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Review

AI dermatology: Reviewing the frontiers of skin cancer detection technologies

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ABSTRACT

The rapid advancements in artificial intelligence (AI) have significantly impacted modern healthcare, particularly for skin cancer detection in the field of dermatology. Skin cancer has become a considerable public health challenge, highlighting the importance of early detection to improve patient outcomes. AI models have revolutionized skin cancer diagnosis by enhancing the accuracy and efficiency of detecting malignancies in the early stages. This review provides a comprehensive comparison of the latest AI technologies used in skin cancer detection, including segmentation, classification, and reinforcement learning models. It also explores the integration of transformer and multimodal technologies, which have further refined the diagnostic process. Despite the remarkable progress, challenges remain in the practical deployment of these AI models, especially those concerning data diversity, model interpretability, and clinical integration. Future research directions should focus on overcoming these limitations to fully harness AI's potential in dermatology, aiming to increase diagnostic accuracy, reduce healthcare costs, and ultimately save lives.

1. Introduction

1.1. Overview of skin cancer

Skin cancer is one of the most common types of cancer worldwide. According to the World Cancer Research Fund, there were 331,000 new cases of skin cancer globally in 2022, with China ranking tenth in the number of new cases. The number of deaths caused by skin cancer reached 58,000, with China ranking second.[a] Between 1990 and 2021, the all-age DALY rate of non-melanoma skin cancer (NMSC) rose by 115 %, and the age-standardized DALY rate increased by 10 %, indicating significant growth in overall disease burden and a continued rise after adjusting for population age differences.[1] Additionally, with the increasing aging population, some studies have shown that the incidence of skin cancer is related to age.[2] Skin cancer can be categorized into malignant melanoma (MM) and nonmelanoma skin cancer.[3] NMSC primarily includes squamous cell carcinoma and basal cell carcinoma, which account for 70 % and 25 % of NMSC cases in the United States, respectively,[4] and frequently occurs in sun-exposed areas, such as the head and neck.[5] Unlike NMSC, the appearance of new spots on the skin, changes in the color, size, or shape of existing spots, or spots

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that differ from others, may indicate MM.[6] If NMSC is not treated promptly, it can lead to the spread of cancer cells, resulting in generally poor outcomes and posing a threat to patient survival.[5] Although MM constitutes a smaller proportion of all skin cancers, its aggressiveness and lethality are greater, accounting for over 80 % of skin cancer-related deaths.[7] MM spreads rapidly, has poor treatment outcomes, and can metastasize to vital organs, such as the lungs, liver, brain, and bones, via the bloodstream and lymphatic system, causing irreversible damage and endangering life.[8] Although patients can now conduct early diagnosis at home through simple internet searches combined with dermatoscopy,[9] lack of experience can lead to misdiagnosis or overlooked symptoms. Additionally, the incidence of skin cancer increases with age,[10–12] and the treatment costs for early-detected skin cancer differ significantly from those for late-detected cases. Therefore, early identification and timely treatment of skin cancer and precancerous lesions are crucial for improving patient survival rates and reducing the economic burden on healthcare systems.

For skin cancer detection, histopathology is an invasive but highly accurate medical diagnostic method. Proper histopathological examination can effectively diagnose the appropriate treatment for patients.[13] However, this method requires experienced professional clinicians to diagnose through visual observation. Most skin cancers develop on the human epidermis and manifest in a relatively obvious manner.[5] In addition to invasive histopathological examination, dermoscopy is a noninvasive detection method. Compared to simple visual inspection, dermoscopy allows a more intuitive observation of the distribution of skin cancer lesions, even revealing some special structures beneath the surface of the skin.[9] Therefore, it can provide professional clinicians with more accurate diagnostic information, thereby improving diagnostic accuracy. However, this method still relies on experienced clinicians for accurate diagnosis. Regardless of the diagnostic approach, even seasoned professionals are susceptible to misdiagnosis, and detection efficiency significantly declines with prolonged diagnosis times (Figure 1).

1.2. Evolution of artificial intelligence (AI) in dermatology

In 1943, the first artificial neural network, composed of electronic circuits, was designed to mimic the activity of brain neurons.[14] Subsequently, a subtype of artificial neural networks, convolutional neural networks (CNNs),[15] laid the foundation for neural networks in computer vision. Entering the 2010s, with the advent of deep learning models,[16] the development of deep learning networks reached a new stage. The rise of deep learning has significantly improved the efficiency and accuracy of skin cancer detection, helping to address various challenges commonly faced by doctors in manual diagnosis. In 2016, the International Skin Imaging Collaboration (ISIC) introduced a large-scale public dataset of skin cancer images,[17] marking a significant milestone in the field. The release of this dataset provided a standardized benchmark for the evaluation of AI models in skin cancer detection, offering researchers worldwide a shared and consistent resource for skin cancer data. This initiative not only accelerated advancements in skin cancer detection technology but also laid a crucial foundation for the development of subsequent datasets, such as ISIC 2018.[18] In 2017, a study demonstrated the immense potential of deep learning CNN models in the automated classification of skin cancer, particularly in the handling of large-scale clinical data.[18] The model was able to effectively learn subtle differences in skin lesions and achieve an efficient and accurate classification of malignant and benign skin lesions. The study also highlighted the embeddability of deep neural networks in mobile devices, which is significant for improving early skin cancer detection and reducing cancer mortality rates. Since then, deep learning has been widely applied to skin cancer detection and classification tasks.[19]

Building on these advancements, the practical application of AI in dermatology has progressed rapidly. In 2020, 3DermSpot became the first AI device in the field of dermatology to receive “Breakthrough Device Designation,” with approval from the US Food and Drug Administration (FDA), making 3DermSpot the first AI product to bring expert-level dermatological diagnostics to primary care.[20] In 2023, DermoSight also received FDA approval as a real-time, noninvasive, AI-driven skin cancer assessment system, enabling remote dermoscopic screening of suspicious skin lesions.[21] In 2024, the FDA authorized the AI device DermaSensor, designed for skin cancer detection in primary care. It is the first AI device for use by nondermatologists in primary care settings.[22] As part of the latest wave of AI medical devices receiving regulatory approval globally, this development is poised to drive the wider application of AI technology in the field of skin cancer detection. Unlike conventioal methods, AI substantially improves the efficiency and accuracy of physicians’ diagnoses. Furthermore, with the broad adoption of AI, its applications in dermatology have diversified, extending beyond clinical diagnostics. For example, the AI skin cancer detection system DERM developed by British

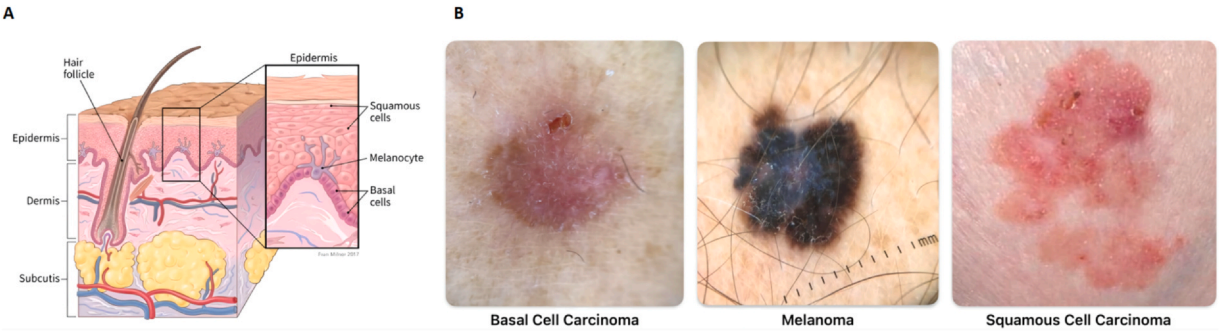


Figure 1. Illustration of skin structure and skin cancer types. A, Skin infrastructure diagram (from Fran Milner, available at link); B, Three common types of skin cancer.

medical technology company Skin Analytics received the European Union's CE certification for Class III medical devices in February 2025. This system provides patients with suspected skin cancer case assessment services, helping secondary medical institutions reduce the need for urgent suspected skin cancer assessment appointments.[23] With the integration of AI technology, the detection accuracy of skin cancer in dermatopathology, especially in noninvasive dermoscopic examinations, can be further improved, reducing misdiagnoses and missed diagnoses.

Although deep learning CNN models have already established mature training and detection workflows, optimization efforts for their application in skin cancer detection are still ongoing. For instance, Kumar et al. introduced the Falcon–Hawk optimization algorithm to efficiently adjust CNN parameters. This algorithm can effectively find the optimal solution within large parameter spaces, improving the accuracy and convergence speed of CNN models, reducing errors in the detection process, and enabling faster skin cancer detection.[24] Additionally, there are ongoing efforts to continuously optimize the architecture of CNN models. Musthafa and his team employed a direct and efficient end-to-end approach to train their self-designed CNN architecture on the HAM10000 dataset. They also introduced innovative data augmentation techniques to balance the model's biases across different skin lesion categories. As a result, they achieved excellent performance, with accuracy, precision, recall, and F2 scores of 97.78%, 97.9%, 97.9%, and 97.8%, respectively.[25]

In the field of image segmentation, Chen et al. introduced the DeepLab model,[26] which excels in achieving high-precision segmentation while maintaining computational efficiency. In image classification, the implementation of an explainable AI (XAI) model enhances the interpretability in the diagnostic process by giving reasonable diagnostic basis and reasoning process while giving the diagnostic results, and simultaneously increases the accuracy of melanoma classification.[27] AI has significantly contributed not only to the analysis of skin cancer lesion images but also to advancements in the study oftissue pathology of skin cancer cell.[28,29]

Another example of high collaboration with AI is seen in reinforcement learning, where the AI model can maximize task exploration while adhering to target objectives through manually set reward and punishment mechanisms.[30] This approach not only enhances interpretability of the model but also builds greater trust among developers and clinicians.

According to the research findings of MONet,[31] the model application of multimodal and metadata—the latest group of model applications—has been in full swing. The combination of skin lesion images and other nonimage data can greatly promote the accuracy of skin cancer detection and prediction.

Achieving high-quality detection results with a model not only makes certain demands on the model architecture but also relies heavily on high-quality data processing, especially for supervised learning tasks. In training the skin cancer detection model, the limited amount of data and imbalanced class distribution can cause some bias in the model's training results. Therefore, the most commonly used data preprocessing technique in skin cancer data is data augmentation. For skin cancer, it typically includes reducing noise in skin cancer images, improving image quality (such as annotation quality and segmentation quality), and controlling class distribution.[25,32] This paper will also list existing high-quality data processing methods and compare their advantages and disadvantages.

2. Review methods

This review adopts a narrative review method to summarize and synthesize all the literature related to the application of AI in skin cancer detection, particularly those involving deep learning and computer vision techniques. We focus on evaluating the progress of both unimodal models (including classification and segmentation) and multimodal models, with a special emphasis on advancements in datasets, model architectures, and results. After preliminary screening, several studies were selected as the most relevant and influential in terms of methods, datasets, and results. These studies have significantly contributed to advancing AI technologies in the field of skin cancer diagnosis, especially in strengthening detection accuracy, robustness, and model interpretability.

In the review process, we referenced commonly used datasets from the 15 reviewed papers (such as the ISIC Challenge, HAM10000 dataset, and Kaggle's skin cancer image dataset). We focused on their content, format, and structure while performing statistical analysis to compare key attributes, such dataset size, image quality, and label consistency.

To ensure a comprehensive understanding of the methods used in the reviewed articles, we conducted a qualitative synthesis of their research findings. This process involved a detailed analysis of the AI models employed (such as deep convolutional neural networks [DCNNs], hybrid models, and multimodal techniques), evaluation metrics, and the impact of dataset variations on model performance.

3. Data collection and preprocessing

3.1. Datasets

The ISIC project is an international collaboration focused on skin cancer research,[17,18,33,34,35] with the aim of promoting early detection and diagnosis of skin cancer by providing high-quality dermoscopic image datasets. Its dataset has become one of the most important resources in the field of skin cancer research and is widely used for training and validating algorithms, such as those used in machine learning and deep learning. The ISIC dataset contains a large number of high-quality images of skin lesions that cover various types of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, with each image accurately annotated by professional physicians. The dataset consists mainly of 2D digital images of skin lesions, typically presented as high-resolution color photographs, captured using standard digital cameras or specialized skin imaging devices, with resolutions ranging from 512 × 512 pixels to 6621 × 4441 pixels. Since 2016, new versions of the ISIC dataset have been released annually, focusing on different research tasks and challenges. For example, the ISIC 2024 involves classifying histologically confirmed skin cancer cases using images of skin lesions obtained from 3D full body photography.

Table 1
Detailed information of the skin lesions datasets.

Dataset name	Publication year	Task type	Modality	Number of images	Image format
ISIC 2016[13]	2016	classification, segmentation	Dermoscopy	900 training, 379 testing	jpeg, png
ISIC 2017[18]	2017	classification, segmentation	Dermoscopy	2000 training, 150 validation, 600 testing	jpeg, png
ISIC 2018[33,36]	2018	classification, segmentation	Dermoscopy	2594 segmentation, 10,015 classification	jpeg, png
ISIC 2019[18,36,37]	2019	classification	Dermoscopy	25,331 training	jpeg
ISIC 2020[34]	2020	classification	Dermoscopy	33,126 training, 10,982 testing	jpeg
ISIC 2024[35]	2024	classification	Photograph	401,059	jpg
BCN20000[37]	2019	classification	Dermoscopy	12,413 training, 6,533 testing	jpg
HAM10000[36]	2018	classification	Dermoscopy	10,015	jpeg
PH^2 [40]	2018	segmentation	Dermoscopy	200	png
MED-NODE[41]	2015	classification	Dermoscopy	170	jpeg
DERM7PT[42]	2018	classification	Dermoscopy	2000	jpg
PAD-UFES-20[43]	2020	classification	Photograph	2298	png
Fitzpatrick17[38,39]	2022	classification	Dermoscopy	16,577	jpg
MRA-MIDAS[44]	2024	classification	Photograph	2919	jpeg, jpg
SkinCancer[45]	2022	classification	Pathology	129,364 (29,419 skin cancer-related)	jpg
SKINL2[46]	2019	classification	Dermoscopy	330	png

Within the ISIC datasets, several sets of data (ISIC 2017–2020) utilized the HAM10000 and BCN20000 datasets.[36,37] These datasets are known for their diversity, high resolution, and detailed annotations, providing researchers with abundant image resources to help develop and validate skin cancer detection models. The HAM10000 dataset contains 10,015 images and is renowned for its diversity and detailed annotations. The images are sourced from multiple medical institutions, covering individuals of different races, ages, and genders, with precise annotations from dermatology experts, ensuring both sample diversity and accuracy, although there is an issue with category imbalance. This dataset has been used to develop and validate skin cancer diagnostic systems and to train medical students and primary care physicians, helping them improve their ability to identify skin cancer lesions and thus improve healthcare quality. The BCN20000 dataset contains 12,413 training images and 6533 test images and, along with the HAM10000, offers excellent data annotation and image quality. This dataset includes a wider variety of types of lesions and a larger volume of data. Together with HAM10000, it serves as a rich resource for the automated detection and classification of skin cancer, driving the application of AI technologies in dermatology and contributing to the early diagnosis and treatment of skin cancer.

In the data presented in Table 1, another dataset Fitzpatrick17 is notable for its diversity in skin types.[38,39] In addition to having large data volumes, precise annotations, and a variety of lesion types, it also categorizes skin types into six levels, from Type I (the lightest and most prone to sunburn) to Type VI (the darkest and least prone to sunburn). This classification of skin types by skin color is of great significance for cross-ethnic skin cancer detection. This data are beneficial to the development of more universal skin lesion classification models, enabling them to better adapt to people of different skin tones and improving diagnosis rates of skin cancer in multiethnic populations, thereby reducing biases.

In addition to the basic classification task data, there are also segmentation task datasets focused on skin cancer lesion areas, such as the ISIC 2016–2018 datasets and the PH^2 dataset.[40] These datasets not only annotate the type of skin lesions but also indicate the boundaries, size, and shape of the lesions, further enhancing the accuracy of the annotations. While their scale may be relatively small and their diversity in terms of skin tone, lesion types, and patient groups may be limited, their pixel-level annotations significantly advance the development of algorithms for skin lesion classification and segmentation.

In addition, there are more specialized datasets, including the SkinCancer dataset,[45] which uses pathological slide images, and the SKINL2 dataset,[46] which uses multilight field dermoscopic images. The SkinCancer dataset contains samples of scanned pathological slide images of skin lesions, generated by microscopy, with very high resolution to capture tissue structure and cellular-level details. The dataset includes not only annotations for skin lesions but also various anatomical tissue structures of the skin (e.g., epidermis, dermis, and fat layer) and possible tumor or lesion areas. These image annotations support tumor segmentation, anatomical structure recognition, and tissue classification tasks. The SkinCancer dataset plays a crucial role in the automation of skin cancer detection, pathology diagnosis systems, and related medical research. The SKINL2 dataset using light field imaging technology expands the dimensionality of skin cancer images from another perspective. This technology captures both brightness and depth information from multiple angles, providing rich spatial image information and three-dimensional structural data of skin lesions, helping to improve the accuracy of skin lesion detection, particularly for complex or small lesions.

Further details of the datasets and data sources are shown in Tables 1 and 2.

3.2. Data preprocessing

Data cannot initially fit perfectly into any model for training, as it may be influenced by various factors (such as noise, class imbalance, or insufficient data), requiring preprocessing to adapt it to our training tasks. For skin cancer data, many studies encounter issues such as unclear images and blurry key areas of lesions during model training. Ali et al. developed a skin cancer data

Table 2
More information on the skin lesions datasets plus with links.

Dataset name	Number of lesions (or classes)	Size (Smallest one)	Link
ISIC 2016[17]	2	1024 × 768	https://challenge.isic-archive.com/data/#2016
ISIC 2017[18]	1	540 × 576	https://challenge.isic-archive.com/data/#2017
ISIC 2018[33,36]	7	1022 × 767	https://challenge.isic-archive.com/data/#2018
ISIC 2019[18,36,37]	8	256 × 256	https://challenge.isic-archive.com/data/#2019
ISIC 2020[34]	2	640 × 480	https://challenge.isic-archive.com/data/#2020
ISIC 2024[35]	2	133 × 133	https://challenge2024.isic-archive.com/
BCN20000[37]	Not specified	1024 × 1024	https://figshare.com/articles/journal_contribution/BCN20000_Dermoscopic_Lesions_in_the_Wild/24140028/1
HAM10000[36]	7	450 × 600	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T
PH^2 [40]	1	560 × 768	https://www.fc.up.pt/addi/ph2%20database.html
MED-NODE[41]	2	201 × 257	https://www.cs.rug.nl/~imaging/databases/melanoma_naevi/
DERM7PT[42]	19	474 × 626	https://derm.cs.sfu.ca/Welcome.html
PAD-UFES-20[43]	6	147 × 147	https://data.mendeley.com/datasets/zr7vgbcyr2/1
Fitzpatrick17[38,39]	3	66 × 130	https://github.com/mattgroh/fitzpatrick17k
MRA-MIDAS[44]	16	Photography with a contemporary model iPhone or iPad device	https://aimi.stanford.edu/datasets/mra-midas-Multimodal-Image-Dataset-for-AI-based-Skin-Cancer
SkinCancer[45]	16	395 × 395	https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.1022967/full
SKINL2[46]	8	7716 × 5364	https://www.it.pt/AutomaticPage?id=3459

preprocessing pipeline to standardize image sizes and unify color space information across different datasets.[32] They used adaptive filters and adaptive median filters to reduce noise interference in the images while preserving image details. Additionally, mathematical morphology methods were applied to remove hair from images, minimizing the impact of hair on analysis.

Another notable issue with skin cancer datasets is class imbalance (where some classes have fewer samples). This issue requires appropriate data augmentation. For example, the HAM10000 dataset faces class imbalance, and Musthafa's team addressed this by applying specific transformations, such as rotation, scaling, flipping, cropping, and brightness adjustments, to balance the sample size across different classes.[25] These augmentations improved the generalizability of the model to new and unseen data, thus enhancing its predictive accuracy.

Through these data preprocessing steps, the quality and consistency of skin cancer image data can be effectively improved, addressing problems such as noise, image blurriness, and class imbalance. This creates a solid foundation for subsequent model training. Proper preprocessing not only promotes the accuracy and robustness of the model but also enhances its ability to generalize to unseen data, especially when dealing with complex medical image data.

4. Current AI technologies

AI is currently undergoing a revolutionary development phase, evolving from traditional machine learning and deep learning to large models and multimodal models primarily based on the transformer architecture. As a result, AI models' understanding and feature extraction of skin cancer images have become increasingly accurate. As the most popular foundational deep learning networks in computer vision, traditional models such as CNNs, fully convolutional networks, and You Only Look Once(YOLO) have demonstrated high accuracy and efficiency in both classification and segmentation tasks,[47–49] even reaching levels comparable to professional doctors in terms of diagnostic classification ability.[27] However, their limitations are also quite evident. These models often have high data costs and require large amounts of training data to achieve effective detection performance. They also have limited generalizability, meaning that even trained models may misjudge the type of skin lesion when confronted with previously unseen data. Additionally, they are sensitive to noise, and their accuracy can be compromised when dealing with blurry or flawed images, which necessitates data preprocessing, as mentioned earlier (Figure 2).

4.1. Segmentation

With the advancement of deep learning and computer vision technologies, image segmentation technology for skin cancer detection is also constantly improving. In particular, AI-assisted image segmentation models based on CNNs have achieved remarkable results in this field.[50] Among these, models such as U-Net,[51] SegNet,[52] YOLO,[53] and DeepLab[26] stand out for their exceptional performance.

U-Net, a kind of fully convolutional networks, features an encoder–decoder structure, in which the encoder extracts image features and reduces spatial resolution, while the decoder restores it using convolutional and upsampling layers.[51] Skip connections preserve high-resolution details, enhancing segmentation accuracy. The symmetric design of the U-Net allows for effective

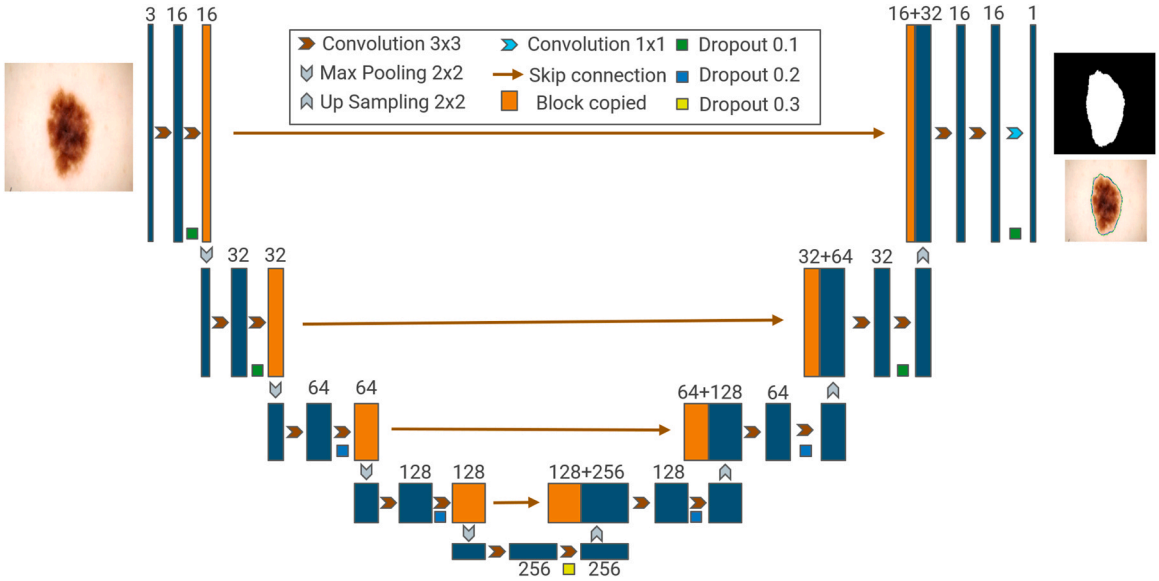


Figure 2. A basic segmentation network pipeline.

segmentation even with limited data, making it particularly useful in medical imaging, especially when data are scarce. To improve the performance of U-Net, Zhao et al. introduced a residual network structure in the encoder section, stacking this structure to capture more feature information.[47] Additionally, they incorporated multiscale feature fusion to improve segmentation accuracy. The integration of the transformer architecture addresses the limitation of capturing long-range dependencies. Eskandari et al. proposed a transformer-based U-shaped hierarchical structure and introduced an inter-scale context fusion method,[54] enabling the model to adaptively combine context information from each stage and reduce semantic gaps. While the introduction of the transformer structure enhances test results, the computational resource requirements of the improved U-Net are smaller due to its network structure differences, making it more suitable for deployment in clinical applications.

SegNet, aDCNN-based semantic segmentation model developed by a team from the University of Cambridge, also utilizes a symmetric encoder–decoder architecture.[52] However, unlike U-Net, SegNet performs precise upsampling in the decoder using pooling indices to restore spatial resolution. Kibriya et al. demonstrated the effectiveness of SegNet in clinical environments for melanoma detection, particularly highlighting its robustness in dealing with image artifacts and challenging features, making it an excellent candidate for clinical applications.[55] Furthermore, Şahin et al. proposed a Bayesian optimization-based version of SegNet for precise skin lesion segmentation.[56] Compared to the standard SegNet, the Bayesian-optimized version showed a 16% performance improvement on the ISIC 2016 dataset and a 7% performance improvement on the ISIC 2017 dataset. Although both studies highlight the SegNet model's potential for skin cancer detection and its good prospects for clinical applications, the model has certain computational complexity and resource requirements. The SegNet model needs more training data and training time to achieve high performance.

YOLO is a fast real-time object detection model that directly predicts bounding boxes and categories from images, with continuous updates improving its accuracy and speed.[53] Integrated into systems such as the Health of Things Melanoma Detection System, YOLOv8 aids in mobile-based melanoma detection and lesion segmentation using cloud-connected deep learning models.[49]

Meanwhile, DeepLab introduced atrous convolution and encoder–decoder structures for precise image segmentation.[26] In a study by Zaw et al., a new two-stage transfer learning approach was proposed to segment skin lesions from skin images.[57] The nSknRSUNet architecture combines the advantages of U-Net and DeepLabV3, further improving segmentation accuracy through an enhanced U-Net model. It also integrates design concepts from DeepLabV3, such as multiscale feature extraction and efficient spatial information capture, while optimizing segmentation performance through residual learning and skip connections. This model achieved a dice similarity coefficient of 94.63% and an accuracy of 99.12% on the HAM10000 dataset. In another study, a team led by Toprak created a hybrid network model based on DeepLabv3+ that accurately segments lesion areas while maintaining computational efficiency, providing clear input data for multiclass skin cancer classification and improving the overall performance of the classification models.

In current skin cancer image segmentation tasks, AI models such as U-Net, SegNet, and DeepLab offer high-precision segmentation capabilities, while the YOLO model provides efficient training and deployment. These AI image segmentation models exhibit high generalization, strong scalability, and high accuracy in segmenting skin cancer lesions. This establishes a solid foundation for future intelligent hospitals, cloud-based hospitals, or remote deployment applications for smart cities, such as the Health of Things Melanoma Detection System.[49]Tables 3 and 4 provide a comparative summary of the segmentation task models.

Table 3
The indicators of the segmentation models.

Model name	Used data	Dice	Jaccard	Accuracy
Transformer-based U-Net with inter-scale context fusion[47]	ISIC 2017, ISIC 2018 segmentation tasks	0.9257	Not specified	0.9698
Improved U-shaped network[54]	ISIC 2017	0.9384	0.9679	0.9662
Robust optimization of SegNet[56]	ISIC 2016, ISIC 2017	0.925	0.875	Not specified
SegNet for melanoma lesion segmentation[49]	ISIC 2016, ISIC 2017	Not specified	Not specified	0.89
YOLO-v8[58]	PH^2, ISIC 2017	Not specified	Not specified	0.9867
nSknRSUNet[57]	MoleMap, HAM10000	0.9413	Not specified	0.9806

Table 4
Advantages and shortcomings of the segmentation models.

Model name	Advantages	Shortcomings
Transformer-based U-Net with inter-scale context fusion[47]	High accuracy and robustness	High computational complexity
Improved U-shaped network[54]	Improved accuracy via multiscale feature fusion; Expanded feature information via residual network structure	High computational complexity; Low generalizability to unknown data
Robust optimization of SegNet[56]	Improved SegNet segmentation performance by optimizing hyperparameters; Enhanced optimization efficiency via Bayesian optimization algorithm	High computational complexity; Computational resource requirements
SegNet for melanoma lesion segmentation[49]	Deployable in Clinical environments; Automating lesion segmentation clinical potential	Substantail computational resources required
YOLO-v8[58]	Efficient, fast, accurate, small, and suitable for edge computing; Medical diagnostic support systems in smart cities	Large datasets required; Further validation of generalizability needed
nSknRSUNet[57]	Essential skin knowledge extraction; Efficient network training and improved performance via natural images	Substantial computational resources and time needed

4.2. Classification and detection

In the field of skin cancer auxiliary detection and classification, several AI visual models have been prominently applied, including Inception V3,[59] ResNet-50,[60] NASNet,[61] EfficientNet,[62] and MobileNet V3.[63] These models are notable for their high usage rates and accuracy, demonstrating outstanding performance in skin cancer classification and detection (Figure 3).

Inception V3 uses a parallel convolutional structure to extract features at different scales,[59] improving performance through wider networks and stacked Inception modules. SkinFLNet combines Inception's multiscale feature integration with ResNet's residual connections,[64] enhancing skin lesion recognition. Through model fusion and lifelong learning techniques, SkinFLNet demonstrates strong robustness across different datasets, enabling training on relatively small datasets, which is crucial for clinical skin cancer screening. Trained on 1215 diagnostic and 463 clinical images from Taichung and Taipei Veterans General Hospitals, SkinFLNet achieved 85% accuracy, 85% precision, 82% recall, and 82% F1 score, demonstrating its effectiveness in both small dataset training and clinical applications.

ResNet addresses the vanishing gradient problem with its deep residual structure,[60] and ResNet-50 is commonly used for deep feature extraction tasks. In skin cancer detection, Mehra et al. evaluated ResNet-50 on the HAM10000 dataset, achieving high accuracy and precision with recall and F1 scores of 85%.[65] Their model is notably effective for training on smaller datasets. Singh et al. proposed a deep neural network combining Inception and residual blocks,[66] achieving 97% accuracy in melanoma classification on ISIC datasets (2018–2020), significantly outperforming other models and capturing multiscale features. Chanda et al. developed

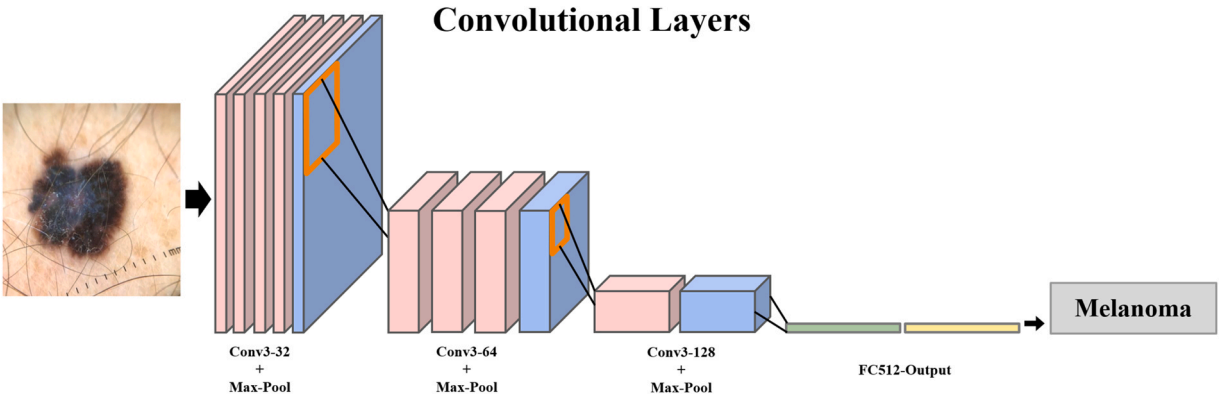


Figure 3. One of the basic classification network pipelines.

an XAI model using ResNet-50 annotations to increase transparency, making the system more understandable for dermatologists, although no experimental results were provided.[27] This model enhances clinical decision-making by offering interpretable text- and region-based explanations.

NASNet, with its modular design, stacks identical units to form a scalable and portable network.[61] Abbas et al. utilized the NASNet pretrained model for feature transfer, enhancing it with global average pooling and classification layers, achieving 97% accuracy on the ISIC 2020 dataset through transfer learning.[67] This model effectively automates high-level feature extraction, reducing the need for manual feature engineering. To further boost NASNet's performance in cancer diagnosis, Altamimi et al. optimized the network structure and trained it on raw, LBP, and multistep preprocessed features, achieving an impressive 99.85% accuracy on the HAM10000 dataset and outperforming existing methods across various metrics.[68]

EfficientNet utilizes compound scaling to optimize network width, depth, and input resolution, achieving high performance with fewer parameters and computational resources, making it suitable for resource-constrained applications. Anand et al. improved the EfficientNetB0 model using K-means clustering for image segmentation to enhance image quality and model robustness for skin cancer detection on Kaggle datasets.[69] Additionally, Das et al. integrated Choquet fuzzy integrals with EfficientNet, improving prediction accuracy and robustness by addressing class imbalance in the ISIC dataset through a reward–penalty mechanism based on macro F1 score.[70]

MobileNet, developed by Howard et al., is a lightweight convolutional network designed for deployment on mobile and embedded devices with limited memory.[63] It reduces computational complexity by using depthwise separable and pointwise convolutions, improving speed on mobile devices. Sharmila et al. optimized MobileNet using techniques such as pruning, weight clustering, and quantization and combined it with transfer learning from ResNet, resulting in superior memory usage, though with a slight drop in detection accuracy.[71] Lilhore et al. improved MobileNet by combining it with standard U-Net and optimizing hyperparameters through Bayesian methods, achieving 97.84% accuracy and 98.86% precision on the HAM10000 dataset.[72] This enhancement increased model performance, eastablishing the tool's value for early skin cancer detection, reducing misdiagnoses, and improving prognostic outcomes.

AI has significantly contributed to the study of pathological sections of skin cancer, in addition to the detection of skin epitomic cancer cells. Hekler et al. were among the pioneers in applying deep learning to melanoma pathology image classification.[73] Despite using a limited dataset of 695 annotated H&E-stained lesion samples, their CNN achieved diagnostic accuracy comparable to human pathologists. By digitizing and randomly cropping samples, the model utilized "subvisual" features from small datasets, demonstrating the potential of deep learning as a valuable tool for pathologists in early melanoma detection.

Recently, CNN models have continued to undergo optimization and updates. For example, Musthafa et al. designed a multilayer convolution, pooling, and fully connected layer model to better capture the complex visual features of skin lesions, achieving an accuracy of 97.78% on the HAM10000 dataset.[25] Additionally, Kumar's team proposed a novel skin cancer detection model based on a modified Falcon finch deep CNN classifier.[24] By combining the Falcon-Sparrow Optimization Algorithm with deep CNNs, and simulating the foraging behaviour of falcons and sparrows to explore the hyperparameter space of DCNNs, the model successfully improved skin cancer diagnostic accuracy. Both models enhance detection accuracy on skin cancer datasets by integrating optimized CNN models with suitable data augmentation strategies.

Currently, models such as Inception V3, ResNet-50, NASNet, EfficientNet, and MobileNet V3 offer high accuracy and precision in skin cancer classification and detection tasks. Each model has demonstrated performance across various datasets and tasks through transfer learning and hyperparameter tuning. The structural designs of EfficientNet and MobileNet maintain high performance under limited computational resources. While these models show good flexibility and broad applicability, combined models can further strengthen computational efficiency and resource utilization. However, challenges remain, including reliance on large-scale, high-quality annotated data, the impact of data diversity on generalization, and robustness issues in handling noise. Although their models have not undergone extensive generalization validation, the strong performance on experimental data and the optimization adjustments suggest a promising trend for clinical detection or deployment on edge computing devices. A comparative summary of the classification task models can be seen in Tables 5 and 6.

4.3. *Transformer, multimodal, and other technologies*

Despite significant progress made by traditional CNN and deep learning models in skin cancer detection, they still face numerous limitations when dealing with complex datasets, especially in situations with high noise, imbalanced annotations, and blurred image details. In such cases, the performance of traditional CNN models may be constrained. Furthermore, traditional methods often rely on specific image feature extraction techniques and struggle to capture long-range dependencies, limiting their effectiveness in handling complex image patterns. In contrast, transformers and multimodal models represent innovative directions in current AI technology. Transformers effectively capture both global and local information in images through the self-attention mechanism, overcoming the shortcomings of traditional convolutional networks in modeling long-range dependencies. They show stronger capabilities, particularly when handling large-scale and complex datasets.[74] Multimodal models integrate various data sources, such as images, clinical data, and genetic information, to enhance the comprehensiveness and accuracy of diagnoses and address the information loss issues that arise from using a single data modality. The combination of these approaches not only increases the models' ability to detect skin cancer but also brings higher precision and robustness to clinical applications, marking a technological breakthrough in AI-driven skin cancer detection (Figure 4).

To reduce the inference cost of AI models in practical applications, SkinDistiViT leverages knowledge distillation techniques to achieve performance comparable to the Vision Transformer (ViT) model while significantly reducing computational resources.[75]

Table 5
The indicators of the classification models.

Model name	Used data	Accuracy	F1 score	Sensitivity	Specificity
SkinFLNet[64]	Clinical images from Taichung and Taipei Veterans General Hospitals	0.85	0.82	0.82	0.93
ResNet-50-based DCNN[65]	HAM10000	0.8487	0.85	Not specified	
Inception-ResNet-based DCNN[66]	ISIC 2018 – 2020	0.97	0.97	0.99	0.93
XAI[27]	Not specified	Not specified	Not specified	Not specified	Not specified
Deep features of NASNet[67]	ISIC 2020	0.97	Not specified	Not specified	Not specified
NASNet transfer learning model[68]	HAM10000	0.9985	Not specified	Not specified	Not specified
K-means-based EfficientNetB0[69]	Kaggle database	0.87	Not specified	Not specified	Not specified
Fuzzy ensemble model based on EfficientNet[70]	ISIC database	0.8815	Not specified	Not specified	Not specified
Optimizing deep learning networks[71]	Not specified	Not specified	Not specified	Not specified	Not specified
Hybrid U-Net and improved MobileNet-V3[72]	HAM10000	0.9886	Not specified	0.9635	0.9732
Deep neural networks for pathologist-level classification[73]	HAM10000, ISIC 2017, PAD-UFES-20-Modified	0.96	0.97	0.99	0.93
Optimized CNN[25]	HAM10000	0.9778	Not specified	Not specified	Not specified
Modified falcon finch deep CNN[25]	HAM10000	0.9652	Not specified	0.9669	0.9654

Abbreviations: 1. DCNN: deep convolutional neural network 2. XAI: explainable artificial intelligence 3. CNN: convolutional neural network.

Table 6
Advantages and shortcomings of the classification models.

Model name	Advantages	Shortcomings
SkinFLNet[64]	Strong robustness across different datasets; Enabled training on relatively small datasets	Clinical practice computational resources required; Strongly dependendent on data quality
ResNet-50-based DCNN[65]	Able to train and optimize on smaller datasets	Substantial computational resources required; Strongly dependendent on data quality
Inception-ResNet-based DCNN[66]	High accuracy in melanoma; Able to capture multiscale features	High computational complexity; Unproven generalizability
XAI[27]	Increased AI system transparency; Having text and region explanations	Accuracy improvement not significant; Further validation of clinical practice still warranted
Deep features of NASNet[67]	Automatic extraction of high-level features; Reduced manual feature extraction	Substantial computational resources required; Unproven generalizability
NASNet transfer learning model[68]	High accuracy	Unproven generalizability
K-means-based EfficientNetB0[69]	Enhanced robustness by segmented image via K-means clustering	High computational complexity
Fuzzy ensemble model based on EfficientNet[70]	F1-based reward fixing the class imbalance issue	Unproven generalizability
Optimizing deep learning networks[71]	Reduced memory consumption	Potentail decrease in performance
Hybrid U-Net and improved MobileNet-V3[72]	High accuracy and recall rate; Valuable for dermatologists	High computational demands; Lack of interpretability
Deep neural networks for pathologist-level classification[73]	Valuable for early-stage pathological skin cancer detection	Unproven generalizability
Optimized CNN[25]	High accuracy achieved through data augmentation	Potentially limited clinical acceptance due to poor interpretability
Modified falcon finch deep CNN[25]	High accuracy achieved through data augmentation	Poor interpretability; Demanding computational resources

Abbreviations: 1. DCNN: deep convolutional neural network 2. XAI: explainable artificial intelligence 3. CNN: convolutional neural network.

Verified using skin melanoma data, the model retains 98.33% of ViT's original performance and accelerates inference speed by 69.25% while reducing memory usage by 49.60%, demonstrating its practicality in real-world applications. However, while knowledge distillation enhances efficiency, it introduces additional complexity, requiring more sophisticated training mechanisms to maintain accuracy with fewer resources. This added complexity increases the computational cost during the development phase but is outweighed by the model's ability to offer high performance and improved efficiency, making SkinDistiViT a viable solution for skin cancer detection in resource-constrained environments.

To address the limitations in feature extraction, Omeroglu et al. introduced a novel approach by integrating multimodal data and incorporating a soft attention module, which allows CNNs to focus on the most discriminative parts of skin lesions, thereby improving classification accuracy and robustness.[76] By designing a multibranch architecture and employing soft attention modules, they effectively addressed challenges related to uneven label distribution. Their proposed soft-attention-based multimodal learning algorithm integrates complementary information from dermoscopic images, clinical images, and patient metadata using trichotomous fusion. Evaluated on the Derm7pt dataset, the algorithm achieved an accuracy of 83.04%, significantly enhancing both the accuracy

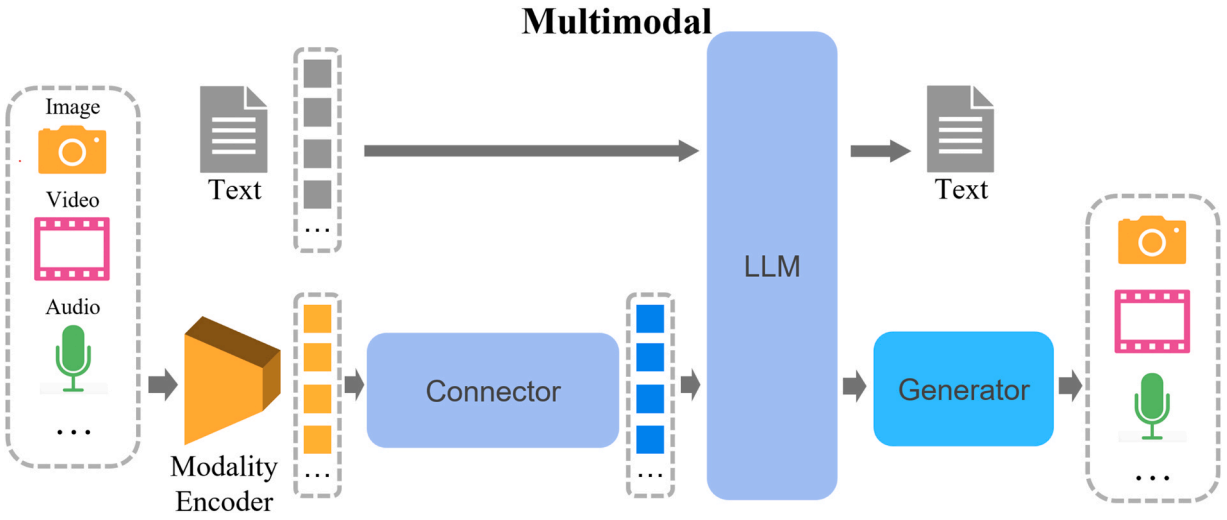


Figure 4. Basic multimodal pipeline.
Abbreviation: LLM: large language model.

and robustness of skin lesion classification. However, while this model boosts classification performance, it also introduces increased complexity, requiring more computational resources and training time. Additionally, the model's effectiveness is heavily reliant on large amounts of labeled data, which can be a limitation in practical settings. Despite these challenges, this approach demonstrates the potential of multimodal learning to advance dermatological AI applications.

A previous study proposed a vision transformer-based method called SkinViT for classifying melanoma and nonmelanoma skin lesions.[77] The model architecture consists of three key components: the outlooker block (which replaces patch embedding in ViT to learn features), the transformer block (which uses the self-attention mechanism to learn important features and ignore noise), and the MLP head block (for final classification decisions). Experimental results show that SkinViT outperforms other existing models across multiple datasets, achieving a notable accuracy of 91.09% on the ISIC 2019 dataset. The model effectively captures fine-grained and global features and demonstrates high robustness when handling imbalanced datasets.

Another research proposed a skin cancer classification method based on ViT,[78] which integrates image preprocessing, the ViT self-attention mechanism, the Segment Anything Model, and various pretrained models to achieve high-precision skin cancer segmentation and classification. Specifically, the model used the HAM10000 dataset, consisting of 10,015 skin lesion images, with data preprocessing and augmentation applied. Using ViT, the model achieved an accuracy of 96.15% on the test dataset, with a low false-negative rate. The Segment Anything Model excelled in tumor region segmentation, achieving 96.01% Intersection over Union and 98.14% Dice coefficient. This approach improves the model's decision-making ability through multimodal data integration, offering high accuracy and strong feature capture capability.

Dagnaw et al. proposed a skin cancer classification method combining ViT and XAI techniques, with a focus on improving the model's interpretability.[79] The study used multiple pretrained models for feature extraction, including ViT and CNNs, and incorporated three XAI methods—Grad-CAM, Grad-CAM++, and Score-CAM—to interpret the model's decision-making process. With these techniques, the model can clearly demonstrate the rationale behind its image analysis decisions, thereby enhancing transparency, interpretability, and its suitability for clinical applications.

Modern multimodal large language models now possess capabilities in image recognition and the integrated analysis of text and images. Prominent models, such as ChatGPT-4o[b], Llama 3.2-Vision[c], ChatGLM4,[80] and Kimi,[81] can perform basic recognition and understanding of dermatological images when combined with textual queries. Although these general-purpose multimodal models may not yet accurately analyze specific types of skin cancer lesions, their emergence offers new perspectives for research into multimodal diagnostic models for skin cancer (Figure 5).

To build trustworthy and transparent image-based AI medical models, MONet pairs medical skin cancer images with professional text descriptions, providing dense annotations of concepts within images to enhance the development and deployment of medical AI.[31] The model takes skin cancer lesion images paired with natural language descriptions as input and produces outputs driven by classification concept scores and multistage concept analysis within the AI pipeline. Its applications include extracting features from self-test datasets to identify and resolve dataset issues, pinpointing input features that lead to errors in medical AI models to improve transparency and trust, and developing human-concept-driven models for interpretable decision-making in clinical settings. MONet outperforms Contrastive Language-Image Pre-Training in annotating concepts in clinical and dermoscopic images, showing consistent performance across different skin tones and identifying irrelevant artifacts in clinical data, thus enhancing the audit and debugging

[b] More details available at the official website of ChatGPT.
[c] More details available at Meta AI blog.

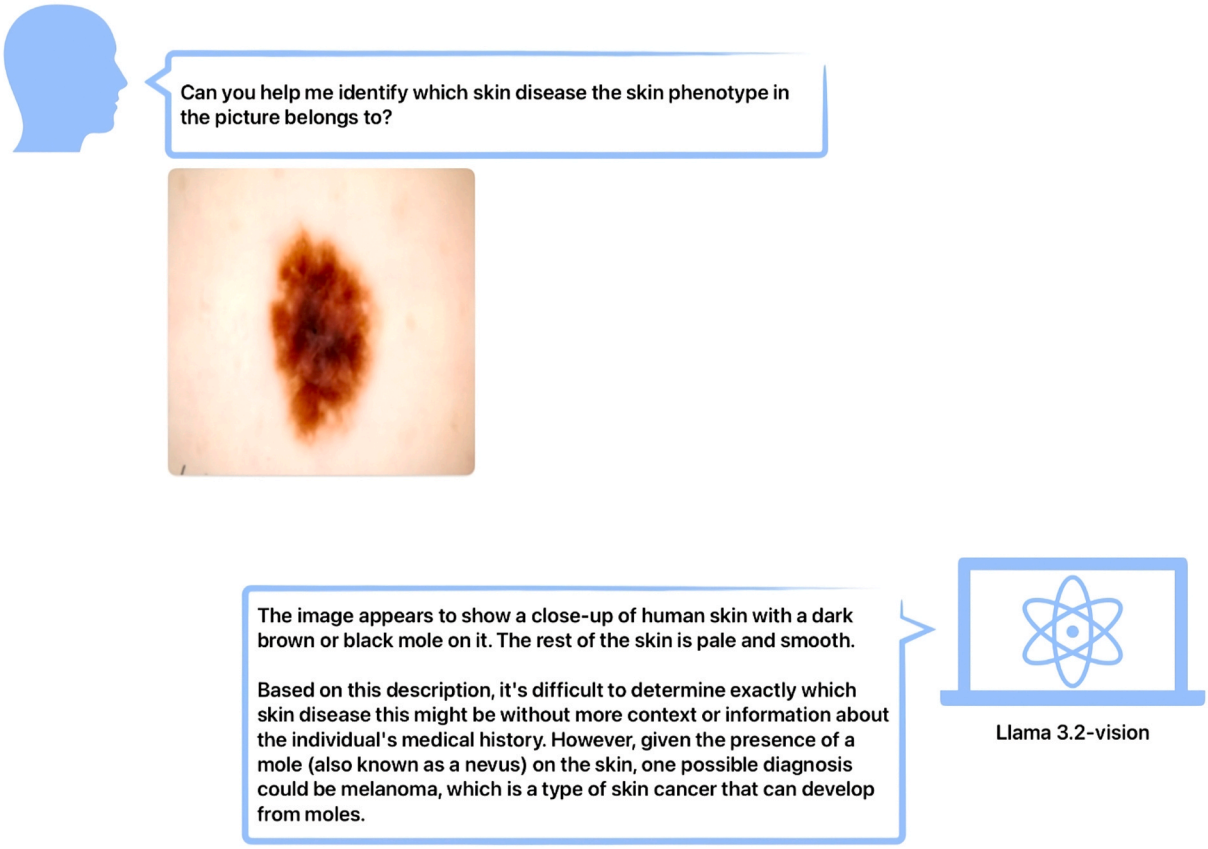


Figure 5. Inference example with Llama 3.2-Vision.

capabilities of medical AI pipelines.[82] However, while MONet achieves high accuracy in annotating dermatological images and supports transparency from data to model auditing, it requires considerable computational resources and time for training, as well as large amounts of labeled data for optimal performance.

Deep learning has also been applied to the inference of genetic features in cancer research. Tran et al. combined high-quality omics data with conventional tissue pathology images and multiple deep learning models to infer critical genetic features.[83] Their experiments demonstrated that deep learning not only provides accurate inferences of key genetic traits but also reduces the cost of gene sequencing, enabling cost-effective, efficient, and precise cancer treatment and management. This approach has been shown to significantly improve patient survival rates, illustrating the potential of deep learning in clinical practice. By integrating multiple models and data types, this methodology offers more comprehensive decision support and automates feature extraction, reducing the need for manual feature engineering. However, it also demands substantial computational resources and a large amount of labeled data for training, which can be a challenge in real-world applications.

Combining ViT,[74] Q-Former,[84] and the large language model Llama-2-13b-chat,[85] Zhou et al. proposed the multimodal large language model SkinGPT-4.[86] This model combines patient-uploaded image and text information to recognize and analyze skin disease images, generating detailed text reports and interactive treatment suggestions. Through quantitative evaluations with professional dermatologists, the diagnostic accuracy of SkinGPT-4 has been validated in real clinical cases. By learning complementary features from different modalities, SkinGPT-4 provides more comprehensive decision support, generating interpretable visual concepts that improve model transparency. This advancement in multimodal AI improves diagnostic accuracy and accessibility while safeguarding patient privacy through local deployment. However, the model's effectiveness comes at the cost of requiring substantial computational resources and training time, as well as large amounts of labeled data for optimal performance.

Additionally, multimodal deep learning model has been applied to the analysis of whole-slide images .[87] This research employed deep learning models to learn information related to subsequent biomarkers from whole-slide images to predict the one-year disease-free survival of melanoma patients. By extracting features from melanoma images, the model accurately predicted the disease-free survival period, establishing a valuable foundation for prognosis prediction in melanoma.

In addition to conventional supervised learning models, there is also a model training approach dominated by reinforcement learning. Barata et al. combined a Q-learning-based reinforcement learning model[88] with Monte Carlo tree search methods[89] to enhance the overall decision-making of the model and avoid local optimization solutions. The model can automatically optimize parameters and better adapt to different skin cancer detection tasks. At the same time, it demonstrates good adaptability, which adjusts decision-making strategies based on different input data, thus improving detection accuracy.

Table 7
Comparative summary of the transformer and multimodal models.

Model name	Used data	Specialty
SkinDistilViT[75]	ISIC 2019	Knowledge distillation
Soft-attention-based multimodal[76]	Derm7pt	Soft attention module
SkinViT[77]	ISIC 2019	Outlooker block and transformer block
Vision transformer[78]	HAM10000	Self-attention mechanism
Vision transformers + XAI[79]	HAM10000	Using the XAI models to explain the decision-making process
MONET [31]	105,550 images paired with natural language descriptions	Conceptual annotation of dermatological images
Mixed multimodal[83]	Not Specified	Data combining imaging, genomic, and clinical data
SkinGPT-4[86]	52,929 images with clinical concepts and notes	Conducting a quantitative evaluation
Reinforcement learning model[88]	HAM10000	Feedback-based training

Abbreviations: 1. XAI: explainable artificial intelligence 2. MONET: medical concept retriever.

Currently, transformer and multimodal technologies have demonstrated significant advantages in skin cancer research. ViT enhances image classification and segmentation performance through modular design and multiscale feature processing, improving the model's ability to capture complex features. SkinDistiViT optimizes model performance and resource consumption using knowledge distillation, making it more efficient in practical applications. MONet and SkinGPT-4 combine image and text information to enhance model transparency, interpretability, and diagnostic accuracy, showing consistent performance across diverse skin tones and strengthening model generalization. These technologies collectively advance the accuracy, interpretability, and feasibility of skin cancer detection. However, these models still heavily rely on large-scale high-quality annotated datasets, and their performance is contingent on the completeness, clarity, and diversity of the data. Additionally, similar to segmentation task models, AI classification and detection models require substantial computational resources (e.g., ResNet-50 and Inception V3). Even optimized models, such as MobileNet and EfficientNet, may face deployment challenges under extreme conditions due to limited computational resources. Therefore, despite transformer and multimodal models significantly improving the classification accuracy and robustness of skin cancer detection while enhancing model transparency and interpretability, they also bring a dependency on large-scale, high-quality data and powerful computational resources. A comparative summary of the transformer and multimodal models can be seen in Tables 7 and 8.

5. Benefits and challenges

With the continuous iterations and upgrading of AI, algorithms, foundational models, and large model architectures are constantly improving to enhance task accuracy. These models showcase the immense potential of AI, particularly deep learning and computer vision technologies, in medical image analysis. They not only improve the accuracy of dermatological diagnoses but also bring efficiency gains to doctors' diagnostic processes. Furthermore, with the advent of large AI models, various industries are experiencing a new wave of technological innovation. For instance, collaboration between large models and dermatology has driven advancements in image processing technology and model architectures, leveraging transformer technology to enable models to obtain more comprehensive feature information from skin cancer imaging data and making AI-assisted detection more precise. At the same time, with the help of multimodal models, skin cancer image diagnosis is enhanced through the integration of multiple data sources, improving the models' interpretability and reliability. This enables medical personnel or patients to gain a clearer understanding of

Table 8
Advantages and shortcomings of the transformer and multimodal models.

Model name	Advantages	Shortcomings
SkinDistilViT[75]	High accuracy	Requiring more computational resources
Soft-attention-based multimodal[76]	Enhanced classification performance	Requiring more computational resources and data
SkinViT[77]	High performance across multiple datasets	Lack of clinical interpretability
Vision transformer[78]	Able to capture complex spatial dependencies	Unproven generalizability
Vision transformers + XAI[79]	Improved transparency and interpretability	Unproven generalizability
MONET [31]	Accurately annotates dermatological images	Requiring more computational resources and data
Mixed multimodal[83]	Providing a more comprehensive analysis	Requiring more computational resources and data
SkinGPT-4[86]	Providing more comprehensive decision support Enhances model transparency	Requiring more computational resources and data
Reinforcement learning model[88]	Improved model transparency and interpretability	Unproven generalizability

Abbreviations: 1. XAI: explainable artificial intelligence 2. MONET: medical concept retriever.

these models' diagnostic processes and further promotes the application of AI in clinical practice. The use of multimodal models allows for a more comprehensive acquisition of diagnostic evidence related to skin cancer. This shift from conventional single-modality image-based diagnostic input to a multimodal, multidimensional information fusion approach allows models to better understand the correlating features of skin cancer from various perspectives, making clinical auxiliary diagnosis more accurate. Additionally, it enables clinical medical detection to provide more accurate and evidence-based diagnoses in a shorter time, thus improving diagnostic efficiency. This not only creates a more reasonable and comprehensive diagnostic approach for AI-assisted skin cancer detection but also enhances the quality and effectiveness of medical services, laying the groundwork for the development of personalized healthcare in the future. This interdisciplinary collaboration further underscores the potential of AI across various fields. In summary, modern AI-assisted skin cancer research validates that the interdisciplinary collaboration between computer science and medicine not only drives development in both fields but also highlights the necessity and significance of such collaboration.

Despite the tremendous potential and prospects of AI in skin cancer detection, there are still many challenges and limitations in practical deployment. In terms of data, although AI technology can achieve high accuracy and efficiency in assisting skin cancer detection, its performance still heavily relies on large-scale, high-quality annotated data. As demonstrated by the high-performance models discussed earlier, many studies require specific data cleaning and augmentation steps before model training to mitigate issues such as insufficient data diversity and unstable quality, which can affect the AI model's generalizability, especially when dealing with specific features or rare lesions. Furthermore, training and clinical data often exhibit balance biases, such as imbalanced categories or significant differences in the quantity ratios between lesion types, which significantly impact the model's generalizability and diagnostic accuracy.[90] In clinical applications, the "black box" nature of AI reduces clinical acceptance, meaning not all research can be effectively applied in practice.[91] Although multimodal models like MONet and SkinGPT-4 have improved interpretability by utilizing multimodal data, their decision-making processes lack the transparency needed for doctors to intuitively understand AI models' decision-making, especially when it comes to complex skin lesion judgments. Therefore, to effectively integrate AI into clinical practice, continuous evaluation and monitoring by medical professionals are still required.[92] Healthcare professionals must actively participate in the development and deployment of AI to ensure its effective use and maximize patient benefits. Ethical considerations, such as autonomy, informed consent, and privacy, must also be addressed. Balancing data security and transparency requires collaboration between patients, doctors, and developers to establish regulatory guidelines and clarify responsibilities, which is crucial for the ethical environment of dermatological AI.[92]

In addition to the aforementioned issues, rapid advancements in computer hardware, such as GPUs, have significantly boosted computational power, allowing modern models to achieve a scale far beyond previous capabilities. In this era where hardware and models are advancing together, the availability of computational resources is crucial for deploying large-scale AI-based skin cancer detection applications. However, the upgrading of computer resources is not synchronized globally, meaning some powerful AI models (such as ViT and ResNet) cannot be "open-sourced" at the hardware level. In the case of deploying clinical skin cancer detection models in particular, the performance gap between different models may require high computational resource costs to bridge, resulting in a situation wherein substantial expenses are needed for relatively small outcomes. Additionally, from a technical standpoint, effectively integrating multimodal data, especially in the context of clinical detection, still requires optimization of data alignment and addressing feature differences and information redundancy between different modalities. In terms of final clinical deployment, AI-assisted skin cancer detection models must also deal with the rapid update of models and the challenges of transfer learning. Furthermore, regarding data privacy and security, models require large volumes of patient data, which include personal information and medical information. Ensuring data collection, processing, and storage are carried out following patient privacy protection is a significant challenge for deploying AI-assisted skin cancer detection models.

Looking ahead, the potential of AI to improve diagnostic efficiency and accuracy is gradually being realized through emerging technologies, such as transformers and multimodal models. Additionally, the development of AI has enhanced model interpretability and expanded its applicability. From simplifying clinical workflows for skin cancer detection to assisting doctors in improving diagnostic accuracy, AI has made significant strides. However, AI-assisted skin cancer detection still faces challenges such as data dependence, computational resource requirements, model interpretability, and technical complexity. To achieve widespread clinical application of these technologies, future research needs to address issues such as data quality in the early stages and make efforts to enhance model transparency in the underlying technologies, optimize computational resource costs, and ensure patient information privacy and security in deployment. These efforts will further enhance AI-assisted skin cancer detection.

AI can effectively assist doctors by analyzing large datasets. Although most current research focuses on validating the accuracy of AI in controlled environments, future applications of AI in dermatology hold enormous potential.[93] Therefore, collaborating with specialists to improve clinical data collection, annotation, and storage, strengthening data privacy and security measures, and establishing unified evaluation standards and regulations will greatly facilitate the practical deployment of AI models. At the same time, to further optimize AI applications in clinical settings, it is essential to enhance model interpretability, optimize computational resources, increase clinical validation, and improve integration and usability. Currently, platforms such as Skinive Cloud have already achieved remote AI diagnosis for skin diseases.[94] By leveraging highly integrated cloud platforms to expand data dimensions, improve diagnostic accuracy, optimize workflows, and empower patients, these platforms demonstrate the feasibility of deploying AI online or remotely in dermatology.

6. Summary

The development of AI is undergoing a transformation, evolving from previously dominant single-modal models to large models, such as transformer architectures and multimodal models. These models have demonstrated multiple advantages in assisting skin

cancer detection, particularly in areas such as feature extraction from skin cancer images, improved model interpretability, and adaptability to various types of data. However, challenges remain in the field of AI-assisted skin cancer detection, including limitations related to data quality, reliance on a large number of categories, consumption of computational resources, and models' generalizability. Although both single-modality and multimodal models show high efficiency and accuracy, their performance still depends on the quality of the training data and sufficient computational resources. Furthermore, the generalizability of most models needs further confirmation in clinical diagnostic assistance.

Ongoing technological advancements are driving the development of more complex AI models, which continue to promote model generalizability and diagnostic accuracy, enabling the completion of more complex tasks. The application of emerging architectures, such as transformers and multimodal models, further strengthens the precision and interpretability of AI-assisted skin cancer detection. While challenges such as data diversity, annotation accuracy, and model interpretability persist, the wave of emerging models will continue to grow. Future developments will foster more effective collaborations between AI experts and healthcare practitioners, taking AI-assisted skin cancer detection to new heights in the future.

CRediT authorship contribution statement

Jingjing Xia: Writing – review & editing, Methodology, Data curation. **Lianyi Han:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Conceptualization. **Zhengyu Yu:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation. **Chao Xin:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Yingzhe Yu:** Writing – review & editing, Resources, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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