INTERNATIONAL JOURNAL OF PHARMACEUTICAL SCIENCES
[ISSN: 0975-4725; CODEN(USA): IJPS00]
Journal Homepage: https://www.ijpsjournal.com

OPEN ACCESS

Review Article

Artificial Intelligence (AI) in Early Detection of Skin Cancer

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ARTICLE INFO

Published: 25 Aug 2026

Keywords:

Artificial intelligence, skin lesions, convolutional neural network (CNNs), deep learning, machine learning

DOI:

10.5281/zenodo.22105710

ABSTRACT

Skin cancer is a growing health problem that is becoming quite common in many populations around the world. Current estimates suggest that between 2 million and 3 million new cases of non-melanoma and melanoma skin cancers will occur globally in 2024 and 2025. Skin cancer ranks as the 17th most commonly diagnosed cancer worldwide. In 2020, there were about 57,000 deaths from melanoma, the most aggressive type of skin cancer, which is characterized by its ability to spread. According to the American Academy of Dermatology, melanoma is responsible for most skin cancer deaths, with nearly 20 Americans dying from it every day. Late detection significantly harms the chances for individuals with melanoma, leading to much lower survival rates. Research shows that once melanoma reaches the metastatic stage, the five-year survival rate drops sharply as the cancer spreads to other organs and tissues. Therefore, early detection is crucial for improving the quality of life for melanoma patients. Detecting skin cancer lesions relies heavily on thorough clinical examinations by trained professionals. This process is supported by dermoscopy, which allows clinicians to better visualize skin lesions through magnification, followed by a diagnosis confirmed by biopsy and histopathological examination. While these traditional diagnostic methods are widely used in healthcare, they have limitations. The quality of dermoscopy can vary because of the subjectivity and differences in skills among practitioners, which can affect diagnostic accuracy. The current method of melanoma detection, based on subjective assessment criteria, may not always be reliable. Furthermore, significant differences exist in the expertise available for skin cancer diagnosis worldwide, influenced by factors such as geographic location, economic development, demographics, and the availability of health resources like insurance. Artificial intelligence is becoming a revolutionary factor in improving skin cancer diagnosis. Healthcare authorities are increasingly recognizing what AI innovations can offer and are allocating resources to support and implement AI-driven solutions in the diagnosis of skin lesions. AI can quickly automate analysis and evaluation, delivering accurate results alongside high-speed processing. This rapid production of results

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Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

enables immediate and ongoing evaluation of operations worldwide. With the rise of skin cancer, there is a pressing need for new devices and diagnostic tools that meet the demands for timely and accurate detection. Therefore, the future lies in these AI tools, which are designed to meet expectations effectively. Another advantage of AI is that it can facilitate diagnostic methods that do not require invasive techniques, thereby improving patient comfort and safety. This report provides a detailed overview of the currently available AI tools for diagnosing skin cancer. It will emphasize the various AI approaches and algorithms used for diagnosing skin lesions. A comparison of dermatologists' diagnostic criteria with those of AI systems will highlight the advantages and limitations of each approach. Additionally, the overall effectiveness of AI for diagnostics will be assessed, along with potential future advancements and trends in using AI technologies for skin cancer detection and management. AI has significantly impacted medical image analysis in dermatology, leading to digital and automated diagnostic systems. This development makes AI an essential and potentially transformative tool in the early detection and diagnosis of skin cancers. It not only analyzes data but also reduces some administrative tasks, allowing medical professionals to focus on key medical decisions. This evolving technology is practical and is changing dermatological diagnostics and clinical workflows. AI models have increased diagnostic accuracy. Convolutional neural networks (CNNs) and other modern algorithms exhibit impressive capabilities in classifying skin lesions, often matching or exceeding dermatologists' performance. This potential highlights AI as a valuable tool in the challenging task of distinguishing between benign and malignant skin conditions. Machines can also detect even the smallest changes in lesions, such as differences in texture, color, and shape, which may go unnoticed by humans. This capability is crucial because early detection of malignant lesions can significantly improve survival rates, especially for aggressive cancers like melanoma. AI has seen widespread acceptance as it improves efficiency and accessibility in dermatological care. AI systems can rapidly process and analyze vast amounts of data, such as skin images, optimizing the diagnostic process and reducing wait times for patients. This increased efficiency enhances clinical workflows, making dermatological expertise more accessible to underserved areas through AI-based telemedicine platforms. These platforms enable remote patients in resource-limited settings to upload skin images for real-time review by dermatologists, supported by AI analysis. A significant advancement has been integrating clinical data into AI models. Contemporary AI systems can evaluate patient demographics and medical histories alongside analyzed images, offering more informed diagnoses that align with the holistic approach of human dermatologists. Recent advancements have also made it possible to perform wide-field and whole-slide imaging analysis. AI algorithms can now evaluate multiple lesions simultaneously in wide-field images, streamlining screening. Additionally, AI can analyze digitized dermatopathology slides, which play a crucial role in confirmatory diagnoses and potentially increase the efficiency of dermatopathologists. The concept of augmented intelligence (AuI) supports the idea that AI can assist dermatologists. AuI can aid in clinical decision-making by determining whether a lesion needs excision and monitoring changes over time, reducing unnecessary surgeries. Moreover, AI is increasingly integrated into advanced imaging techniques such as reflectance confocal microscopy (RCM) for improved diagnostic yield and information. Beyond image analysis, significant progress has been made in using machine learning with RNA profiles. Researchers are developing classifiers that analyze gene expression data to predict skin cancer diagnoses and prognoses, further expanding AI's role beyond visual assessments. Solutions addressing data privacy concerns related to large, diverse datasets have introduced federated learning, which allows for the collaborative training of AI models across multiple institutions without sharing sensitive patient data. owever, it’s crucial to acknowledge that AI models are not perfect. Increasing attention is being given to uncertainty quantification to develop methods that measure the confidence level of AI predictions, aiding clinicians in making informed decisions. The goal of a multimodal learning approach is to train AI models using various data types, including clinical images, histological slides, and patient metadata, to create a more comprehensive diagnostic tool. New techniques in incremental learning are being developed to ensure that AI models can incorporate new data without losing performance on previously learned information, allowing for adaptation to constantly changing clinical data. Vision Transformers (ViTs) are emerging as a competitive alternative to traditional CNNs in medical image analysis, drawing inspiration from successes in natural language processing. Research is ongoing to explore how Large Language Models (LLMs) can assist in clinical decision-making and patient management within dermatology, such as creating visit summaries or providing simplified explanations of patient conditions. Furthermore, there are investigations into self-supervised learning (SSL) techniques to create more robust AI models that can learn from large amounts of unlabeled data, which is often easier to gather than labeled medical images.

INTRODUCTION

AIM

Modern artificial intelligence is used for the diagnosis of skin cancer and for the classification of skin cancer; at present, the techniques and methods of AI are applied in the detection of skin cancer. The accuracy, specificity, precision and sensitivity of AI tools. The advantages and limitations of using AI for the diagnosis of skin cancer.

METHODOLOGY

1) The use of deep learning algorithms for identifying and segmenting skin lesions. One of the most important aspects of applying an AI system in the detection of skin cancer is to carry out the detection and segmentation of skin lesions. In order to achieve accurate detection, all potential cancerous growths must be detected and identified in the image, while segmentation refers to the precise determination of the boundaries of the lesion. This is particularly important for the extraction of particular features that can be used for classification. Accuracy is essential for both the detection and segmentation of lesions, and a number of artificial intelligence algorithms are employed in the detection of skin lesions.

2) Deep learning algorithms which are based on convolutional neural networks have thus been shown to be effective for efficient object detection in medical images. In order to identify the initial area of interest, the K-mean clustering part of these algorithms is combined with the extraction of relevant features and the use of ensemble learning techniques in order to detect the presence of lesions. The system is able to classify a specific pitted hole lesion according to the pixel intensity value. These deep learning methods are expected to work best when it comes to automating the learning of complex features directly from image data, especially in the case of lesion-detection tasks.

3) U-nets are widely accepted and well-justified deep learning models when it comes to skin lesion segmentation in the field of medical imaging. The U-net structure is made up of down-sampling and up-sampling paths.

4) The path used for down-sampling encodes the input image into a lower-dimensional representation.

5) The up-sampling path carries out the reconstruction of the segmented images.

6) In order to train a U-net model for skin lesion segmentation, it is necessary to train the model using skin lesion images together with the corresponding ground truth segmentation masks so that the model will be able to tell the lesion area apart from the normal skin and the background.

There are some more tools that identify skin lesions, these are:

a) Dermo-doctor

b) DermoExper

c) DSNet

7) Reinforcement learning

It is an alternative and innovative method of segmenting skin lesions, consisting of the intelligent agent learning how to segment the lesion area by means of a Markov decision process (MDP), with the agent receiving rewards for each of its actions. Using deep reinforcement learning algorithms such as the deep deterministic policy gradient (DDPG), the intelligence is gradually trained to enhance the segmentation results, progressing from a rough initial segmentation to more detailed boundaries.

Application of convolutional neural network (CNNs) for skin cancer classification

a. It has already been proven that Convolutional Neural Networks will most likely result in the best and most dominant type of architecture for use in medical image analysis; in particular, their most important application is the classification of skin cancer. This kind of architecture is able to learn complex hierarchical features directly from the image data and is therefore very well suited to detecting patterns that indicate malignancy in dermatopathological images.

b. In fact, CNNs are extremely accurate tools having been shown to classify skin cancer with a high degree of precision and have, on various occasions, been reported to outperform those of boar-certified dermatologists. They thus seem to be suitable as tools for self-diagnosis.

c. A multiple-specific CNN structure has been successfully applied to the task of classifying skin cancer. Among the more well-known architectures are Google Net, Inception V3, VGG-16, UGG-19, and Mobile Net. Each of these has its own particular strength and feature. Numerous studies have shown that it is possible to obtain very promising results with models such as Dense Net 201, which achieves an accuracy of 97% on the HAM10000 dataset, or with Inception U3, which attains 90% accuracy on that same dataset.

The researchers have looked at some other advanced hybrid CNN models in order to obtain better performance. In fact, they have managed to reach a very high average accuracy of 97 per cent in the classification of melanoma, basal cell carcinoma and squamous cell carcinoma. An interesting point is that the combination of LBP and CNNs has resulted in the highest value for hybridization in terms of accurate classification. Indeed, such accurate classification will be essential for formulating appropriate treatment strategies and for determining patient outcomes according to the types of skin cancer diagnosed. Nevertheless, the researchers have examined some modified and hybrid CNN architectures with a view to assessing their performance. The hybridizations of CNNs with Local Binary Patterns are inherently used for achieving high accuracy in classification and has been able to attain a very high average accuracy of 97.29 per cent in the research carried out on the classification of melanoma and basal cell carcinoma as well as squamous cell carcinoma. The ability of CNNs to distinguish between these different types of skin cancer is important since it helps in guiding the right treatment and in improving clinical outcomes.

While CNNs have produced promising results when it comes to classifying skin cancer from images, there has been a growing amount of research into other deep learning architectures such as RNNs and Transformers. Specifically, the modified version of RNNs, namely Long Short-Term Memory (LSTM) networks, are suitable for use with sequential input. LSTM networks have been studied in the context of skin cancer diagnosis by considering the temporal evolution of a skin lesion over time, even though this is not the typical application of RNNs but rather the use of CNNs for image classification. Similarly, hybrid systems that combine a CNN with other network architectures (CNN-RNNs) have been developed, these systems benefiting from the strengths of both architectures by having the CNN extract the spatial features of images and the RNN model the temporal dependencies. Some studies have reported very high accuracy being achieved using CNN-RNN models for multi-class skin cancer classification. Since classical RNNs are not very good at carrying out this kind of task, they encounter a number of problems due to their inability to capture the long-range dependencies that exist within images and also because of the vanishing gradient problem.

It will eventually happen that the New Transformation architectures, particularly Vision Transformers (ViTs), will become the foremost contenders replacing CNNs in the field of medical image analysis, including the classification of skin cancer. The true reason for the success of these achievements is natural language processing, since Transformers show how various parts of an input sequence influence the model's predictions through self-attention by assigning different levels of importance to them. Moreover, ViTs are able to model long-range dependencies in an image, a feature that could be valuable when analyzing complex skin lesions since different areas may be subtly connected. The properties of Transformer architectures also allow the entire input set to be processed in parallel, leading to Chetan Faster energy efficient training. Numerous studies have so far achieved very promising results regarding transfer learned multiclass skin cancer classification performance using pre-trained ViTs, with some even outperforming traditional transfer learning models based on CNNs. Because ViTs are robust to different types of perturbations in the input data, they also offer a high degree of architectural flexibility. The Transformer-based architecture is not only being explored for classification but also for other interesting applications in the diagnosis of skin cancer, such as lesion segmentation, lesion detection, and the extraction of semantic information from dermatoscopic images. The bright future prospects that the emerging transformers hold for these areas will mainly consist of opening up new promising avenues in skin cancer diagnosis that could be AI-driven and be beneficial globally in terms of context and precision.

d. Performance Metrics and Evaluation of AI Techniques Applied for Skin Cancer Detection

To measure performance of AI technology on skin cancer diagnosis-old evaluations rely on that it is knowable that there are number of performance measures each of which measures different aspect of machine prediction ability and classification of skin lesions. Some performance measures are (but not limited to) Accuracy which gives the fraction of all predictions made correctly and also the recall or sensitivity which measures machine ability of correctly identifying positive instances (malignant lesion) and specificity which measures machine ability to diagnose negative cases (benign lesion). Others measure that have surfaced on many occasions also include precision which gives the number of true positives out of all who are predicted positive and F1 score which is harmonic mean of precision and recall and gives a measure of accuracy balanced between the two parameters.1 AUC-ROC measures the overall performance of a classifier to accurately classify the outputs over any particular discrimination threshold. At times AUC-PPV-Positive Predictive Value and AUC-NPV-Negative Predictive Value has surfaced in consideration. The performance measures give a more overall measure of the system regarding the diagnosis on many other parameters while comparing the same on malignant or benign lesions.
In many studies, the performance of the AI model and dermatologist had been compared. A number of AI systems have been proven to perform better or equivalent than skin specialists in diagnosis of melanoma. AI algorithms reported high ROC values (>80%) in diagnosis of melanoma with

dermoscopy images, while in general case sensitivity and specificity reported were 83.01% and 85.58%. In several situations, AI CAD systems are better than board certified dermatologist on accuracy in detection of skin tumours, even with small data. It is known that accuracy of human skin specialists for detection of melanoma on average is ranging from 60%-70% and it can easily out beat with the models when measured under lab conditions. The performance may vary from different types of reasons such as type of AI method used, quality and size of training data-sets, actual diagnostic task difficulty. A number of published studies fail to use publicly available data set for training and testing, and evaluation methods are quite different, which add difficulty for better comparison between methods. In any case, the AI models are becoming to demonstrate very good performance in distinguishing different skin tumours, and it relies on many CNN models and Vision Transformer methods for identifying with higher accuracy regarding melanoma. Other commonly occurring tumours such as basal cell carcinoma and squamous cell carcinoma showed promising results for different performance measures.

Study/ Reference	**AI Model/ Algorithm**	**Dataset Used**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**Precision (%)**	**F1 Score (%)**	**AUC-ROC (%)**
Kassem et al. [27]	Deep CNNs (modified Google Net)	ISIC 2016–2019	94.92	79.8	97	N/A	N/A	N/A
Rezvantalab et al. [27]	Four deep learning CNNs	HAM10000; PH2	80.22–89.01	82.26–99.10	79.60–89.01	N/A	N/A	N/A
Gessert et al. [27]	Ensemble of CNN	ISIC-2018, HAM10000	85.1	93.1–97.6	N/A	N/A	N/A	N/A
Haenssle et al. [27]	Deep CNN (Google's Inception v4)	ISIC archive, clinical images	86	86.6–88.9	71.3–75.7	N/A	N/A	N/A
Esteva et al. [27]	Deep CNNs (Google Net Inception v3)	Online repos, clinical data	72.1	N/A	N/A	N/A	N/A	N/A
Mahbod et al. [27]	Multi-scale multi-CNNs (MSM-CNNs)	ISIC-2016, 2017, 2018, HAM10000	96.3	N/A	N/A	N/A	N/A	N/A
Iqbal et al. [27]	Deep CNN	ISIC-2017, 2018, 2019	94	93	91	N/A	N/A	N/A
Qin et al. [27]	Generative adversarial networks (GANs)	ISIC-2018	95.2	83.2	74.3	N/A	N/A	N/A
Cano et al. [27]	NasNet	ISIC-2019	71–99	73–98	70–99	N/A	N/A	N/A

Barhoumi et al. [27]	Transfer learning CNN model	ISIC 2018	95	96	N/A	N/A	N/A	N/A
Ratul et al. [27]	Dilated CNNs (VGG-16,-19, Mobile Net, Inception-V3)	HAM10 000	87–89	87–89	N/A	N/A	N/A	N/A
Rashid et al. 27	Semi-supervised GANs	ISIC 2018	73–94	69–92	N/A	N/A	N/A	N/A
Maron et al. 27	CNNs	ISIC 2018, HAM10 000	N/A	90.2–97.7	94.2–99.5	N/A	N/A	N/A
Sun et al. 27	CNNs	ISIC-2019, MED-NODE, PH2, 7-point	66.2–89.5	66.2–89.5	95.2–99.3	N/A	N/A	N/A
Jain et al. 27	Six transfer learning nets	HAM10 000	66–90	66–90	N/A	N/A	N/A	N/A
Winkler et al. 27	FotoFinder ® Moleanalyz er Pro (CNN)	ISIC archive, clinical images	50.8–95.4	53.3–100	65–94	N/A	N/A	N/A
Binder et al. 27	Artificial neural networks (ANNs)	Oil immersi on images	86	95	88	N/A	N/A	N/A
Arshed et al. 1	Vision Transformer (ViT)	Multi-class skin cancer dataset	92.14	92.14	N/A	92.61	92.17	N/A
Mehmood et al. 29	CNN-RNN (ResNet-50 backbone)	9000 images (9 classes)	99.06	N/A	N/A	N/A	N/A	N/A
Hasan et al. 22	Convolution al Neural Network (CNN)	Benign and maligna nt skin lesions	89.5	N/A	N/A	N/A	N/A	N/A
Pham et al. 23	Deep CNN (InceptionV 4)	ISBI Challeng e, ISIC Archive, PH2	N/A	N/A	N/A	N/A	N/A	N/A

Khan et al. 26	DarkNet19 + multi-layered feed forward NN	ISIC 2017, 2018, 2019 (HAM10000)	97.29	95.63	97.90	N/A	N/A	N/A
Dorj et al. 26	Unified method for histopathological image analysis	Basal cell carcinoma images	N/A	N/A	N/A	N/A	N/A	N/A
Klautau et al. 26	Deep learning (Autoencoder + CNN + Softmax)	Melanoma images	N/A	N/A	N/A	N/A	N/A	N/A
Zhang et al. 31	CNN	DermIS & Dermquest	91	95	92	84	N/A	N/A
Hosny et al. 31	CNN	Internal dataset	98.7	95.6	99.3	95.1	N/A	N/A
Xin et al. 31	CNN	HAM1000	94.3	N/A	N/A	94.1	N/A	N/A
Skreekala et al. 31	CNN	HAM1000	97	N/A	N/A	N/A	N/A	N/A
Samsudin et al. 31	CNN	HAM1000	87.7	N/A	N/A	N/A	N/A	N/A
Reis et al. 31	CNN	ISIC 2018	94.6	N/A	N/A	N/A	N/A	N/A
Razzak et al. 31	CNN	ISIC 2018	98.1	N/A	N/A	N/A	N/A	N/A
Qian et al. 31	CNN	HAM1000	91.6	73.5	96.4	N/A	97.1	N/A
Nguyen et al. 31	CNN	HAM1000	90	N/A	N/A	81	81	99
Naeem et al. 31	CNN	ISIC 2019	96.9	N/A	N/A	N/A	N/A	N/A
Li et al. 31	CNN	HAM1000	95.8	N/A	N/A	96.1	95.7	N/A
Lee et al. 31	CNN	ISIC 2018	84.4	92.8	N/A	78.5	N/A	N/A
Laverde-Saad et al. 31	CNN	HAM1000	77.1	80	86	86	N/A	N/A
La Salvia et al. 31	CNN	HAM1000	N/A	>80	>80	N/A	>80	N/A
Dascalu et al. 31	CNN	Internal dataset	88	95.3	N/A	N/A	N/A	91.1
Benyahia et al. 31	CNN	ISIC 2019	92.3	N/A	N/A	N/A	N/A	N/A
Bechelli et al. 31	CNN	HAM1000	88/72	N/A	N/A	N/A	N/A	N/A

Afza et al. 31	CNN	Ph2/ ISBI2016/ HAM1000	95.4/ 91.1/ 85.5	N/A	N/A	N/A	N/A	N/A
Winkler et al. 31	CNN	HAM1000	70	70.6	69.2	N/A	N/A	N/A
Minagawa et al. 31	CNN	HAM1000	85.3	N/A	N/A	N/A	N/A	N/A
Iqbal et al. 31	CNN	HAM1000	N/A	N/A	N/A	N/A	N/A	99.1
Huang et al. 31	CNN	HAM1000	84.8	N/A	N/A	N/A	N/A	N/A
Wang et al. 31	CNN	Several datasets	N/A	80	100	N/A	N/A	N/A
Qin et al. 31	CNN	HAM1000	95.2	83.2	74.3	N/A	N/A	N/A
Mahbod et al. 31	CNN	ISIC2019	86.2	N/A	N/A	N/A	N/A	N/A
Li et al. 31	CNN	HAM1000	N/A	95	91	78	N/A	N/A
Gessert et al. 31	CNN	HAM1000	N/A	70	N/A	N/A	N/A	N/A
Gessert et al. 31	CNN	Internal dataset	N/A	53	97.5	N/A	N/A	94
Gajera et al. 25	AlexNet, VGG-16, VGG-19	ISIC 2016, ISIC 2017, PH2, HAM10000	98.33	N/A	N/A	N/A	0.96	N/A
Alenezi et al. 25	Deep residual network	ISIC 2017, HAM10000	96.971	N/A	N/A	N/A	0.95	N/A
Shinde et al. 25	Squeeze-MNet	ISIC	99.36	N/A	N/A	N/A	N/A	N/A
Alenezi et al. 25	ResNet-101 with SVM	ISIC 2019, ISIC 2020	96.15/97.15	N/A	N/A	N/A	N/A	N/A
Abbas and Gul 25	NASNet	ISIC 2020	97.7	N/A	N/A	N/A	0.97	N/A
Gouda et al. 25	CNN	ISIC 2018	83.2	N/A	N/A	N/A	N/A	N/A
Alwakid et al. 25	CNN, ResNet-50	HAM10000	N/A	N/A	N/A	N/A	0.859/ 0.852	N/A

CONCLUSION

Skin cancer diagnosis became another prime domain for AI's use. The application of deep learning techniques and convolutional neural networks in particular is the primary driver in this segment. AI shows massive promise for matching skin cancer diagnoses' accuracy with those of dermatologists (and in some cases even exceeding those) in improving detection of lesions in the early stages. Many hurdles need to be overcome prior to widespread clinical adoption of AI based skin cancer diagnostic systems, such as data quality and Diversity, Interpretability of the AI model, and Seamless Health Care Information Systems (HIS) Integration and Health IT Work-flows.

FUTURE DIRECTION

One crucial element to focus on should be on curating diverse, and representative datasets of various skin types and lesion categories as this can address the issue of data bias of AI models across different populations. More is required to develop AI models that explain what is behind their results as a key indicator for clinicians to trust them, also termed Explainable AI (XAI). It also remains a field to investigate specific architectures other than conventional CNNs such as Transformers and Recurrent Neural Networks to gain in performance in particular areas within skin cancer detection and evaluation. AI models for skin cancer must be rigorously evaluated against multiple types of real-word clinical data to earn users' trust and offer real clinical value in the daily practice. Multimodal learning could be explored to achieve more generalized diagnostic frameworks to benefit both diagnostics and prognosis including data of other nature like clinical history, genetics data as well as images. Moreover, personalized diagnosis is possible through AI based personal cancer treatment and Monitoring. Furthermore, it's indispensable that we continuously address fairness in algorithmic design and promote digital health's ethical and legislative frameworks relating the design and implementation of AI technology in dermatological clinics. Mobile AI can facilitate the access for this technology under resource-limited setting as it can be lightweight and easily deployable and federated or self-supervised. AI can provide a great deal for mitigation for wear and tear for the privacy or scarcity of data. The possibility of revolutionizing how we detect and diagnose skin cancers, which translates into better outcomes for patients, via the implementation of AI in this field, is significant; however, this must entail continuous research, collaboration among AI developers and dermatologists and profound reflection on the ethical aspect of the use of AI in the field.

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HOW TO CITE: Atish Pathak, Kesar Bankar, Artificial Intelligence (AI) in Early Detection of Skin Cancer, Int. J. of Pharm. Sci., 2026, Vol 4, Issue 8, 4314-4324. https://doi.org/10.5281/zenodo.22105710