermatology.

Data processing involves the acquisition, cleaning, and standardization of multimodal sources (images, omics, dynamic data, clinical records). Algorithm selection includes ML, DL, hybrid, and task-specific models tailored to clinical requirements. Computational support encompasses GPUs, TPUs, and distributed systems essential for model training and deployment. The top panel outlines four categories of practical questions clinicians must address: data selection, algorithm strategy, computational feasibility, and clinical adaptability, highlighting the need for interdisciplinary collaboration to ensure effective AI integration into dermatological decision-making.

Abbreviations: CPU, central processing unit; GPU, graphics processing unit; TPU, tensor processing unit.

strategies to improve data quality. (2) Algorithm design: decide whether to adopt traditional interpretable models or generalizable models suited for large-scale data; assess the influence of clinician expertise on supervised/semi-supervised models; and clarify whether the algorithm prioritizes biological plausibility or predictive performance. (3) Computing and integration: ensure adequate computational resources (e.g., GPU clusters) to support model training and deployment; confirm compatibility across AI modules to achieve system-level coherence. (4) Clinical applicability: evaluate the real-world feasibility of the AI model, including ease of integration into clinical workflows, user-friendliness for dermatologists, and equitable access for patients in diverse healthcare settings.

### **Challenges in real-world deployment: regulation, governance, and economics**

The transformation of AI models for dermatology from experimental models to clinical tools inevitably requires strict regulatory review. Currently, AI systems are mainly regulated as “Software as a Medical Device (SaMD)”. The U.S. FDA has recognized the iterative nature of ML and introduced the Pre-Certification for SaMD program, allowing algorithms to self-update within a specific range after deployment without the need for reapplication for pre-market approval<sup>[217]</sup>. In Europe, the regulatory framework is dominated by the Medical Device Regulation (MDR) and the newly introduced EU AI Act. Under these frameworks, AI systems for

dermatological diagnosis are typically classified as Class IIa/IIb medical devices or “high-risk” AI systems<sup>[218]</sup>. These classifications mandate: (1) Data governance: the training, validation, and testing datasets of AI systems must be of high quality. Developers must document the source (provenance) of the data, the original purpose of data collection, and conduct rigorous bias assessment. If the dataset is severely imbalanced in terms of skin color (Fitzpatrick classification), gender, or region, which may harm patient health or lead to discrimination, the system will be denied market entry. (2) Algorithm transparency: AI systems must be designed with sufficient explainability to enable medical professionals to understand the system’s output and take appropriate actions. Additionally, manufacturers must provide detailed technical documentation and user instructions, clearly informing doctors of the system’s capability boundaries, expected diagnostic accuracy, and in which specific populations it may fail. (3) Cybersecurity and robustness: AI must have a high level of defense against cyber attacks, hacking, and data tampering. It must also seamlessly integrate with data regulations such as the EU’s General Data Protection Regulation (GDPR). (4) Pre-market assessment: high-risk medical AI cannot be marketed through the manufacturer’s “self-declaration”. They must undergo strict audits by independent third-party notified bodies (such as BSI, GMED). The review includes quality management systems (ISO 13485) and medical device risk management (ISO 14971), and incorporates the special requirements of the AI Act. Only after meeting all standards can they obtain the CE marking and enter the European market. In China, AI medical independent software with auxiliary diagnostic functions (such as directly indicating the risk of melanoma) is uniformly classified as the highest-risk Class III medical device and requires extremely strict clinical evaluation and technical review by the National Medical Products Administration (NMPA) authority to be approved.

Post-market supervision and model performance drift monitoring for dermatology AI One key challenge in clinical deployment is the phenomenon of performance degradation, often referred to as “dataset shift”<sup>[219]</sup>. An AI model primarily trained on specific demographic characteristics (e.g., light-skinned populations) or specific imaging hardware may experience a sharp decline

in diagnostic accuracy when exposed to a diverse real-world population or new dermoscopy devices. To mitigate this issue, a robust post-market supervision mechanism must be enforced to detect performance drift in real time. This includes regular audits using diverse, cross-institutional clinical data, and the implementation of an automatic warning system when the model’s confidence level drops below a preset threshold<sup>[220]</sup>. If the performance of the maintained AI model falls below the threshold, dermatologists should re-examine the misdiagnosed skin lesions and feed them back to the model for re-training to maintain its long-term clinical utility. At the same time, it is necessary to consider: when an AI system misses or misdiagnoses a malignant melanoma, how to define the fault: should it be attributed to the attending dermatologist, the medical institution, or the software developer<sup>[221]</sup>. Additionally, clinicians may become victims of “automation bias”, that is, over-reliance on algorithm outputs and abandonment of their own clinical judgment. To address these governance challenges, dermatology AI must be strictly positioned as an auxiliary tool rather than an autonomous decision-maker, ensuring that “AI is practiced by humans in human medicine”<sup>[222]</sup>. Professional dermatology societies must establish clear clinical governance frameworks and practice guidelines, clearly stipulating that although AI provides probability-based risk assessments, the ultimate responsibility for diagnosis and treatment lies with the qualified doctor.

As an atypical medical device, the wide clinical application of dermatology AI fundamentally depends on the establishment of a sustainable reimbursement model. Currently, healthcare payers lack standardized coding systems (such as specific Current Procedural Terminology [CPT] codes) to provide reasonable compensation for AI-assisted image analysis or remote dermatology triage. To clear the reimbursement channel, developers and researchers must generate strong health technology assessment and health economics evidence<sup>[223]</sup>. This requires conducting prospective trials that not only prove the non-inferiority of the model in diagnosis but also demonstrate its cost-effectiveness. For example, an AI triage system must prove its financial rationality by providing evidence such as significantly reducing unnecessary excision biopsies for benign skin lesions (such as common moles), optimizing the workflow efficiency

of dermatology clinics, or moving the detection of skin cancer forward, thereby avoiding extremely expensive late-stage tumor treatment costs<sup>[224]</sup>. Without convincing cost-saving and value-based medical evidence, the large-scale promotion of AI in routine dermatology practice will face significant financial obstacles.

## Conclusion and perspectives

In dermatology, AI has approached clinical utility in disease classification, severity scoring, therapeutic response prediction, and remote monitoring, marking its transition from an “experimental tool” to a “clinical assistant”. These advances are driving dermatologic care toward greater intelligence, personalization, and precision.

The diverse and complex nature of dermatologic data has surpassed the capabilities of single-modality models. This challenge has led to the development of multimodal and multi-omics approaches that integrate visual, textual, and molecular data inputs. Current AI research is increasingly focusing on integrated frameworks. For instance, early multimodal systems such as SkinGPT-4 and DeepDR-LLM combine image recognition with natural language processing to aid in diagnostics<sup>[33,225]</sup>. The DeepGEM model integrates imaging with genomic data to improve spatial mutation prediction<sup>[226]</sup>, while Evo, a generative model for DNA sequences, expands AI applications to target identification and synthetic biology<sup>[227]</sup>.

The clinical integration of AI in dermatology encounters challenges including data heterogeneity, limited interpretability, clinician skepticism, and inadequate regulatory and ethical frameworks<sup>[228]</sup>. These obstacles are especially pronounced in intricate immune-mediated skin conditions, where modeling and assessment methods lack standardization. Future developments in dermatologic AI will emphasize: (1) Model architecture: image recognition model, multi-omics models, LLMs, and multimodal frameworks will enable a shift from simple data fusion to mechanism-driven modeling. Omics-based algorithms will identify key molecular targets and integrate clinical context for precision stratification and treatment planning. LLMs will power intelligent pre-consultation systems, enhancing diagnostic workflows. (2) Clinical deployment: next-generation platforms will

fuse imaging, text, and lab data; knowledge graphs will inform intelligent decision-making; dynamic physiological monitoring will enable “digital twin” simulations; and protein structure prediction will support personalized drug design. (3) Training and infrastructure: improving model interpretability and training efficiency will be critical, alongside implementing standardized frameworks such as FHIR and OMOP to enable data integration, governance, and equitable deployment. By aligning technical innovation with clinical needs and embedding AI into ethical and regulatory structures, dermatology can advance toward intelligent, inclusive, and patient-centered care.

With ongoing progress in algorithmic design, clinical adaptation, and treatment feedback, AI is anticipated to transition from a decision-support tool to an intelligent collaborator throughout the dermatologic care process. This evolution is poised to facilitate the advancement of more equitable, efficient, and reliable precision medicine in the foreseeable future.

## Author contributions

Z.X.L. and K.L.C. reviewed the literature, and drafted and revised the manuscript. Y.J., H.J.W., and K.L.C. provided critical input, discussion, and revision of the manuscript. H.J.W. and Q.J.L. created the overall plan for the study and provided funding. All authors reviewed, edited, and approved the final version of the manuscript and agreed to its publication.

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## Ethics statement

All figures are either original to this work or properly attributed. No original images have been previously published, and all images comply with research integrity standards without inappropriate manipulation or misrepresentation.

## Data availability statement

No datasets were generated or analyzed for this work.

## AI statement

The authors declare that no generative artificial intelligence (AI) or AI-assisted technologies were used in the preparation, analysis, writing, image generation, or image processing of this manuscript.

## Conflicts of interest

Author Qianjin Lu serves as an advisor of this journal. He was not involved in the editorial review or decision-making process for this manuscript. All editorial decisions were made independently by other members of the Editorial Board who have no conflicts of interest.

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