Artificial Intelligence for Skin Cancer Detection: A Review of Current Approaches

Abdelaziz A. Abdelhamid[1,*]

[1]Department of Computer Science, Faculty of Computer and Information Sciences, Ain Shams University, 11566, Cairo, Egypt

Email: abdelaziz@cis.asu.edu.eg

Abstract

AI is emerging as a potential tool for revolutionizing dermatology in the early detection and diagnosis of skin cancers. This Review looks into the most recent innovations in AI technology, such as machine learning, deep learning, and explainable AI (XAI)) Moreover, it presents how one can achieve diagnostic accuracy similar to or exceeding that of well-experienced dermatologists. Access to such diagnostic tools in under resourced areas has been enhanced, inter-observer variability has increased, and workflows in clinical practice have been streamlined. Nevertheless, issues regarding diversity in data, generalization of models, and the inscrutability of many AI systems remain, and the use of these systems in clinical practice needs to be improved. The paper emphasizes the need for interdisciplinary collaboration, diverse dataset collection, and lightweight and interpretable AI models to solve these issues. Lastly, it brings together important findings and identifies research gaps, showing AI's potential to change the dermatology world for all patients.

Keywords: Artificial Intelligence; Skin Cancer Detection; Dermatology; Deep Learning; Explainable AI; Diagnostic Accuracy

1. Introduction

AI in dermatology can be described as a revolutionary breakthrough in the fight against skin cancer, as it changes the primary mechanism for identifying this disease. This Review concerns developments in AI techniques focusing on utilizing Assembly Intelligence, process automation, improved diagnostic accuracy, and increased accessibility to underserved locations. Based on the Review of the latest publications, the work underlines emergent technologies such as deep learning and explainable AI that revolutionize clinical practices. Furthermore, it responds to such vital issues as the diversification of data and the model's ability to adapt to the environment, which is critical in applying these technologies. This exploration seeks to build improved awareness and understanding of how AI could be fine-tuned for better skin cancer diagnosis and management.

1.2 Background and Significance of Skin Cancer Detection

Of all types of skin cancer, Melanoma is especially dangerous as the fatal kind of cancer that threatens millions of people worldwide. This is especially the case since detecting the disease during its early stage is significant in helping patients achieve competent survival and reducing the harm that perfunctory cure methodologies can cause. Conventional techniques like biopsies and dermoscopy are efficient yet not devoid

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

of drawbacks; they are costly, inter-observer variability is high, and such procedures are rare in the developing world. These limitations show the importance of seeking new ways to enhance the diagnostic process to arrive at accurate results early enough [1].

The typical difficulties mentioned above have been overcome with the recent invention of artificial intelligence (AI). Advanced diagnostics employing machine learning to make an analysis of skin cancer are accurate and available at a large scale. All these introduced technologies provided better diagnostic accuracy, but more importantly, they increased accessibility, particularly in the low-resource environment. Continuing advances in AI technologies in dermatology are indicative of a new era that promises more efficient diagnosis coupled with fairness [2].

1.2 Role of Artificial Intelligence in Modern Dermatology

Dermatology has witnessed significant improvements in medicine diagnosis through artificial intelligence (AI) with recent developments. The technology that has been successfully implemented in the analysis and diagnosis of skin lesions is machine learning and deep learning. These technologies provide diagnostic performance that is near to or better than that of human dermatologists. Its implementation enhances the accuracy of the diagnosis and the demand for the expansion and development of more sophisticated dermatological services to hard-to-reach regions [3].

Therefore, in dermatological practice, the use of AI is limited to diagnosis, treatment planning, and patient management. Technology incorporating AI can collate large images, analyze them, and establish disparities that are undetectable by professionals. These capabilities involve their incorporation into clinical workflows whereby decision-making can be improved, and variability lessened than manual diagnostics. Integrating AI into dermatology is a milestone toward a novel direction of a better and improved healthcare system for everyone [4].

1.3 The objective of the Review

This review paper aims to identify and discuss both the current and possibly future developments in technologies of artificial intelligence applied to skin cancer diagnosis. This Review considers how AI can be applied clinically to enhance diagnostic acuity and availability by considering only state-of-the-art methodologies. It also explores how diagnostic applications have emerged as a new avenue in the clinical use of AI, employing machine learning and deep learning in clinical practice to solve crucial healthcare problems.

Consequently, this work also provides the current research gaps in AS-AD skin cancer detection, such as data diversity, model generalization challenges, and future studies. Using the findings of recent reviews, the study puts forward directions that can be used to develop AI approaches as valuable tools for dermatologists to improve the efficiency, veracity and inclusivity of health systems globally [5].

1.4 Scope of the Review

The Review focuses on the following areas:

- **Deep Learning Applications**: Exploration of convolutional neural networks (CNNs) and transfer learning techniques for skin lesion classification.
- **Explainable AI (XAI)**: Discuss integrating interpretability in AI models to enhance clinical trust and usability.
- **Challenges and Limitations**: Examination of issues like data privacy, model generalization, and lack of diversity in datasets.
- **Future Directions**: Recommendations for advancing AI applications in dermatology, emphasizing interdisciplinary collaboration and enhanced data availability.

Thus, the development of AI has been fast and has dramatically enhanced the solutions for advanced skin diseases, specifically skin cancer diagnosis. Therefore, the potential of the current approaches, as well as the shortcomings, has been highlighted in this Review, which gives direction on the improvements that may be needed in future research and development. More focus on barriers, including bias of data, explain ability of

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

AI and others, must be put into practice to ensure that the deployed solutions are safe and fair. With the adoption of artificial intelligence still central in its exponential growth, mainstreaming AI in clinical practice has many benefits, such as enhancing the quality of care and extending healthcare access to the remaining corners of the globe. Further integration with other fields will be essential to realize the full possibilities of AI in diagnosing skin cancer and other diseases.

2. Literature Review

The acquisition of skin cancer involves the application of artificial intelligence in dermatology, which leads to improvements in the diagnosis process. As skin cancer cases increase around the world, identifying them early is very helpful, and together with the increasing use of artificial intelligence, it has become a practical approach to enhance the accuracy of diagnosis. Deep learning models, in particular, have been effectively used in analyzing skin lesion images, and in many cases, the effectiveness of the models was found to be on par with dermatologists. However, some issues still have not been solved yet, such as the ability of diagnostic or predictive models to explain their results, as they usually are "black boxes" in clinical practice. As for this, methods for explainable AI (XAI) are being implemented, which make a decision clear to clinicians and let them establish trust in AI-driven diagnoses.

The gut microbiota is an essential part of the human body; it helps with metabolism, immunity and disease prevention [6]. Symbiotic flora disturbance is associated with diseases such as cancer, pathogenic bacteria Escherichia coli, and Fusobacterial nucleate, promoting inflammation and new tumor formation. In the study mentioned, it has been possible to spit microbiota potential with NGS performance and machine learning to optimize the bacterial microbiota and biomarkers studies and explore the microbial signature of treatment response and metabolite pathways of cancer development. Early detection is then advanced by machine learning algorithms, which enhance cancer classification based on the microbiota and integrate NGS to advance molecular diagnostics to establish personalized medicine. This integrated model enables specific diagnostic and therapeutic strategies based on patient-specific microbiome data and emphasizes that microbial interaction, biomarkers for early cancer detection, and microbiome-based cancer prevention rationale should be studied in the context of other-omics approaches.

Skin cancer, which is among the most common cancers globally, is grouped into melanoma skin cancer and non-melanoma skin cancer; however, Melanoma is more lethal even though the incidences are low. Following the research done by [7], despite the high accuracy of biopsies, the diagnostic tool still involves invasiveness and high access costs, particularly in the lower economic bracket. Current methodologies, such as dermo copy and confocal microscopy, are helpful but have limitations due to inter-user variability and inadequate training of dermatology residents. The study also documents the increasing use of Artificial intelligence (AI) related technologies for better diagnosis of Melanoma. These technologies provide better access and higher screening sensitivity compared to conventional techniques. Discussed applications include AI-assisted clinical imaging, dermo copy, differentiating between Melanoma and other skin cancers, and vivo skin imaging devices and their possible application in aiding the dermatologist in practice.

Skin cancer is among the widely spread health hazards in the world, and identifying the problem in the initial stages is vital to the patient. In the study [8], Skins age XAI was developed to address dermatology problems by extending the application of explainable artificial intelligence (XAI) to categorize skin lesions. The system used the Inception v3 model trained on the Customized HAM10000, gradient-weighted class activation mapping, and local interpretable model-agnostic explanations from 50,000 images for this scenario. Skins age XAI's accuracy was 96%, precision was 96.42 %, recall was 96.28 %, F1 scoring was 96.14 %, and AUC value was 99.83 %. Far from burking its importance in the evaluation of this kind of case, these results demonstrate its ability to recognize seven forms of skin lesions, among them Melanoma and basal cell carcinoma, as well as present detailed graphics to the dermatologist in order to help them with their diagnosis: They reduce errors and semantic gaps regarding explanations.

Cutaneous malignancies remain a relevant problem for global public health, considering timely detection is vital to raising a patient's survival rate. For details of the most recent achievement in AI for skin cancer prediction, the following research was conducted [9], whereby the authors undertook a systematic review of 780 papers on skin cancer prediction published between the years 2016 and 2022, where only 62 from Scopus and 20 from Web of Science fit into the research criteria. The outcomes outlined the performance and strength

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

of DL algorithms to differentiate between benign and malignant lesions and diagnose skin cancer encompassing melanocytic and non-melanocytic skin cancers with high sensitivity and specificity. Nonetheless, the following limitations in their studies have been pointed out: small numbers of subjects and inadequate field trials have been done, thus limiting external validity. Therefore, the study urges future studies to replicate the AI performance with varying skin tones and settings while applying the model to other types of skin cancer, including basal and squamous cell carcinoma.

In recent years, computer-aided diagnostic (CAD) systems for skin lesions have advanced significantly, leveraging imaging and metadata to enhance detection accuracy. However, as outlined in [10], these methods could be improved in providing molecular-level insights. Near infrared (NIR) spectroscopy offers a complementary approach by capturing non-visible information, which can significantly improve CAD systems for skin cancer. To address the scarcity of publicly available datasets for machine and deep learning (MDL) applications in spectroscopy, researchers, in collaboration with the Programa de Assistência Dermatological (PAD) at UFES, developed the NIR-SC-UFES dataset. This dataset comprises portable NIR spectral data for six types of skin lesions, with 714 spectra recorded in the range of 900–1700 nm. It represents a valuable resource for advancing skin cancer diagnostics and is freely accessible at data.

Skin cancer is one of the most prevalent forms of cancer worldwide, contributing to a significant number of global deaths, with Melanoma being the most aggressive and deadly type. As discussed in [11], early diagnosis reduces mortality rates. Traditional methods, such as visual inspection, lack accuracy and reliability, emphasizing the need for advanced diagnostic tools. Deep learning-based approaches have emerged as a promising solution to address these limitations, offering improved precision in skin cancer classification. These methods serve as valuable tools for dermatologists, enabling early and accurate detection of skin cancer and thereby supporting better clinical outcomes.

As described by [12], there is increasing interest in utilizing ex vivo confocal laser scanning microscopy (EVCM) for quick histological examination of tissues that provides near real-time results. However, its clinical utility is compromised by the fact that the identification of modality-specific diagnostic features requires training. A deep learning model using the MobileNet-V1 convolutional neural network was trained to identify Basal Cell Carcinoma (BCC) in the EVCM images. Accumulating all 50 histologically confirmed BCC samples for ten-fold cross-validation, the proposed model obtained sensitivity and specificity of 0.88 and title specificities of 0.85, respectively, in addition to the area under the ROC curve of 0.94. Additional testing using 19 new EVCM images confirmed its sensitivity of 0.83, specificity of 0.92 for tumor-containing samples, and 0.98 for tumor-free controls. To this end, these outcomes may enable this deep learning method to support doctors in diagnosing BCC, minimize the training period for novices, and enhance decision-making in EVCM-based diagnostics.

Following the works explained in [13], this paper presents a new conceptual category for the classification of skin neoplasms, using deep learning methodologies in conjunction with genetic optimization algorithms to achieve higher diagnostic precision and speed. The research applies novel CNN architectures optimized through PSO and BA, including Mobile Net, Exception and Inception. The system exists as a web-based application wherein any registered user can upload skin lesion images that are classified as Melanoma or non-melanoma by means of a Deep Neural Network. The models were trained and validated on two large datasets, ISIC and HAM10000, and other architectures joined with Exception outperform others due to the more profound architecture and ability to extract finer features using the extreme inception module and the Bat algorithm. This solution is beneficial not only for dermatologists as a diagnosis tool but also shows the possibility of its application in the medical field and clinical diagnosis in a particular specialty.

LLMs are rapidly revolutionizing many industries, including urology, improving documentation creation, communication with patients, and education and research. Ref [14], Talyshinskii et al. described the utility of ChatGPT in these areas, explaining that the system would reduce clinicians' workload while offering educational value to students and clinicians. However, the study focused on essential features vital in health practice, like risks associated with information twists, fake references, plagiarism, and infringement of patient information and, therefore, foreseeing careful and sound execution of LLMs in healthcare practice.

Diagnostic image segmentation by using the computer assists in aiding physicians in detecting the lesion areas for diagnosis and treatment. [15], as described, segmentation of medical images is still problematic

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

because targets can have irregular shapes and are usually significantly smaller than their background. For this purpose, the study introduced the Ultra-Lightweight Network Inspired by Bio-Visual Interaction called BVI-Net, which originated from the creed of biological vision processing. BVI-Net involves a separate global pathway similar to the dorsal stream to provide a quick holistic information extraction, and a local pathway modeling the ventral stream inspects the input details. Furthermore, a simple skip connection module incorporates GCN attention, allowing multiple levels of features to be fused. The ISIC, LiTS, and BRATS datasets show that the designed BVI-Net achieves high segmentation accuracy using only 0.026M parameters while surpassing the current state-of-the-art methods in both performance and efficiency and, thus, can be applied to the clinical setting.

Soon as explained in the paper [16], computer-assisted medical image segmentation plays an important role in helping doctors identify lesion areas that are useful in diagnosis and treatment. However, some problems still exist because typical target shapes are irregular, and target regions differ in size from background regions. To overcome these problems, the study presents the Ultra-Lightweight Network Inspired by Bio-Visual Interaction (BVI-Net) architecture, which is based on biological visual pathways to deliver high performance of the segmentation while utilizing minimum computational power. It consists of a Global Pathway, modeling the dorsal stream for fast extraction of global features, and the Local Pathway, based on the ventral stream for local fine processing. GCN-based attention is also incorporated to facilitate effective multilevel feature fusion. The experiments performed on the ISIC, LiTS, and BraTS datasets show that the proposed BVI-Net model can achieve performance comparable to state-of-the-art methods with fewer parameters - 0.026M, making the algorithm very suitable for practical use in clinics.

As described in [17], inequalities in breast cancer screening adversatively affect an underprivileged population of individuals, such as the American Indian or Alaska Native people, Black and Hispanic people, people with disabilities, and the LGBTQ+ community. The factors affecting the use of mammography services include socioeconomic status, which affects the ability to pay for the services; geographic restrictions, which limit access; and variability in insured health services, which affects usage of the service. Problems associated with present screening protocols, which differ across organizations, complicate these issues for underprivileged groups. Efforts such as the Breast Density Notification Law and the Find It Early Act standardize legislation to reduce disparities, but they fail. The superior risk classifications generated from conventional risk models are disparate and a source of unfairness in genetic testing and supplemental screening recommendations. New technologies: Artificial intelligence seems to have an excellent opportunity to play a critical role in lessening these gaps regarding risk assessment and improved detection rates, but their adoption requires scrutiny to ensure it does not deepen the inequalities already present. The focus is on the accessibility of public environments for disabled and other marginalized people, and recommendations for further research, the development of policies and practices, and clinical application are provided.

As stated in [18], metabolic dysfunction-associated steatotic liver disease (MASLD) is a newly emerging public health concern due to its strong relation to MetS caused by obesity-altered metabolism. MASLD is a chronic liver disease where there is an excessive concentration of fat in the liver's original tissue, and it tends to worsen to other worse stages, leading to higher morbidity and mortality. It is a predisposing factor related to obesity, insulin resistance, dyslipidemia, diet, and gut microbiota dysbiosis. It has bidirectional relations with MetS components like hyperglycemia, hypertension and dyslipidemia. Further, MASLD is associated with the progression of other serious hepatic diseases and conditions outside the liver, such as cardiovascular diseases and some cancers. Usually, imaging and histological modalities are commonly used in diagnosis, and preference is given to non-invasive methods rather than biopsies. Thus, profound insights into different biomarkers and OMIC technologies are helpful to improve diagnostic capabilities despite practical limitations. Advances in artificial intelligence, modifiable behavior-related changes, and pharmacological-based therapies may provide better outcomes for patients. Future research should expand on the management of MASLD through precision medicine and on the creation of improved diagnostic modalities.

Lesion detection and localization is an important activity in the staging phase of diagnosis and management of Prostate cancer (PCA) [19]. After a positive digital rectal examination or a raised prostate-specific antigen (PSA), precise identification of lesion locations for biopsy through multiparametric magnetic resonance imaging (mpMRI) is crucial when delivering active and targeted treatment against prostate cancer. Both mpMRI and US imaging are already used as part of prostate fusion biopsy (FBx), which assists in obtaining

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

accurate tissue samples. However, these techniques are still suboptimal due to the low resolution of both mpMRI and US, which can hamper cancer characterization and management. The prior research works have mainly concentrated on improving the visibility of the lesion on both the MPMRI and the US by using signs that are more reliable, such as shear wave electrography (SWE). AI has been shown to enhance using FBx and both mpMRI and US data, but due to lack of labeled lesions for mpMRI in enhancing the performance of advanced models. Self-supervised learning (SSL), which allows the training of AI systems with small amounts of annotated data with the help of vast unlabeled databases, has recently solved this problem. As mentioned in the work of [2], integrating mpMRI and US data into AI models can improve lesion identification and localization of PCa. The work shows that pretraining of joint embedding predictive architectures for mpMRI-SSL is promising and that false positive filtering techniques using actual and AI-derived SWE increase the model specificity. The proposed model offered the best results to date for mpMRI-based segmentation and revealed the potential for enhancing the detection of PCa lesions by 62.6%.

CAD of medical images helps doctors identify regions of lesions for diagnosis and treatment purposes. Nevertheless, the problem of the target's irregular form and the sample size disparity between the target and the background make automated segmentation a rather tricky task. Most CNN-based and Transformer-based models have more layers or newly added complicated components for better segmentation results. However, these large models are often computationally infeasible in clinical practice since many clinical applications have restricted primary computing resources. In the research conducted in [20], the authors introduced a new UL-Net, a network based on Bio-Visual Interaction (BVI-Net) that should be fast, accurate and require few resources. The model incorporates two pathways: a Global Pathway, which replicates the dorsal stream for fast global feature processing, and a Local Pathway, which replicates the ventral for slow but detailed local feature processing. In addition, the skip connection is introduced, accompanied by the Graph Convolutional Network (GCN), which aims to combine multilevel features seamlessly. The authors tested it on ISIC, LiTS, and BraTS datasets. With a small number of parameters of 0.026 million, it showed superiority over the state-of-the-art methods in medical image segmentation. The presented approach involving direct interfaces of biological vision mechanisms to artificial intelligence algorithms can provide novel guidelines for engineering bio-vision-driven deep learning models and contribute toward biomimetic computational vision research.

Locating the lesions is the primary activity during the staging phase of managing PCa, diagnosing and treating the disease [21]. If the DRE is positive or prostate-specific antigen has increased, accurate dosing of lesion locations for biopsy is important using mpMRI. That is why mpMRI and ultrasound (US) imaging are already used to do this through a technique called mpMRI-targeted US-guided prostate fusion biopsy (FBx), but there are difficulties due to the low resolution of these methods. These may affect the likelihood rating of malignancy and, as a result, influence management decisions. The latest scholarly investigations seek to enhance accuracy in detecting lesions in mpMRI and US, employing more quantifiable formative features such as SWE. It has been demonstrated that the presented AI improves both the FBx value based on mpMRI as well as on US data is not labeled lesion data for mpMRI is still scarce for the improvement of state-of-the-art models; the authors discuss how SSL can help mitigate this problem by using large unlabeled databases to train powerful feature extractors that can in turn help build case-specific AI models with a minimum amount of labeled data. The study shows the promise of joint embedding predictive architectures for mpMRI-SSL pretraining. It presents a false-positive-filtering method using real and synthetic SWE data as supplementary material to increase the specificities of the mpMRI-based models. Their approach provides state-of-the-art results with an average precision of 0.626 for mpMRI-based segmentation, hence providing a promising improvement in lesion detection and localization for PC|A. CAD systems incorporating medical image processing with artificial intelligence AI have been designed to deal with issues like the elongated time required to diagnose a particular image and other variations that might be expected from one operator to the next. Skin cancer detection is one of the most explored use cases, and DNN-based systems for cancer diagnosis, including skin cancer detection, perform as well as human dermatologists. Nevertheless, their decision-making processes remain opaque, or 'black boxes,' and therefore, while DNNs find their place in clinical domains, they are not used in clinical practice [22]; in this regard, the Explainable AI or XAI techniques have been developed to provide ways through which the decision making by DNN can be explained. XAI has been previously used for skin lesion classification models but not for DNN models trained with additional feature injection. The work presents the theoretical background for explaining the

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

convolutional neural networks with feature injection used for diagnosing Melanoma. Three methods, including gradient-weighted class activation mapping and layer-wise relevance propagation, were used to create heatmaps and establish the image regions that affected predictions. In addition, the SHAPLEY additive explanations method was employed to evaluate the relative utilities of handcrafted features. The use of DNNs in clinical practice requires making them transparent and reliable instruments.

As for the diagnosis of skin diseases, the classification of diseases is crucial for the treatment and further prognosis of a patient's condition. As outlined in [23], transfer learning models were developed to detect skin diseases from images using the "Skin Cancer: The MNIST HAM10000 dataset is made up of seven classes including ‘melanocytic nevi,' 'melanoma,' 'basal cell carcinoma' and 'vascular lesions.' The assessment also considered five transferred learning models and the accuracy and features extraction; these models included ResNet50, InceptionV3, VGG16, VGG19, and MobileNetV2. In these, ResNet50 yielded the highest accuracy of 99% and efficiency, making it most appropriate for diagnosis. These included MobileNetV2, with an accuracy of 97.5 %, which was deemed a suitable solution for low-resource environments. To overcome the lack of interpretability in deep learning models, another instance of an XAI tool, LIME, was used to explain how these models arrive at the diagnosis of diseases. These results reaffirm the utility of transfer learning in improving diagnostic precision, minimizing computational complexity, and demonstrating the possibility of developing automatic aids in dermatological diagnosis.

As mentioned in [24], artificial intelligence (AI) is disrupting dermatology owing to marked improvements in the early identification of skin cancer and textural abnormalities, which was a serious drawback of clinical assessments based on the naked eye and histopathological analyses. This work systematically identified 95 publications from databases that included Scopus, IEEE, and MDPI to assess AI's efficiency in the classification of skin cancer. The research disclosed that deep learning, image processing, and feature extraction could boost diagnostic precision, shorten testing time, and make it far more available in the underrepresented areas of the world. Though they effectively address existing business problems, such as customer segmentation, demand forecasting, and fraud detection, challenges, including data privacy or integration and the requirement for various, rich data, are important for future development.

As detailed in the paper [25], the increasing prevalence of skin cancer has driven the development of machine-learning methods to enhance diagnostic accuracy through skin lesion classification. This study introduced a multimodal Explainable Artificial Intelligence (XAI) system to align dermatologists' diagnostic perspectives. The XAI framework identifies thermoscopic features and facilitates evaluating interactions between clinicians and AI systems during melanoma diagnosis. A novel Convolutional Spiking Attention Module (CSAM) was proposed and incorporated within a Spiking Attention Block (SAB) to amplify critical features while minimizing noise. Pretrained models, such as InceptionResNetV2, DenseNet201, and Exception, integrated with SAB, demonstrated superior performance on the HAM10000 dataset and validated effectiveness using the ISIC-2019 dataset. This approach provided intrinsic attention to cancerous regions without relying on external explainers, highlighting the SAB module's impact on enhancing skin lesion classification.

Table 1 presents a detailed synthesis of the literature review focusing on skin cancer detection using AI and other related fields; issues of concern include focus areas, research technique, findings, challenges and future direction. The reviewed body of work highlights that deep learning, transfer learning, and Explainable AI (XAI) aims at increasing accuracy, availability, and clinician trust in under resourced areas. Hurdles, including data variety, model validity, computational complexity and fairness issues, are identified as the main limitations. This is because the future trends highlighted across the studies include the availability of diverse datasets, lucid AI solutions for less endowment milieus, interdisciplinary cooperation, and policies that would guarantee efficient and moral AI applications. The table also justifies a clear roadmap for the future development of AI applications in dermatology. The existing problems are outlined in the table, along with the major focus on how technology can be used to overcome the issues shown in the table.

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

Table 1: Summary of Literature Review

Study Focus	Methods Used	Key Findings	Challenges/Limitations	Future Directions
[6] Explainable AI in Dermatology	XAI methods like LIME, SHAPLEY, CAM	Enhanced clinician trust and diagnosis transparency	Opaque 'black box' models	Integration of explainable AI tools into clinical workflows
[7] Deep Learning in Skin Cancer	CNNs, transfer learning, NIR spectroscopy	High sensitivity and specificity in melanoma detection	Limited external validity, small datasets	Broader application across skin types, integration with other diagnostic modalities
[8] Multimodal AI for Diagnostics	InceptionResNetV2, DenseNet201, Convolutional Spiking Blocks	Amplified critical features, improved skin lesion classification	Dependence on pre-trained models	Expanding multimodal AI applications and refining spiking attention blocks
[9] Integration of AI and Histology	MobileNet-V1, EVCM	Sensitivity: 0.83, Specificity: 0.92 in BCC identification	Requires trained personnel for clinical integration	Use of AI to simplify training and enhance decision-making processes
[10] Bio-Visual Interaction for CAD	BVI-Net	Accurate segmentation with low computational resources	Limited generalizability	Exploration of bio-vision-driven deep learning for real-world clinical application
[11] AI in Skin Lesion Classification	Transfer learning (ResNet50, MobileNetV2)	High accuracy (99% with ResNet50, 97.5% with MobileNetV2)	Complexity and computational needs	Application in low-resource environments with optimized computational frameworks
[12] Socioeconomic Inequalities	AI risk assessment models	Enhanced early detection and risk stratification	Risk of exacerbating existing health disparities	Development of equitable AI tools that reduce biases in cancer risk assessment
[13] Skin Lesion Segmentation	UL-Net with BVI-Net architecture	High segmentation accuracy using minimal computational resources	Irregular shapes and size disparity between target and background	Enhanced bio-inspired AI designs for segmentation tasks

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

[14] Deep Learning for Skin Cancer Diagnosis	A systematic review of DL algorithms	High sensitivity and specificity for Melanoma and non-melanoma cancer	Small study populations, lack of real-world trials	Expanding trials to include diverse populations and real-world settings
[15] AI in Microbiota Analysis	Machine learning, NGS	Improved cancer classification through microbiota analysis	Limited integration with other -omics approaches	Expanding microbiota-based diagnostics for personalized medicine
[16] Non-invasive Imaging and AI	Near-infrared spectroscopy	Enhanced skin cancer diagnostics at molecular levels	Lack of publicly available datasets for spectroscopy applications	Increasing dataset availability and combining imaging with AI
[17] Transfer Learning in Dermatology	ResNet50, InceptionV3, VGG16, VGG19, MobileNetV2	ResNet50 achieved the highest accuracy (99%), and MobileNetV2 is ideal for low-resource environments	Lack of interpretability in deep learning	Broadening the use of XAI tools to increase trust and transparency
[18] Prostate Cancer Lesion Detection	mp-MRI, ultrasound, self-supervised learning (SSL)	Improved lesion identification and localization for prostate cancer	Limited labeled datasets	Increased use of SSL to leverage large unlabeled datasets
[19] AI in Early Skin Cancer Detection	Explainable AI (XAI), multimodal deep learning	High diagnostic precision with clinician-aligned diagnostic tools	Model integration into clinical workflows	Development of clinician-friendly diagnostic systems
[20] Global Application of AI in Dermatology	Review of AI for skin cancer	Improved diagnostic precision and accessibility in underserved regions	Challenges in data privacy, diversity, and integration	Creation of more equitable and secure AI applications
[21] AI in Prostate Cancer Management	mp-MRI, ultrasound, SSL-based predictive architectures	Enhanced detection and localization of prostate cancer lesions	False positives due to limited specificity	Development of integrated SWE and mpMRI-based models
[22] Use of AI in Imaging Systems	Computer-aided diagnostics (CAD)	AI-driven CAD systems improve lesion identification and diagnosis	High computational demands and opaque decision-making	Exploration of lightweight AI models and integration of XAI for transparency

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

[23] Integration of AI and Genetic Algorithms	CNNs (MobileNet, Exception, Inception) optimized by PSO and BA	Increased diagnostic speed and precision for melanoma and non-melanoma classification	Dependence on large datasets for model accuracy	Application of genetic optimization in resource-constrained environments
[24] Socioeconomic Gaps in Screening	AI risk assessment tools	Improved detection rates and risk stratification	Risk of deepening health disparities	Policy development to ensure equitable AI implementation
[25] Emerging Techniques in MASLD Diagnosis	AI, OMIC biomarkers	Enhanced precision in MASLD diagnosis through non-invasive imaging and AI-driven analysis	Limited integration of AI with behavioral and pharmacological therapies	Expansion of interdisciplinary methods for MASLD management

In conclusion, due to new trends, we can conclude that the application of AI in skin cancer diagnosis has developed with purchased diagnostic capacities and effectiveness. The durability of using XAI in improving the clinical application of AI models is that dermatologists can explain and believe these models. However, issues still need to be dealt with to make such models clinically practical; these are Data privacy Model generalization and how to integrate the models into clinical workflows. Future work should concentrate on enhancing the methodologies of explain ability and providing proper, various datasets to increase the utilization of AI for populations. Further development of interdisciplinary cooperation and the creation of new synergy approaches are necessary for the consequent development of AI and XAI in dermatological practice.

3. Discussion

AI, particularly in dermatology, focusing on skin cancer, is a perfect example of the paradigm shift in health care. This section presents the data analysis in the literature review section concerning the various opportunities that remain to be exploited.

3.1 Significant Achievements

It has also been seen that with the help of AI technology like machine learning and deep learning, their diagnostic ability is as good as, or even better than, that of a dermatologist. Notable advancements include:

- Improved Diagnostic Accuracy: Machines can accurately detect skin cancer, hence improving the chances of ruling out the disease at an early stage. For instance, Deep learning models such as Transfer learning models, including ResNet50, delivered an impressive accuracy of one hundred % for this study and can, therefore, be used in clinical practice [26].
- Accessibility and Equity: The advancement of the AI concept has extended diagnostic tools to regions deprived of such services.
- Explain ability and Trust: This was made possible by advanced XAI techniques such as LIME and SHAPLEY, which have helped clients understand the decision-making processes [27].

3.2 Key Challenges

Despite these advancements, several limitations persist:

- Data Diversity and Bias: Although it is an improvement, most datasets are still relatively homogeneous regarding skin tones and geographic origin to impede generalization [28].

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

- Integration into Clinical Workflows: The fact is that some of the AI models are black box systems, and their complexity becomes the factor preventing their application in actual practice [29].
- Resource Limitations: The reception of the computational requests of the current models limits them from being implemented in environments that could be better-endowed [30].

3.3 Emerging Trends

The Review identified several promising trends that are shaping the future of AI in dermatology:

- Multimodal AI Approaches: The use of structural imaging, molecular, and clinical data is improving diagnostics and prognostics of diseases [31].
- Lightweight Neural Networks: These developments, such as BVI-Net and UL-Net, mean that AI tools can be practically viable in low-resource areas for they are accurate and computationally efficient [32].
- Self-Supervised Learning (SSL): SSL methodologies solve the problem of the absence of labeled data for large datasets and enable large-scale software testing [33].

3.4 Future Directions

The full potential of AI in dermatology can only be realized through interdisciplinary collaboration and strategic advancements:

- Data and Model Inclusivity: The necessity of forming a heterogeneous dataset and avalanche model is the key to reachable and fair solutions in healthcare.
- Explainable AI: Clinicians' trust and ability to incorporate AI into the clinical environment require improving the interpretability of these models.
- Global Accessibility: Resources should be allocated to promoting stronger, slimmer AI solutions to bring healthcare to hard-to-reach areas.
- Interdisciplinary Research: It has been demonstrated how coupling artificial intelligence with related disciplines, such as genomics and bioinformatics, creates new possibilities for precision medicine and innovative diagnostics.

AI is confirmed as a game-changer in Dermatology, with high accuracy, access and efficiency in skin cancer diagnosis. However, that is still far from becoming possible if one fails to discern the current problems and opportunities that must be addressed to achieve the full potential. Discipline-specific cooperation and appropriate and ethical approaches to implementation will make the foundation for future AI integration into healthcare facilities worldwide.

4. Conclusion

The application of artificial intelligence, particularly skin cancer in dermatology, is a big leap towards technological innovations in medicine. Deep and machine learning techniques of AI have shown incredible efficiency in detecting skin cancer with accuracy rates of, or even higher than, humans, including dermatologists. These technologies have been beneficial in offsetting problems such as inter-observer variability and a shortage of diagnostic equipment in areas where care delivery is scarce. From the use of artificial intelligence in diagnosis, there is improvement in the detection frequency, especially with skin malignant diseases; therefore, mortality rates are lower.

Despite these accomplishments, several setbacks further hinder the realization of AI in dermatology. The issue of a limited representation of the necessary data, particularly skin images with low tones, is a disadvantage of training AI models. Furthermore, implementing some of the AI algorithms is challenging mainly because the algorithms are black boxes that encompass values that clinicians cannot understand, which enables them to trust the algorithm they are using. The requirements of computational resources and the dependence on large amounts of labeled data make AI implementation challenging in low-resource environments; therefore, new simple and interpretative AI models that would meet clinical demands should be developed.

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

Interdisciplinary collaboration and innovation would push future advances in AI for dermatology through these barriers. Fully representative datasets that show various skin tones and demographics are needed to develop fair AI tools. In addition, adopting methodologies like Explainable AI (XAI) will help enlighten clinicians and facilitate integration into medical practice. Lightweight neural networks and self-supervised learning (SSL) approaches would be most beneficial for their limitations in computation and the data available, such that AI-based diagnostics can be made available even in low-resource environments.

Because of these changes, in the future, AI should not only be a diagnostic tool in dermatology; it should expand its role into treatment planning, personalized medicine, and continuous patient monitoring. Multimodal AI systems for clinical patient care, incorporating imaging, genomics, and clinical data, hold enormous potential. However, many major ethical and regulatory questions of data privacy, bias, and equitable implementation must be answered before such systems can be widely available. Through strategic advances and collaborative efforts, AI holds the potential promise of revolutionizing dermatology into a high quality and accessible healthcare solution for patients worldwide.

Reference

[1] A. Takiddin, J. Schneider, Y. Yang, A. Abd-Alrazaq, and M. Househ, "Artificial Intelligence for Skin Cancer Detection: Scoping Review," J Med Internet Res, vol. 23, no. 11, p. e22934, Nov. 2021, doi: 10.2196/22934.

[2] D. N. Dorrell and L. C. Strowd, "Skin Cancer Detection Technology," Dermatol Clin, vol. 37, no. 4, pp. 527–536, Oct. 2019, doi: 10.1016/j.det.2019.05.010.

[3] F. Mahmood, S. Bendayan, F. M. Ghazawi, and I. V. Litvinov, "Editorial: The Emerging Role of Artificial Intelligence in Dermatology," Front Med (Lausanne), vol. 8, Nov. 2021, doi: 10.3389/FMED.2021.751649.

[4] A. Elder, C. Ring, K. Heitmiller, Z. Gabriel, and N. Saedi, "The role of artificial intelligence in cosmetic dermatology—Current, upcoming, and future trends," J Cosmet Dermatol, vol. 20, no. 1, pp. 48–52, Jan. 2021, doi: 10.1111/JOCD.13797.

[5] V. D. Midasala, B. Prabhakar, J. Krishna Chaitanya, K. Sirnivas, D. Eshwar, and P. M. Kumar, "MFEUsLNet: Skin cancer detection and classification using integrated AI with multilevel feature extraction-based unsupervised learning," Engineering Science and Technology, an International Journal, vol. 51, p. 101632, Mar. 2024, doi: 10.1016/J.JESTCH.2024.101632.

[6] M. A. Hemmati et al., "Using New Technologies to Analyze Gut Microbiota and Predict Cancer Risk," Cells 2024, Vol. 13, Page 1987, vol. 13, no. 23, p. 1987, Dec. 2024, doi: 10.3390/CELLS13231987.

[7] B. İ. Mendi et al., "Artificial Intelligence in the Non-Invasive Detection of Melanoma," Life 2024, Vol. 14, Page 1602, vol. 14, no. 12, p. 1602, Dec. 2024, doi: 10.3390/LIFE14121602.

[8] G. Munjal, P. Bhardwaj, V. Bhargava, S. Singh, and N. Nimish, "SkinSage XAI: An explainable deep learning solution for skin lesion diagnosis," Health Care Science, 2024, doi: 10.1002/HCS2.121.

[9] G. Kumari and V. K. Joshi, "Artificial Intelligence in Skin Cancer Detection: Recent Advances and Future Directions," National Academy Science Letters, pp. 1–5, Nov. 2024, doi: 10.1007/S40009-024-01545-7/METRICS.

[10] P. H. P. da Cunha et al., "NIR-SC-UFES: A portable NIR spectral dataset to skin cancer in vivo," medRxiv, p. 2024.11.27.24317165, Nov. 2024, doi 10.1101/2024.11.27.24317165.

[11] L. K. Behera and S. Narayan Tripathy, "E-healthcare system for skin care : A sustainable approach from deep learning to explainability in artificial intelligence," Sustainable Materials, Structures and IoT, pp. 215–219, Nov. 2024, doi: 10.1201/9781003596776-44.

[12] P. Avci et al., "Detection of basal cell carcinoma by machine learning-assisted ex vivo confocal laser scanning microscopy," Int J Dermatol, Dec. 2024, doi: 10.1111/IJD.17519.

[13] M. R. Mundada et al., "Skin Cancer Prediction by Incorporating Bio-inspired Optimization in Deep Neural Network," SN Computer Science 2024 5:8, vol. 5, no. 8, pp. 1–20, Dec. 2024, doi: 10.1007/S42979-024-03501-0.

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

[14] L. Tzelves, P. Juliebø-Jones, and B. K. Somani, "' ' The Evolution of Minimally Invasive Urologic Surgery: Innovations, Challenges, and Opportunities''," Front Surg, vol. 11, p. 1525713, doi: 10.3389/FSURG.2024.1525713.
[15] Z. Cai, Y. Fan, M. Zhu, and T. Fang, "Ultra-Lightweight Network for Medical Image Segmentation Inspired by Bio-Visual Interaction," IEEE Transactions on Circuits and Systems for Video Technology, pp. 1–1, 2024, doi: 10.1109/TCSVT.2024.3507383.
[16] R. Barik et al., "Comparative Analysis for Detecting Cancer in Various Organs using Cellular Automata based Segmentation Technique," Advancing Healthcare through Data-driven Innovations, pp. 80–103, Nov. 2024, doi: 10.1201/9781003475392-6.
[17] S. Fazeli et al., "Access to Breast Cancer Screening: Disparities and Determinants—AJR Expert Panel Narrative Review," https://doi.org/10.2214/AJR.24.32151, Nov. 2024, doi: 10.2214/AJR.24.32151.
[18] B. Basil, B. K. Myke-Mbata, O. E. Eze, and A. U. Akubue, "From adiposity to steatosis: metabolic dysfunction-associated steatotic liver disease, a hepatic expression of metabolic syndrome – current insights and future directions," Clinical Diabetes and Endocrinology 2024 10:1, vol. 10, no. 1, pp. 1–19, Dec. 2024, doi: 10.1186/S40842-024-00187-4.
[19] M. Bauer, A. Gurwin, C. Augenstein, B. Franczyk, and B. Małkiewicz, "SWJEPA: Improving Prostate Cancer Lesion Detection with Shear Wave Elastography and Joint Embedding Predictive Architectures," pp. 359–375, 2025, doi: 10.1007/978-3-031-78398-2_24.
[20] Z. Cai, Y. Fan, M. Zhu, and T. Fang, "Ultra-Lightweight Network for Medical Image Segmentation Inspired by Bio-Visual Interaction," IEEE Transactions on Circuits and Systems for Video Technology, pp. 1–1, 2024, doi: 10.1109/TCSVT.2024.3507383.
[21] M. Bauer, A. Gurwin, C. Augenstein, B. Franczyk, and B. Małkiewicz, "SWJEPA: Improving Prostate Cancer Lesion Detection with Shear Wave Elastography and Joint Embedding Predictive Architectures," pp. 359–375, 2025, doi: 10.1007/978-3-031-78398-2_24.
[22] F. Grignaffini, E. De Santis, F. Frezza, and A. Rizzi, "An XAI Approach to Melanoma Diagnosis: Explaining the Output of Convolutional Neural Networks with Feature Injection," Information 2024, Vol. 15, Page 783, vol. 15, no. 12, p. 783, Dec. 2024, doi: 10.3390/INFO15120783.
[23] M. Z. Mahmud, M. S. Reza, S. R. Alve, S. Islam, and N. Fahmid, "Advance Transfer Learning Approach for Identification of Multiclass Skin Disease with LIME Explainable AI Technique," medRxiv, p. 2024.12.02.24318311, Dec. 2024, doi 10.1101/2024.12.02.24318311.
[24] K. Behara, E. Bhero, and J. T. Agee, "AI in dermatology: a comprehensive review into skin cancer detection," PeerJ Comput Sci, vol. 10, p. e2530, Dec. 2024, doi: 10.7717/PEERJ-CS.2530.
[25] I. M. Nasir, S. Tehsin, R. Damaševičius, and R. Maskeliūnas, "Integrating Explanations into CNNs by Adopting Spiking Attention Block for Skin Cancer Detection," Algorithms 2024, Vol. 17, Page 557, vol. 17, no. 12, p. 557, Dec. 2024, doi: 10.3390/A17120557.
[26] A. Al Kuwaiti et al., "A Review of the Role of Artificial Intelligence in Healthcare," J Pers Med, vol. 13, no. 6, p. 951, Jun. 2023, doi: 10.3390/JPM13060951.
[27] E. Bilgic et al., "Exploring the roles of artificial intelligence in surgical education: A scoping review," Am J Surg, vol. 224, no. 1, pp. 205–216, Jul. 2022, doi: 10.1016/J.AMJSURG.2021.11.023.
[28] M. Naqvi, S. Q. Gilani, T. Syed, O. Marques, and H. C. Kim, "Skin Cancer Detection Using Deep Learning—A Review," Diagnostics 2023, Vol. 13, Page 1911, vol. 13, no. 11, p. 1911, May 2023, doi 10.3390/DIAGNOSTICS13111911.
[29] H. Abdelhalim et al., "Artificial Intelligence, Healthcare, Clinical Genomics, and Pharmacogenomics Approaches in Precision Medicine," Front Genet, vol. 13, p. 929736, Jul. 2022, doi: 10.3389/FGENE.2022.929736.
[30] P. K. Mall et al., "A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities," Healthcare Analytics, vol. 4, p. 100216, Dec. 2023, doi: 10.1016/J.HEALTH.2023.100216.
[31] X. Zeng, N. Abdullah, and P. Sumari, "Self-supervised learning framework application for medical image analysis: a review and summary," BioMedical Engineering OnLine 2024 23:1, vol. 23, no. 1, pp. 1–36, Oct. 2024, doi: 10.1186/S12938-024-01299-9.

DOI: https://doi.org/10.54216/MOR.020103
Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024

[32] M. E. Hasan, M. J. Islam, M. R. Islam, D. Chen, C. Sanin, and G. Xu, "Applications of Artificial Intelligence for Health Informatics: A Systematic Review," Journal of Artificial Intelligence for Medical Sciences, vol. 4, no. 2, pp. 19–46, 2023, doi: 10.55578/JOAIMS.230920.001.

[33] T. Madaan et al., "Advances in Microbiome-Based Therapeutics for Dermatological Disorders: Current Insights and Future Directions," Exp Dermatol, vol. 33, no. 12, Dec. 2024, doi: 10.1111/EXD.70019.

DOI: https://doi.org/10.54216/MOR.020103

Received: April 25, 2024 Revised: July 24, 2024 Accepted: November, 14, 2024