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REVIEW ARTICLE

Artificial Intelligence in Skin Cancer: A Literature Review from Diagnosis to Prevention and Beyond

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Abstract

Artificial Intelligence (AI) in medicine is quickly expanding, offering significant potential benefits in diagnosis and prognostication. While concerns may exist regarding its implementation, it is important for dermatologists and dermatopathologists to collaborate with technical specialists to embrace AI as a tool for enhancing medical decision-making and improving healthcare accessibility. This is particularly relevant in melanocytic neoplasms, which continue to present challenges despite years of experience. Dermatology, with its extensive medical data and images, provides an ideal field for training AI algorithms to enhance patient care. Collaborative efforts between medical professionals and technical specialists are crucial in harnessing the power of AI while ensuring it complements and enhances the existing healthcare framework. By staying informed about AI concepts and ongoing research, dermatologists can remain at the forefront of this emerging field and leverage its potential to improve patient outcomes. In conclusion, AI holds great promise in dermatology, especially in the management and analysis of Skin cancer (SC).

In this review we strive to introduce the concepts of AI and its association with dermatology, providing an overview of recent studies in the field, such as existing applications and future potential in dermatology.

Key Words: *Artificial intelligence; Skin cancer; Skin cancer screening; Dermoscopy; Melanoma; Neural network*

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1. Introduction

Skin cancer (SC) is the most common type of cancer in humans both melanoma (MM) and non-melanoma skin cancers (NMSC) are becoming more prevalent globally, particularly among the Caucasian population [1-4]. Early detection is associated with reduced morbidity and improved survival and is for that reason critical [5]. Utilizing safe and implementing accurate artificial intelligence (AI)-based detection aids in melanoma and skin cancer diagnosis can consequence more accurate and faster diagnosis and treatment of SC from lesions, increased and more equitable access to an expert standard of treatment, fewer needless biopsies, decreased healthcare costs to both individuals and the government, and improved patient outcomes [6,7]. AI is a field of computer science focused on developing programs that mimic human cognition and the ability to analyze complex data [8].

AI-based dermatology tools are being developed to determine the severity of psoriasis [9] and to differentiate between healthy nails and onychomycosis [10,11]. Convolutional neural networks (CNNs) have been used in recent studies that showed similar or better sensitivity and specificity than dermatologists in distinguishing melanomas from nevi. This illustrated that AI-based classification systems can greatly benefit patients with suspicious skin lesions, as early diagnosis of melanomas improves prognosis and distinguishing between melanomas and harmless lesions can be challenging [12-14].

Nevertheless, the utilization of AI in real-life clinical settings continues to be a topic of controversy. There are various concerns that arise, such as biases, lack of transparency and scalability, explainability, data integration and interoperability, privacy, reliability, safety, and the ethical implications of aggregated digital data. These concerns highlight the need for careful consideration and addressing of these issues to ensure the responsible and effective implementation of AI in clinical settings [15,16].

Dermatology has a strong potential for early adoption of AI due to its extensive clinical image databases. Dermatologists will need to grasp the fundamentals of AI to design and interpret medical studies in this field. This review begins by explaining AI processes and then explores the existing literature on AI applications in dermatology. Lastly, it addresses the potential concerns associated with this technology.

2. Fundamental and Development Principles of Artificial Intelligence (AI)

Clinicians typically use experience and personal knowledge when assessing patients' symptoms and signs. While this clinical information can be used for diagnosing diseases, it has been necessary to attend that the accuracy of the diagnosis cannot be guaranteed, and mistakes can occur. This aspect illustrated the limited capacity of the human brain to process large amounts of data. On the other words, AI models excel at handling large amounts of data [17]. Overall, AI is divided into two categories: strong and weak. Strong AI refers to machines that possess human-level intelligence, though this concept is mostly depicted in popular media and science fiction [18].

In contrast, weak or narrow AI refers to the current state of technology where machines are trained to achieve specific objectives. Machine Learning [19] is a technique and one subset of AI, wherein computer programs generate their own code to accomplish predefined tasks.

However, the use of AI/ML technologies in precision oncology and their integration into clinical practice poses a technological challenge to the development of models. This technology processing can be carried out through supervised, semi-supervised, or unsupervised learning. In the supervised learning approach, the machine is provided with labeled data, where each example in the dataset is associated with a corresponding answer. This enables the machine to learn and make predictions based on the provided labeled data [17,20-22].

Unsupervised learning involves analyzing input data without a predetermined answer, while semi-supervised learning combines labeled and unlabeled data. Deep learning (DL), on the other hand, is a specific type of machine learning that utilizes artificial neural networks capable of utilizing numerous layers [23]. The researcher is not required to manually extract features from the image. DL, in addition to being faster than the traditional machine learning approach, also exhibits improved performance [24]. A neural network takes inspiration from the neurons in the human brain and dynamically optimizes its performance [25]. In the case of skin lesion classification, the various layers of a neural network utilize lines, shapes formed from lines, and complex structures composed of these shapes to ultimately categorize the lesion into diagnostic groups including basal cell carcinoma ,papule or sebaceous hyperplasia [26].

AI programs are often evaluated using multiple statistical measures, such as sensitivity and specificity, and the area under the receiver operating characteristic curve (AUROC) is a commonly used statistical measure for the evaluation of AI programs [27]. The diagnostic accuracy of AI in dermatology has been compared to that of dermatologists in several studies and the results are promising. For instance, Esteva et al. in 2017 published the first study comparing a supervised CNN performance with dermatologist assessments for skin cancer diagnosis [14]. Though, these retrospective studies have been undertaken in experimental settings and have certain limitations. Prospective randomized clinical trials are needed to better validate the algorithms and ensure generalizability [14,28].

3. The Role of AI in Prognosis and Therapeutic Decision-Making

AI has shown promising results in predicting melanoma prognosis and therapeutic response. In a study by Kulkarni et al. [29], a CNN was trained using a dataset of 108 Whole Slide Images (WSIs) to predict distant metastatic recurrence (DMR) in melanoma patients. The model achieved high accuracy, with Area Under the Curve (AUC) values of 0.91 and 0.88 for larger and smaller validation sets, respectively. The model's output also correlated with disease-specific survival ($p<0.0001$) [29].

Furthermore, AI has been utilized to predict therapeutic response to immune checkpoint inhibitors (ICI). Johannet et al. [30] integrated deep learning on melanoma histology specimens with clinical data to develop a CNN that accurately classified patients as high or low risk for disease progression. The multivariate classifier achieved an AUC of 0.805 in predicting therapeutic response to ICI. High-risk patients had significantly worse progression-free survival compared to low-risk patients. In another study by Hu et al. [31], a CNN based solely on histology was able to predict ICI response in 54 melanoma cases with an AUC of 0.778. The model recently classified 65.2% of responders and 74.2% of non-responders. Although experienced surgical pathologists have a fairly accurate and reliable histopathological diagnosis for cutaneous melanocytic lesions, it is not always perfect, especially in cases of melanoma. The gold standard for definitive diagnosis of melanoma is the microscopic examination-clinicopathological correlation. Pathologists may face diagnostic controversies when melanoma closely resembles Spitz's nevus or blue nevus, exhibits amelanotic histopathology, or is in situ. Automating the diagnosis of cutaneous melanocytic lesions using deep learning, particularly to assist surgical pathologists with their workload, would be beneficial [32].

These findings demonstrate the potential of AI in assisting clinicians with prognosis estimation and therapeutic decision-making in melanoma patients.

4. Datasets for Skin Cancer Analysis

In dermatology, dermatoscopic and clinical images are usually used to monitor changes in skin conditions. The emergence of new applications allows algorithms to access the vast amount of existing and future data, such as those generated in hospitals, leading to improvements in CNNs. Several datasets are already available for research purposes. The ISIC archive gallery offers numerous clinical and dermoscopic skin lesion datasets, such as the ISIC Challenges datasets, BCN20000, and HAM10000 [33-35]. The Interactive Atlas of Dermoscopy provides 1000 clinical examples, including 270 melanomas and 49 seborrheic keratoses, with each case having at least two images - dermoscopic and close-up. The Asan Dataset is comprised of 17,125 clinical photos that depict 12 different forms of skin illnesses commonly found in Asians. This dataset is available for research download. The Hallym Dataset contains 125 clinical photos specifically focusing on BCC cases (34Han JID). There are two datasets, namely the SD-198 and SD-260 datasets. The SD-198 dataset contains 6584 clinical photos of 198 different skin illnesses, while the SD-260 dataset is more balanced with 20,600 photos representing 260 skin illnesses. Dermnet NZ offers a comprehensive collection of clinical, dermoscopic, and histology photographs. They also provide additional high-resolution pictures that can be purchased. Derm7pt is a dataset consisting of 1011 dermoscopic images, including 252 cases of melanoma and 759 cases of nevi. These images are based on a seven-point checklist.

Lastly, the Cancer Genome Atlas provides a vast collection of 2871 pathological skin lesion slides, making it one of the largest available collections for research purposes [36,37].

5. AI in Dermatology: Applications and Advancements

The ability to recognize visual patterns plays a vital role in dermatology diagnostics, and the integration of AI has the potential to significantly enhance image analysis and improve diagnostic accuracy in this field [38,39]. Recently developed computational neural networks have been utilized to diagnose skin conditions through visual image recognition. Surprisingly, these networks have demonstrated comparable, and in some cases even superior, sensitivity and specificity in classifying images compared to experienced dermatologists [40]. In a noteworthy study conducted by Brinkler et al., convolutional neural networks outperformed the diagnostic capabilities of 136 out of 157 dermatologists. This achievement was accomplished by accurately classifying 12,378 dermatoscopic images of suspicious skin lesions, like melanoma [13]. CNNs have been utilized to classify various skin diseases beyond just skin cancers. Han et al. conducted a comprehensive assessment of 12 skin conditions, including seborrheic keratoses, actinic keratoses, melanocytic nevi, pyogenic granulomas, hemangiomas, warts, and common skin cancers, using algorithmic analysis of clinical images [41]. A convolutional neuronal network, the Microsoft ResNet-152 model, was trained with 19,838 images from the training segment of the Asan dataset, MED-NODE dataset, and atlas site images. This trained model was then validated with the testing segment in 3 datasets including the Edinburgh and Asan datasets. The study illustrated that the algorithm's performance using 480 Asan and Edinburgh images, showed similar performance to 16 dermatologists [42]. Smartphone applications using artificial intelligence-based analysis have not yet demonstrated sufficient promise in terms of accuracy, and they are associated with a high likelihood of missing melanomas [43]. Chuchu et al. [42] assessed the diagnostic accuracy of four AI smartphone apps that classified skin lesions as either melanoma or high-risk lesions were assessed. Sensitivities ranged of these apps variedfrom 7%-73%, and specificities ranged from 37%- 94% [42]. In a study by Haenssle et al, a CNN was compared to a group of 58 dermatologists, including 30 specialists, and found to have a higher area under the ROC curve of 0.86 compared to 0.79 for the dermatologists. CNN outperformed most dermatologists in diagnostic accuracy [44]. AI has the potential to improve diagnosis and treatment in dermatology. However, concerns have been raised by dermatologists about its use. While AI can improve diagnostic accuracy and efficiency, it should not replace other diagnostic tools such as history and clinical context. Precise and fast annotation of skin images could be used to provide a ground truth for computational neural networks to classify new clinical images. However, there are challenges in integrating AI into clinical workflow systems and a lack of standardization in skin imaging [45]. To establish a ground truth for automated algorithm development in deep neural networks, further studies are needed [46].

6. Challenges in the Implementation of AI

There are several challenges that hinder the wider application of AI. The lack of imaging standards is a significant challenge in dermatological image analysis. Various factors, such as lighting conditions, camera specifications, and color calibration, can affect the appearance of a lesion in an image. Currently, the imaging process in dermatology lacks standardization, making it difficult to ensure the reproducibility of AI algorithms across different datasets and clinical settings. Although attempts have been made to establish standards in dermatological photography, they are complex and not easily implemented [47]. Another challenge is the lack of metadata accompanying images in most imaging databases used to train AI algorithms. Clinical significance can vary for lesions that appear similar but occur in different clinical settings. Including metadata, such as patient information and clinical context, along with images could enhance the accuracy of AI diagnosis [48]. The limited generalization capability of machine learning algorithms trained on databases with a narrow range of diagnoses is another challenge. Most image databases focus on a limited number of lesion types, which may not adequately represent the diverse range of skin conditions encountered in clinical practice. Additionally, there is a disproportionate representation of lighter skin types in imaging archives, which can impact algorithm performance in clinical settings that include all skin types [49]. Furthermore, the lack of prospective studies conducted in real clinical settings poses a challenge. Previous studies evaluating ML technologies for skin cancer diagnosis have been performed in controlled experimental environments using dermoscopic or close-up images, which may not accurately reflect real-world clinical scenarios. Prospective studies conducted in actual clinical settings are necessary to develop ML algorithms that are relevant and effective in practice. Moving on to the challenges in the implementation of AI, one primary obstacle is the scarcity of labeled patient data. Unlike other medical imaging modalities, photographs of human skin lack standardization. Multiple lesions can be present in a single photograph, requiring specific training of the algorithm for the lesion of interest. Human curation of images becomes necessary to provide selective instruction for neural networks, as algorithms without this guidance are less accurate [50-52]. However, this curation process is costly, time-consuming, and subject to the imperfect and inconsistent standards of human decision-making. Another challenge is the potential selection bias in the databases used to train deep-learning algorithms. Existing databases predominantly consist of images from fair-skinned populations in the United States, Europe, and Asia, which may limit the robustness of melanoma detection in individuals with colored skin. Besides, the "black box" nature of AI models presents a challenge, as the rationale behind the model's decisions may not be easily interpretable by humans. This lack of understanding can lead to skepticism and wariness, despite numerous studies confirming the accuracy of AI [44,51,53]. Incorporating patient data, such as age, sex, and lesion characteristics, has been shown to improve the performance of CNNs. Collaborative efforts between clinicians and AI have also demonstrated enhanced accuracy compared to either working alone [54]. Also, it is essential to consider the impact of human factors and potential cognitive bias when implementing AI in clinical practice [50]. In addition, the rise in melanoma incidence has been attributed to increased SC screening, biopsies, and a lower threshold for diagnosing melanocytic neoplasms as melanoma. AI has the potential to amplify these factors by increasing sensitivity among pathologists and clinicians, although its effect on specificity remains unclear [55]. More research is needed to evaluate the impact of AI on clinical practice and address potential challenges and biases that may arise.

7. Effective Approaches for Overcoming Limitations

The recognition of the limitations of emerging technologies is crucial for improving and advancing existing algorithms. To overcome these weaknesses before these algorithms become a part of daily clinical practice, several strategies can be implemented. Firstly, expanding CNNs training sets to reflect the diversity of the general population is essential. This is particularly important due to the increasing diversity resulting from immigration waves, which require physicians to examine patients from unfamiliar backgrounds. Most algorithms are usually trained on either Asians or Caucasians patients [41,56-58].

Training algorithms on a broader range of ethnicities, including patients with skin of color, can be more beneficial as it can help detect advanced diseases and improve survival rates by reducing delays in diagnosis [51]. Algorithms tend to underperform when presented with data from populations not included in the training dataset, emphasizing the need for broader ethnic representation. In addition to expanding the training datasets, including metadata for patients being examined should be an integral part of the data provided to the algorithm [41,51]. This metadata can include information such as age, gender, skin type, and anatomic location, which mirrors the diagnostic approach of clinicians who consider a patient's history [59]. Providing this metadata to both clinicians and machines allows the algorithm to analyze the information and potentially improve accuracy. Some studies have already integrated clinical metadata, showing promising results for more accurate classification [48,60]. Future studies will determine if this approach yields better accuracy compared to CNNs alone [53]. Plus, clinical close-up images can be utilized for the artificial classification of skin lesions [48]. Clinical close-up images can also be utilized for the artificial classification of skin lesions. These images provide additional data that may not be visible under dermoscopy, such as specific appearances or characteristics of certain lesions. Combining clinical and dermoscopic image analysis, known as combined CNN (cCNN), is likely to become the primary reference point in future studies. Previous studies have already used cCNN classifiers to enhance algorithm performance [48,60,61]. These datasets of clinical images could potentially be used to train algorithms for smartphone applications that are mentioned above. However, it is important to note that even the best algorithms still have room for improvement. To address confounding factors in images, techniques such as image segmentation can be employed to separate the lesion from the background image. Various techniques for lesion segmentation have been proposed and could be explored in future studies [62]. It is important to control the quality of segmentation, as it may introduce new challenges that require further investigation. When evaluating classifiers, it is essential to consider using out-of-distribution (OOD) data, which refers to data from a different source than the training and validation data [54]. The use of OOD images for evaluation can serve as a gold standard and enhance the generalizability of classifiers. Instead of viewing human and artificial intelligence as opponents, the scientific community should encourage studies that promote collaboration between the two. Combining the expertise of dermatologists with AI algorithms has shown improved diagnostic accuracy compared to either AI or physicians alone [51]. This finding has been supported by multiple researchers [63,64]. The impact of AI systems, such as MelaFind, on dermatologists' decision-making has also been evaluated, demonstrating that dermatologists use the information provided by AI as complementary to their own judgment, resulting in increased sensitivity [65]. To ensure quality use of imaging, the adoption of a standardized protocol is crucial. The Digital Imaging and Communications in Medicine (DICOM) standard is widely used in other medical specialties and can be implemented in dermatology to improve image processing. DICOM allows for the attachment of supplementary material, such as resized or down-sampled images, segmentation images, and the algorithm's lesion classification output, as well as metadata [51,66]. The existence of standardized datasets can help overcome pitfalls in AI and contribute to the external validation of machine learning algorithms, enhancing generalizability. Furthermore, metadata-based retrieval can facilitate the selection of images with specific characteristics for future studies. Privacy concerns can be addressed through DICOM's de-identification profiles, ensuring patient identity protection in clinical trials [51]. In summary, acknowledging the weaknesses of emerging technologies and implementing strategies such as expanding training datasets, including metadata, utilizing clinical images, addressing confounding factors, using OOD data for evaluation, promoting human-AI collaboration, and adopting standardized protocols like DICOM can contribute to the improvement and effective use of AI in dermatology.

8. The Acceptance of AI by Clinicians and Patients

Jutzi et al. [11] conducted a survey-based inquiry into the perspectives of patients residing in Germany regarding the utilization of artificial intelligence (AI) for identifying melanoma. The purpose of this investigation was to comprehend what individuals diagnosed with melanoma in Germany truly think about employing AI as a diagnostic tool. A total of 298 people were surveyed, out of which 154 had already received a diagnosis of melanoma. Surprisingly, the majority of respondents (94%) expressed their support for using AI technology within healthcare. This revelation brings optimism since patient acceptance holds significant importance when making effective decisions related to healthcare management. Additionally, results from the study highlighted that 88% of participants were open to sharing their medical records in order to contribute towards developing AI applications. Of notable interest, individuals previously diagnosed with melanoma showed heightened enthusiasm for implementing AI systems as a means for early detection purposes. Another smaller-scale study involving 48 patients exhibited similar findings wherein patients displayed positive attitudes towards utilizing AI specifically for facilitating skin cancer screenings—an endorsement conditioned on not undermining the trust and rapport between physicians and patients [67]. Conversely, Oh et al. [68], carried out research via questionnaires among 669 physicians where it was discovered that only a mere 5.9% claimed familiarity with AI technology; however, an overwhelming percentage composed of 83.4% firmly believed in its potential helpfulness within the healthcare sector at large. Likewise, numerous participants shared sentiments leaning towards endorsing disease diagnosis as being one promising domain where implementation could benefit substantially from integrating advancements in machine learning algorithms [19]. Intriguingly enough, nearly half—or more precisely—around approximately 43.9% of respondent opinions lean favorably toward acknowledging an apparent superiority demonstrated by AI over human doctors when it comes down to diagnosing diseases.

While there aren't many specific studies looking at how well dermatologists accept ML for SC diagnosis, it's expected that clinicians will accept it if it can improve accuracy and enable early detection. It's crucial to remember that AI is meant to help clinicians manage and evaluate patients rather than replace them. Although the literature backs up ML's usefulness in the diagnosis of SC, clinicians' acceptance will determine how widely it is used.

9. Ethical Considerations in AI Implementation

Based on the studies mentioned, the supervision of AI-based SC screening by physicians is seen as a positive aspect by both patients and healthcare providers. From an ethical standpoint, it can be argued that without the clinical input of licensed physicians, the widespread use of direct-to-patient screening tools may lead to increased moral hazards. For instance, relying solely on smartphone apps for screening may give patients a false sense of security, leading them to spend more time outdoors, use less sunscreen, or visit physicians less frequently. This becomes problematic if these technologies are less effective in detecting SC compared to physicians. Health literacy and access to technology may also influence the utilization of such screening tools, potentially widening existing gaps in healthcare access [69]. Moreover, it is important to take into account the emotional repercussions of this technology, as being informed about one's SC diagnosis via an application can induce notable anxiety and distress. Physicians, on the other hand, can provide nuanced information about diagnosis, prognosis, and treatment, helping to alleviate specific fears and providing better emotional support. There are several important ethical considerations when it comes to using AI in medical decision-making. Two key considerations are patient privacy and algorithm transparency. When handling sensitive patient information for diagnostic purposes, it is crucial to have strict privacy regulations in place. Additionally, patients have the right to understand how their data is being used and the decision-making process employed by AI technology. Transparency in these processes and regulations is essential to establish trust in AI-based technologies. It is significant to recognize that AI technologies are not infallible. Machine-made decisions, which are based on algorithms designed by humans, can be biased depending on the input data. This issue is particularly concerning as it may exacerbate existing healthcare disparities [69]. Research has indicated that there is a lack of transparency when it comes to how race is represented in the datasets used to train deep-learning algorithms for detecting SC [70,71].

To prevent the worsening of healthcare disparities, it is important to utilize inclusive, extensive, and representative datasets that include images of malignancy across all skin tones in the development of screening and detection algorithms for SC. By doing so, we can strive for more accurate and equitable outcomes in the field of skin cancer detection.

10. Conclusion

Recently, there have been significant advancements in AI health technology, particularly in the accuracy of AI algorithms for diagnosing SC. The potential benefits of having an accessible, safe, and reliable AI diagnostic aid in this field are tremendous. Although, it is crucial to acknowledge that there may be barriers, unintended consequences, and biases that could affect the practicality of using AI SC diagnostic tools in real-world scenarios. To ensure the effectiveness and safety of AI diagnostic tools, it is important to consider human factors during their design and development. By incorporating human factor knowledge, clinicians will be able to utilize these tools more effectively and safely. This highlights the importance of collaboration between dermatologists, who possess a deep understanding of clinical care and processes, and technical specialists in the design of AI technology for the clinical setting. This interdisciplinary collaboration will help address potential challenges and ensure that AI diagnostic tools are well-suited for practical use in healthcare.

While there may be concerns about the utilization of AI in diagnosis and prognosis, dermatologists should embrace AI and work alongside technical specialists. In the complex field of diagnosis, and management of melanocytic neoplasms, AI has the potential to improve access to medical care and improve medical decision-making. It is necessary to note that AI will not replace practitioners in the foreseeable future, as they fulfill several roles for example diagnosticians, counselors, and trusted confidants for patients.

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