

**Applied molecular biology**  
Vol.4, issu.8, Autumn. 2025  
pp.99-109

## **Role of Artificial Intelligence in the Diagnosis and Treatment of Skin Cancers**

**Leila Jafarian khaled-Abad<sup>1</sup>, Soham Mohebbi<sup>2\*</sup>**

1. Assistant professor ,Department of mathematics ,Faculty of Basic Science, Ale Taha Institute of Higher Education, Tehran, Iran.
2. Assistant professor, Department of Biology, Faculty of Basic Science, Ale Taha Institute of Higher Education, Tehran,Iran

\* Corresponding author: soha.moheb@gmail.com. ORCID: 0000-0002-4512-175X

Article history:

Received: 14/11/2025

Revised: 30/11/2025

Accepted: 17/12/2025

### **Abstract**

Artificial intelligence is transforming the detection and management of skin cancers by augmenting visual assessment, dermoscopy, and histopathology with objective, image-driven algorithms that can approach or exceed expert-level diagnostic performance. In this paper, the current burden and clinical challenges of melanoma and non-melanoma skin cancers are outlined, followed by an overview of traditional diagnostic pathways and their limitations, including variability between clinicians and restricted access to specialist care. The main body of the work describes machine learning and deep learning approaches for classifying dermoscopic, clinical, and histopathologic images, highlighting key datasets, regulatory milestones, smartphone-based and teledermatology applications, and evidence comparing algorithm performance with that of dermatologists and dermatopathologists. Advantages such as improved triage, support for self-surveillance, reduced unnecessary biopsies, and potential time and cost savings are balanced against persistent concerns regarding dataset quality, generalizability, bias, privacy, and the need for standardized evaluation metrics. The paper concludes that, while only a small number of AI systems for skin cancer diagnosis have regulatory approval, judicious integration of these tools alongside clinical expertise could substantially enhance early detection and treatment planning, provided that technical, ethical, and regulatory gaps are systematically addressed.

**Keywords:** Artificial intelligence, Skin cancer, Deep learning, Dermoscopy, Histopathology images

## Introduction

Skin cancer represents a major global health challenge, with melanoma and non-melanoma skin cancers accounting for substantial morbidity and mortality. In 2025, the American Cancer Society projected over 104,960 new invasive melanoma cases in the United States alone, alongside approximately 8,430 deaths, underscoring the persistent rise in incidence driven by UV exposure and aging populations. Non-melanoma skin cancers, including basal cell and squamous cell carcinomas, affect millions of individuals annually, imposing significant healthcare burdens through early detection needs and treatment demands.[1, 2]

Visual examinations, dermatoscopes, and biopsies are the traditional means of diagnosis but suffer from interobserver variation, lack of specialist availability, and subjective interpretation, leading to delays in diagnosis. In many underserved areas, up to 20 percent of melanoma cases are diagnosed after the fact due to limited access to specialists. The visual aspect of dermatology benefits the most from computational augmentation. As a result, there is an opportunity for dermatological assessment to move away from being clinician-dependent and be driven by data.[3, 4]

Advancements in Artificial Intelligence are predominantly attributed to Deep Learning via Convolutional Neural Networks. In Dermatology, these types of AIs are now providing dermatologists with the same or greater ability to detect skin cancers from dermoscopic, clinical, and histopathological images with the same or greater level of accuracy. Recently released models use multimodal data that integrate Imaging Data with Genomic Data to provide melanoma classification at 92.5% accuracy and an Area Under Curve (AUC) of 0.96, as well as objective feature extraction from Imaging Data at early convolutional layers to complex features of entire lesions at later convolutional layers.[5-7]

The ISIC and HAM10000 datasets are important for developing algorithms, whereas regulatory achievements demonstrate the clinical feasibility of these algorithms. In 2024, DermaSensor became the first AI-based device approved by the FDA for use in primary care for skin cancer triage after MelaFind was approved as an AI device for dermatological diagnosis. Smartphone technology and teledermatology have also lowered the barrier to entry for accessing dermatological diagnoses, resulting in a reported 20%–30% reduction in unnecessary biopsies when used for triage.[8-10]

However, these advances also require that bias related to different skin tones be addressed to ensure equitable access, and the data they collect be

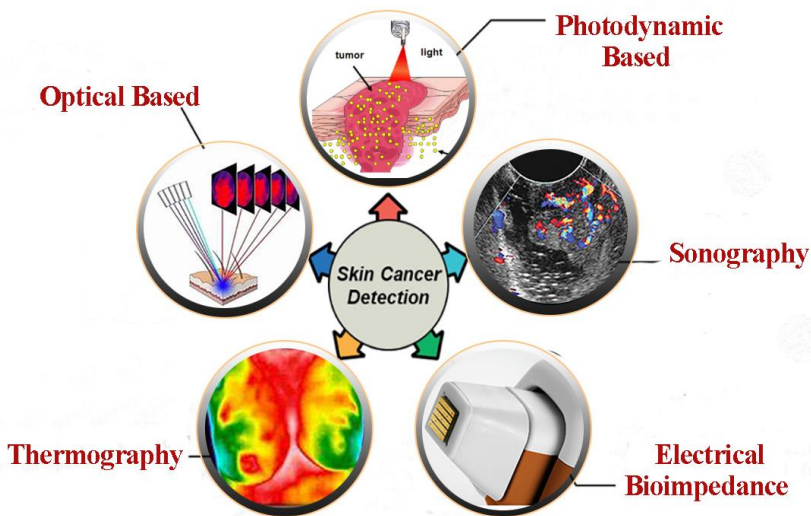
recorded while maintaining HIPAA data privacy requirements, along with the establishment of standardized evaluative metrics (e.g., CLEARDERM) for demonstrating algorithm performance. With the continued enhancement of dataset refinement and the development of ethical frameworks regarding the algorithms that are part of precision dermatology, it is expected that AI will continue to be a significant partner for clinicians in the future.[11, 12]

### **Skin cancer detection methods**

Traditional methods of early skin cancer detection include visual examination by the patient and skin clinical examination (screening) (Figure 1).[13] Self-examination of the skin, in which the patient or a family member finds a lesion, is a random procedure, nevertheless, because people may overreact or underreact. A dermoscope, microspectroscopy, and laser-based instrument are only a few examples of the pricy, specialized medical equipment that takes training, effort to operate, time, and routine follow-ups to conduct clinical exams.[14] A growing number of people need prompt diagnosis and ongoing monitoring due to the high prevalence of skin malignancies. Better patient self-surveillance techniques and the use of decision support systems for less experienced doctors may help alleviate the significant strain this places on specialized medical services. Machine diagnosis is objective and unaffected by outside variables. Human diagnosis, however, is subject to subjective variations and may be influenced by some outside factors. The use of AI for the detection and progression of skin cancer may lead to fewer biopsies if it is implemented with the necessary regulations. Skin cancer patients and their guardians can perform self-skin examinations (SSE) after receiving training. Additionally, it encourages teledermoscopy, which reduces the need for doctor visits. In order to obtain quicker diagnosis, individuals have begun adopting mobile technologies like cellphones to communicate photographs with their physicians. However, online image sharing could jeopardize privacy. Even worse, inadequate image quality could result in incorrect diagnoses. Artificial intelligence (AI), which is the human-like intelligence demonstrated by trained robots,[15] has evolved to the point where the majority of people use AI-based products on a daily basis. This helps physicians make decisions and reduces the disparity in physician decisions. It is important to note that even with these AI technologies, a skilled dermatologist is still required for diagnosis and treatment.[16]

Dermatology utilized AI in the early 2000s to determine how likely a skin lesion was to be malignant. Computer vision algorithms might be able to

identify skin lesions based on their morphology because the diagnosis of skin diseases is primarily based on visual perception. The US Food and Drug Administration (FDA) had approved AI technologies for clinical use by September 2018,[17] including devices to identify skin cancer from clinical images obtained using a smartphone app. MelaFind, an early use of AI in dermatology, used 10 distinct light wavelengths to treat skin lesions, assessed how the light was scattered by the lesions, and predicted morphologic disarray to help decide whether or not to perform a biopsy. However, MelaFind was unable to predict the diagnosis of the lesions it treated.[18]



**Figure 1.** Principles and mechanisms for skin cancer detection.

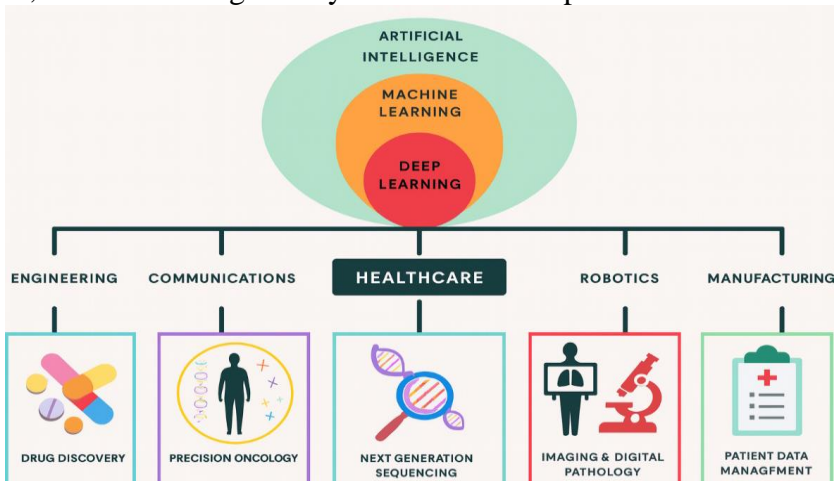
The first time AI was applied to evaluate reflectance confocal microscopy images was in 2008. In the past ten years, AI tools for interpreting dermatopathology or dermoscopy have also been available.[19] In order to do a point-of-care dermatologic assessment, physicians and patients are now being exposed to mobile devices or smartphone applications more frequently. Dermatology is a visual field, hence image-based machine learning-based methods are well suited. However, competent diagnostic ability requires years of training, and there are not enough dermatologists to fulfill the growing demand.[20]

Artificial intelligence-based tools are being created in the dermatology area to assess the severity of psoriasis [21] or to discriminate between onychomycosis and healthy nails.[22, 23] In experimental conditions,

dermatologists' sensitivity and specificity for differentiating melanomas from nevi were comparable to or superior to AI-based algorithms.[23-25] AI-based classification systems may be extremely helpful for patients with worrisome skin lesions because melanomas are best detected early in the disease process, and making the distinction between melanomas and innocuous lesions is frequently not simple.

Combining AI with clinical knowledge may increase clinical efficacy, diagnostic accuracy, and accessibility to efficient skin cancer evaluation by both specialists and nonspecialists. Considering the variation in how cutaneous lesions are evaluated, utilizing standardized technologies could increase doctors' diagnostic consistency. Additionally, these technologies may support clinical judgments about whether to biopsy a lesion or refer a patient to a specialist.[26] In order to demonstrate the viability of this method for the categorization of skin lesions, DNN were initially used in AI research on skin lesions in 2016.[27] The accuracy of detecting keratinocytic and melanocytic carcinomas has been improved through gradual algorithm and dataset refining, mostly in silico.

Patients and physicians can use a number of portable gadgets and smartphone applications constructed using DNN algorithms for the detection of skin cancer, and more are being developed. By cataloguing patient lesions and offering automated detection and tracking of lesions of concern, these technologies may enhance skin inspections.



**Figure 2.** Overview of artificial intelligence applications across industries, highlighting healthcare uses relevant to skin cancer, including AI-driven drug discovery, precision oncology, next-generation sequencing, imaging and digital pathology, and patient data management.

The data that AI algorithms were trained on has a significant impact on the precision and quality of their outputs.[28] If the clinical diagnosis was incorrect, training data with clinically established diagnoses but no histopathologic confirmation could lead the algorithm astray. The standard of care in many situations is clinical diagnoses with monitoring, therefore data labeling requirements have not yet been developed. Histopathologic confirmation may be the gold standard of diagnosis, according to the Defined guidelines (Checklist for Review of Image-Based Artificial Intelligence Algorithm Reports in Dermatology, or CLEARDERM), however even dermatopathology may have limits due to dermatopathologist interobserver discordance, which may be decreased with clear diagnostic criteria and rigorous evaluation.[29]

### **Datasets for skin cancer**

Clinical and dermatoscopic images are frequently created to track changes in skin conditions, especially in dermatology. The enormous amounts of data that already exist and will be created in the future, such as in hospitals, will become accessible to algorithms thanks to new applications, which will improve CNNs. Data sets are already available for research. The ISIC Challenges datasets, HAM10000, and BCN20000 are just a few of the clinical and dermoscopic skin lesion datasets that can be found in the ISIC archive gallery.[30, 31][27,28,29] 1000 clinical examples, including 270 melanomas and 49 seborrheic keratoses, are included in the Interactive Atlas of Dermoscopy. A minimum of two close-up and dermoscopic images are included for each case. It is available for purchase for \$250 and can be used for research.[32] 1300 high-resolution images of skin lesions are available in the Dermofit Image Library, organized into 10 categories. With the availability of an academic license, a licensing agreement is necessary, along with a one-time license fee.[32]

### **Skin Cancer Machine Learning Algorithms**

A growing number of people need prompt diagnosis and ongoing monitoring due to the high prevalence of skin malignancies. Better patient self-surveillance techniques and the use of decision support systems for less experienced doctors may help alleviate the significant strain this places on specialized medical services. Machine diagnosis is objective and unaffected by outside variables. Human diagnosis, however, is subject to subjective variations and may be influenced by some outside factors. The use of AI for the detection and progression of skin cancer may lead to fewer biopsies if it

is implemented with the necessary regulations. Skin cancer patients and their guardians can perform self-skin examinations (SSE) after receiving training. Additionally, it encourages teledermoscopy, which reduces the need for doctor visits. AI integration in smartphone apps can instruct users on how to conduct a skin examination and communicate their findings to a doctor.

In order to create a new ML skin cancer algorithm, each type of skin lesion is given a class, such as "benign" and "malignant," or "naevi" and "melanoma." Before being tested on a new image, deep learning algorithms are taught on a large number of images in each class. The process is composed of three fundamental steps. Digitalized macroscopic or dermoscopic images are fed to the algorithm in the first stage and labeled with the "ground truth" (in this case, the ground truth is the lesion diagnosis, which is determined by an expert dermatologist or by histological study).

Convolutional layers are used in stage 2 to extract the feature map from the images. Several levels of abstraction are present in a feature map, which is a visual representation of the data. The first convolutional layers extract low-level features like forms, corners, and edges. The higher-level data is extracted by later convolutional layers to identify the type of skin lesion. The stage 3 feature maps are used by the machine learning classifier to distinguish between various types of skin lesion patterns. Deep learning can now be used to classify a brand-new image.[33]

### **Images from histopathology and deep learning**

Dermatopathologists use histopathologic analysis of a tissue biopsy under a microscope to confirm the diagnosis of skin cancer. The high rates of discrepancy between various pathologists is one of the significant difficulties in making a confirmatory diagnosis of skin cancer. There may be disagreement regarding whether a melanoma lesion is benign or malignant when making a diagnosis. Deep learning methodologies have been successful for digital pathology with whole-slide imaging.

These techniques are used to categorize biopsy tissue samples in order to identify cancers. Numerous researchers have conducted studies to contrast an expert's performance with that of an AI system. Heckler and others[34] used a deep learning approach to compare pathologists' performance in identifying melanoma and nevi. In a recently released study, Brinker et al.[35] compared the effectiveness of CNN in separating melanomas from nevi on whole slide images (WSI) stained with hematoxylin and eosin. The performance of CNN in this study, which used complete slide images of 50 melanomas and 50 nevi, was comparable to that of the experts. Using

histopathology images taken with a smartphone, Jiang et al.[36] developed a deep learning technique for diagnosing BCC. They discovered that the algorithm performed similarly on smartphone-captured images and WSI, with an AUC of 0.95. They employed a deep segmentation network for a thorough analysis of the challenging cases, which produced scores of 0.987 (AUC), 0.97 (sensitivity), and 0.94 (specificity). According to Jiang and colleagues' research, deep learning techniques can diagnose BCC with high sensitivity and specificity.

It should be noted that various findings from various studies imply that the volume of information provided to the AI system, the research design, and the complexity of the disease may influence the difficulty of a given task and, consequently, the performance of both AI algorithms and human observers.

In general, it appears that CNNs can be a great help to people in the diagnosis of skin cancers like melanoma. Similar to that, the diagnosis of BCC necessitates intensive work because numerous images must be examined. The diagnosis of BCC can be aided by deep learning techniques. The development of neural network models for the diagnosis of BCC can benefit from the use of WSIs and microscopic ocular images captured by smartphone cameras. Some of the benefits of CNN in the diagnosis of skin cancers include a shortened diagnosis time and cost savings.[33]

## **Conclusion**

AI has great potential to simplify the process of diagnosing skin cancer. Shallow and deep techniques, the two main branches of AI, are used to identify and categorize skin cancer. However, since various data set sizes, image types, and a number of diagnostic classes are being used and evaluated with various evaluation metrics, the dependability of such AI tools has been questioned. Although accuracy is the primary evaluation metric that is most frequently used, it does not allow for the independent evaluation of FN and FP rates. Promising developments in the application of AI to the detection of skin neoplasms may ultimately have a significant impact on doctors and patients. The limitations of AI in dermatology continue to be a problem, though. Although many are being developed and have received FDA breakthrough device designation, only two AI-based tools or systems for skin cancer classification have been approved by the FDA.

## **Conflict of Interests Statement**

The authors declared no conflict of interest.

## References

1. Wang, M., Gao, X., and Zhang, L. (2025). "Recent global patterns in skin cancer incidence, mortality, and prevalence". *Chin Med J (Engl)*, **138**(2): p. 185-192.
2. Zhou, L., et al. (2025). "Global, regional, and national trends in the burden of melanoma and non-melanoma skin cancer: insights from the global burden of disease study 1990–2021". *Scientific Reports*, **15**(1): p. 5996.
3. Nawaz, K., et al. (2025). "Skin cancer detection using dermoscopic images with convolutional neural network". *Scientific Reports*, **15**(1): p. 7252.
4. Gupta, P., Nirmal, J., and Mehendale, N. (2024). "A survey of recent advances in analysis of skin images". *Evolutionary Intelligence*, **17**(5): p. 4155-4178.
5. Yu, Z., et al. (2025). "AI dermatology: Reviewing the frontiers of skin cancer detection technologies". *Intelligent Oncology*, **1**(2): p. 89-104.
6. Iglesias, L.L., et al. (2021). "A primer on deep learning and convolutional neural networks for clinicians". *Insights Imaging*, **12**(1): p. 117.
7. Ganthya, M. (2024). *Convolutional Neural Networks in Dermatology: Skin Cancer Detection and Analysis*.
8. Tschandl, P., Rosendahl, C. and Kittler, H. (2018). "The HAM10000 dataset, a large collection of multi-source dermoscopic images of common pigmented skin lesions". *Scientific Data*. **5**(1): p. 180161.
9. *Digital imaging and AI for melanoma diagnosis*. (2018). CC-BY-NC: ViDIR Group, Department of Dermatology, Medical University of Vienna (11,720): <https://www.isic-archive.com/>.
10. Velaga, N., et al. (2023). "Skin Cancer Detection Using the HAM10000 Dataset: A Comparative Study of Machine Learning Models". *Global Conference on Information Technologies and Communications (GCITC)*.
11. Hanna, M.G., et al. (2025). "Ethical and Bias Considerations in Artificial Intelligence/Machine Learning". *Modern Pathology*, **38**(3): p. 100686.
12. Radanliev, P. (2025). "AI Ethics: Integrating Transparency, Fairness, and Privacy in AI Development". *Applied Artificial Intelligence*, **39**(1): p. 2463722.
13. Loescher, L.J., et al. (2013). "Advances in skin cancer early detection and diagnosis". in *Seminars in oncology nursing*, Elsevier.
14. Lieber, C.A., et al. (2008). "In vivo nonmelanoma skin cancer diagnosis using Raman microspectroscopy". *Lasers in Surgery and Medicine: The Official Journal of the American Society for Laser Medicine and Surgery*, **40**(7): p. 461-467.
15. Murphy, R.R. (2019). *Introduction to AI robotics*, MIT press.
16. Takiddin, A., et al. (2021). "Artificial Intelligence for Skin Cancer Detection: Scoping Review". *J Med Internet Res*, **23**(11): p. e22934.
17. Chan, S., et al. (2020). "Machine learning in dermatology: current applications, opportunities, and limitations". *Dermatology and therapy*, **10**: p. 365-386.
18. Young, A.T., et al. (2020). "Artificial intelligence in dermatology: a primer".

- Journal of Investigative Dermatology*, **140**(8): p. 1504-1512.
19. Scheetz, J., et al. (2021). "A survey of clinicians on the use of artificial intelligence in ophthalmology, dermatology, radiology and radiation oncology". *Scientific Reports*, **11**(1): p. 5193.
  20. Wiltgen, M., et al. (2008). "Automatic identification of diagnostic significant regions in confocal laser scanning microscopy of melanocytic skin tumors". *Methods Inf Med*, **47**(1): p. 14-25.
  21. Shrivastava, V.K., et al. (2017). "A novel and robust Bayesian approach for segmentation of psoriasis lesions and its risk stratification". *Computer methods and programs in biomedicine*, **150**: p. 9-22.
  22. Han, S.S., et al. (2018). "Deep neural networks show an equivalent and often superior performance to dermatologists in onychomycosis diagnosis: Automatic construction of onychomycosis datasets by region-based convolutional deep neural network". *PloS one*, **13**(1): p. e0191493.
  23. Hogarty, D.T., et al. (2020). "Artificial intelligence in dermatology—where we are and the way to the future: a review". *American journal of clinical dermatology*, **21**: p. 41-47.
  24. Brinker, T.J., et al. (2019). "Deep neural networks are superior to dermatologists in melanoma image classification". *European Journal of Cancer*, **119**: p. 11-17.
  25. Brinker, T.J., et al. (2019). "Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task". *European Journal of Cancer*, **113**: p. 47-54.
  26. Beltrami, E.J., et al. (2022). "Artificial intelligence in the detection of skin cancer". *Journal of the American Academy of Dermatology*, **87**(6): p. 1336-1342.
  27. Pham, T.-C., et al. (2021). "AI outperformed every dermatologist in dermoscopic melanoma diagnosis, using an optimized deep-CNN architecture with custom mini-batch logic and loss function". *Scientific Reports*, **11**(1): p. 17485.
  28. Nasr-Esfahani, E., et al. (2016). "Melanoma detection by analysis of clinical images using convolutional neural network". *Annu Int Conf IEEE Eng Med Biol Soc*, p. 1373-1376.
  29. Murphree, D.H., et al. (2022). "Deep learning for dermatologists: Part I. Fundamental concepts". *J Am Acad Dermatol*, **87**(6): p. 1343-1351.
  30. Codella, N.C., et al. (2018). *Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic)*. in *2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018)*, IEEE.
  31. Tschandl, P., Rosendahl, C. and Kittler H. (2018). "The HAM10000 dataset, a large collection of multi-source dermoscopic images of common pigmented skin lesions". *Scientific data*, **5**(1): p. 1-9.

32. Argenziano, G., et al. (2000). *Interactive atlas of dermoscopy (Book and CD-ROM)*.
33. Das, K., et al. (2021). *Machine Learning and Its Application in Skin Cancer*. Int J Environ Res Public Health, 2021. **18**(24).
34. Hekler, A., et al. (2019). "Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images". *Eur J Cancer*, **118**: p. 91-96.
35. Brinker, T.J., et al. (2022). "Diagnostic performance of artificial intelligence for histologic melanoma recognition compared to 18 international expert pathologists". *J Am Acad Dermatol*, **86**(3): p. 640-642.
36. Jiang, Y.Q., et al. (2020). "Recognizing basal cell carcinoma on smartphone-captured digital histopathology images with a deep neural network". *Br J Dermatol* **182**(3): p. 754-762.