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Review

Advanced Artificial Intelligence Techniques for Comprehensive Dermatological Image Analysis and Diagnosis

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Abstract: With the growing complexity of skin disorders and the challenges of traditional diagnostic methods, AI offers exciting new solutions that can enhance the accuracy and efficiency of dermatological assessments. Reflectance Confocal Microscopy (RCM) stands out as a non-invasive imaging technique that delivers detailed views of the skin at the cellular level, proving its immense value in dermatology. The manual analysis of RCM images, however, tends to be slow and inconsistent. By combining artificial intelligence (AI) with RCM, this approach introduces a transformative shift toward precise, data-driven dermatopathology, supporting more accurate patient stratification, tailored treatments, and enhanced dermatological care. Advancements in AI are set to revolutionize this process. This paper explores how AI, particularly Convolutional Neural Networks (CNNs), can enhance RCM image analysis, emphasizing machine learning (ML) and deep learning (DL) methods that improve diagnostic accuracy and efficiency. The discussion highlights AI's role in identifying and classifying skin conditions, offering benefits such as a greater consistency and a reduced strain on healthcare professionals. Furthermore, the paper explores AI integration into dermatological practices, addressing current challenges and future possibilities. The synergy between AI and RCM holds the potential to significantly advance skin disease diagnosis, ultimately leading to better therapeutic personalization and comprehensive dermatological care.

Keywords: AI; CNN; ML; DL; RCM; dermatology

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1. Introduction

Reflectance Confocal Microscopy (RCM) represents a significant advancement in medical imaging, providing a non-invasive method to capture highly detailed images of the skin and surrounding tissues [1]. It is essential to highlight that RCM can be used in both in vivo (in living organisms) and ex vivo (outside of living organisms) settings. This flexibility means that RCM can be applied in various clinical situations, giving it a broad range of applications. On the other hand, confocal fluorescence microscopy (CFM) is limited to ex vivo use, as it requires samples to be taken out of the body for imaging. Understanding these differences helps clarify what each technique can and cannot do in dermatological assessments. In vivo RCM has repeatedly exhibited its significance as a crucial imaging modality for dermatologists [2]. This technology allows doctors to visualize the skin's interior without any invasive procedures, almost like looking at a detailed map of the skin's structure, revealing both tissue layout and individual cells. RCM can show details as deep as 200–250 µm beneath the skin's surface [3–5]. While dermoscopy is currently widely used for screening skin cancer, RCM has proven to be much better at accurately diagnosing several types of skin tumors [6–9].

RCM has become an invaluable tool in modern medicine, allowing doctors to see live images of tissue without needing to resort to invasive procedures like biopsies. RCM technology started with a recognition of the need for better, less invasive ways to diagnose skin conditions. As time passed, RCM technology improved significantly. Better lasers, more sensitive detectors, and smarter image processing algorithms have all contributed to clearer and more detailed images. Essentially, RCM works by shining a focused laser onto the skin, and the way the tissue interacts with this light helps create detailed images. Special detectors then capture the reflected light, and clever computer programs turn these signals into highly detailed images of the tissue, showing even the tiniest cellular structures with incredible clarity and accuracy [1].

RCM is transforming dermatology by providing a non-invasive way to examine skin conditions. This means doctors can diagnose issues like melanoma and carcinoma more accurately. RCM is highly effective in identifying skin cancers, with over 70% accuracy. RCM's high-resolution imaging allows for a detailed look at the skin's cellular level, making it better than traditional methods like ultrasound and MRI. RCM also helps track treatment progress and manage chronic skin conditions, ultimately leading to better patient care and outcomes. Additionally, RCM helps map out the edges of tumors before surgery, improving the chances of complete removal and reducing recurrence rates. When combined with dermoscopy, RCM can also decrease the number of unnecessary biopsies [10–19].

Interpreting RCM images can be complicated because there are not many training programs for it, unlike other methods such as dermoscopy. This lack of training leads to differences in how practitioners interpret the images. On top of that, RCM images can be complex and have subtle details that need a keen eye and a lot of expertise to analyze accurately, making the interpretation process even more difficult. However, ML offers a promising solution. By using advanced algorithms, ML can analyze these images more objectively, helping to identify potential skin cancers without needing a doctor to interpret every detail. AI, especially CNNs, has further improved this process, making it easier to detect and diagnose skin conditions accurately. This study reviews new techniques to better analyze RCM images, aiming to make this technology even more reliable for dermatologists [20–23]. Various AI-based techniques are enhancing the analysis of RCM images. For instance, Wodzinski et al. developed a CNN approach to classify skin lesions using RCM mosaics, achieving an impressive 87% accuracy on a test set of 429 RCM mosaics [20]. Meanwhile, D'Alonzo et al. created a weakly supervised machine learning model for the semantic segmentation of pigmented lesions in RCM mosaics. Their deep learning model, trained on 157 RCM mosaics, achieved an average AUC of 0.969 and a Dice coefficient of 0.778 [24]. These studies demonstrate the significant potential of AI in improving the diagnostic accuracy and analysis of RCM images, making it a valuable tool in dermatology.

2. The Technical Foundations of Reflectance Confocal Microscopy

RCM works like a high-tech camera for biological tissues, especially in skin studies. RCM uses a special optical system to focus a laser light onto the tissue and then captures the reflected light. This process creates detailed 3D images of tissue structures without needing to cut or stain the tissue. RCM's super-clear images let us see individual cells and even smaller parts, all in real time. By enhancing contrast and using fancy computer tricks, RCM helps doctors spot abnormalities and track changes over time, improving both diagnosis and research in dermatology. In RCM, a special type of light source is employed—a low-power laser emitting near-infrared light, specifically an 830 nanometer diode with a power of less than 35 milliwatts. This laser emits a single-colored, coherent light beam that traverses a sequence of optical lenses and mirrors, similar to a camera's setup. Once directed towards the tissue, it scans a focused point within. Reflected light from the tissue subsequently passes through a small aperture, known as a gating pinhole, to reach the detector [25,26]. This pinhole selectively permits light from the focal area under examination, blocking any out-of-focus scattered light (Figure 1). RCM images are depicted in grayscale, where the brightness is contingent upon the relative refractive indices of tissue components. For instance, substances with higher refractive indices, like melanin—boasting an index of 1.7—exhibit brighter appearances compared to neighboring tissue elements.

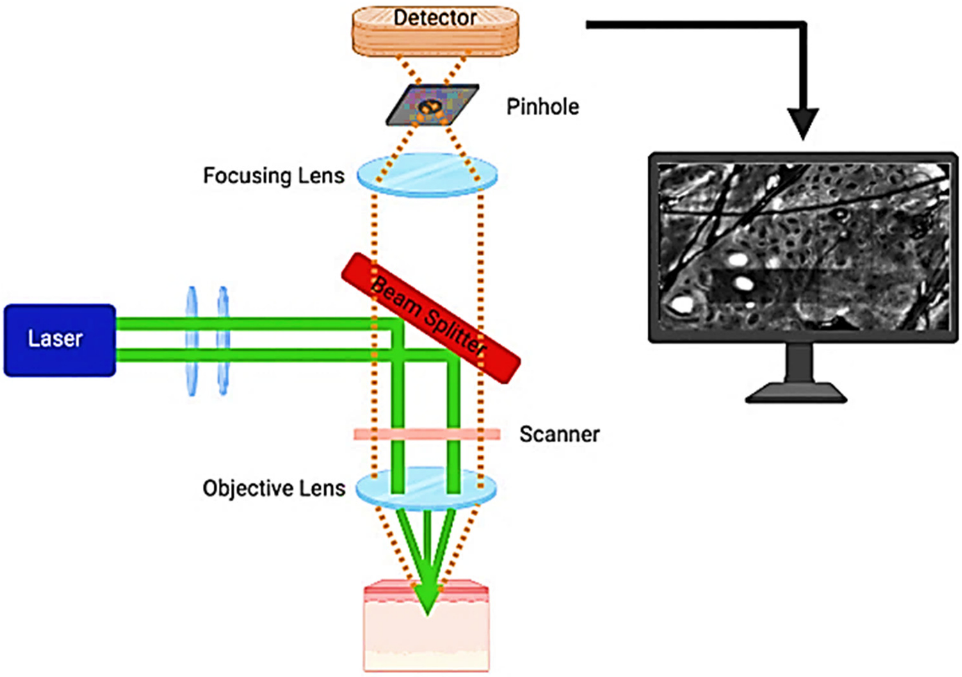

Figure 1. The principles of Reflectance Confocal Microscopy [27].

RCM imaging, while a valuable tool in dermatology, presents several limitations and artifacts. These include a limited depth penetration of a few hundred micrometers, resolution variability influenced by tissue type and imaging depth, susceptibility to motion artifacts from patient movement or breathing, and a restricted field of view necessitating multiple scans. Surface irregularities like hair or skin folds can interfere with imaging, while refractive index variations within tissue may cause optical distortion. Additionally, interpreting RCM images requires expertise, with challenges posed by artifacts such as noise or background signal. Furthermore, RCM systems can be costly and may not be universally accessible. Recognizing and addressing these limitations are vital for optimizing RCM imaging protocols and ensuring the accurate interpretation of results in both clinical and research settings [25–29].

RCM extends its applicability beyond dermatology, showing significant potential to transform disciplines such as ophthalmology, neurology, and oncology, where non-invasive imaging is imperative, envisioning the ability to observe the intricacies of the eye, brain, or tumors without resorting to invasive procedures. Through the integration of RCM with state-of-the-art technologies like augmented reality and 3D imaging, its utility can be broadened across diverse medical domains.

3. Tele-Reflectance Confocal Microscopy

Becoming proficient in RCM requires spending a significant amount of time in a clinical setting, examining numerous lesions. To make this learning process more accessible, the Skin Confocal Microscopy Website was launched in 2007. Initially, it aimed to assess the consistency of RCM descriptors by training specialists from six centers across three continents through an online tutorial. They then evaluated high-resolution images in a blinded manner. The results showed good agreement on most parameters, especially those crucial for diagnostic algorithms. As interest in RCM grew, the website expanded to offer free online tutorials and interactive training sections, catering to novices interested in learning RCM. This online platform has become instrumental in democratizing access to

RCM expertise, offering a valuable resource for clinicians and researchers alike to enhance their understanding and proficiency in this innovative imaging technique.

Tele-RCM facilitates remote diagnosis and consultation through two methods—storing and sending information or real-time video conferencing. Its primary aim in teledermatology is to promote the integration of microscopy into day-to-day clinical practice and research projects. With the growing interest in RCM, numerous online tutorials have emerged, offering comprehensive training modules containing dermatoscopic images, RCM mosaics, and patient clinical data. Through platforms like skinconfocalmicroscopy.net, e-learning becomes accessible. Additionally, in cases of ambiguity, tele-RCM allows for the consultation and sharing of confocal images for expert analysis. Tele-RCM comprises confocal tele-microscope consultations and educational programs, highlighting its dual role in clinical practice and training [30–33].

In the field of dermato-oncology, RCM has emerged as a revolutionary tool, demanding specialized expertise in lesion assessment and diagnosis. The advent of tele-RCM has raised concerns about image security and sharing. Enter VivaNet®—a sophisticated server system designed to safeguard medical images while facilitating continuous collaboration among healthcare professionals worldwide. Currently undergoing testing in Europe and the US, VivaNet® holds the promise of transforming medical imaging practices for the better [34].

In clinical settings, confocal images are taken according to a specific imaging protocol, including additional image stacks. Once acquired, the confocal imager activates a dedicated web link on the VivaScope display (Figure 2), enabling the transfer of both RCM and VivaCam dermoscopic images, along with pertinent patient data. Mandatory fields such as age and sex are filled out, with the option for additional information via free text or checkboxes. This data package is then transmitted to the selected confocal reviewer for evaluation. Utilizing a specialized two-screen viewing station tailored for RCM cases, the reviewer can swiftly assess thumbnail images on one screen while examining a magnified view on the other, allowing for efficient correlation between dermoscopic and architectural RCM features. Following assessment, the reviewer generates a report, digitally signs the evaluation, and forwards it to the VivaNet® server to be archived as a medical record, accessible for subsequent review by the confocal imager [33,35]. The streamlined workflow facilitated by VivaNet® ensures the efficient collaboration and comprehensive evaluation of confocal images, ultimately enhancing diagnostic accuracy and patient care in dermatology. The comprehensive data package, including high-quality confocal images and detailed patient information, provides a robust foundation for informed clinical decisions. The system improves the efficiency of dermatological evaluations, reduces the likelihood of diagnostic errors, and enhances patient care through better coordination and access to expert opinions.

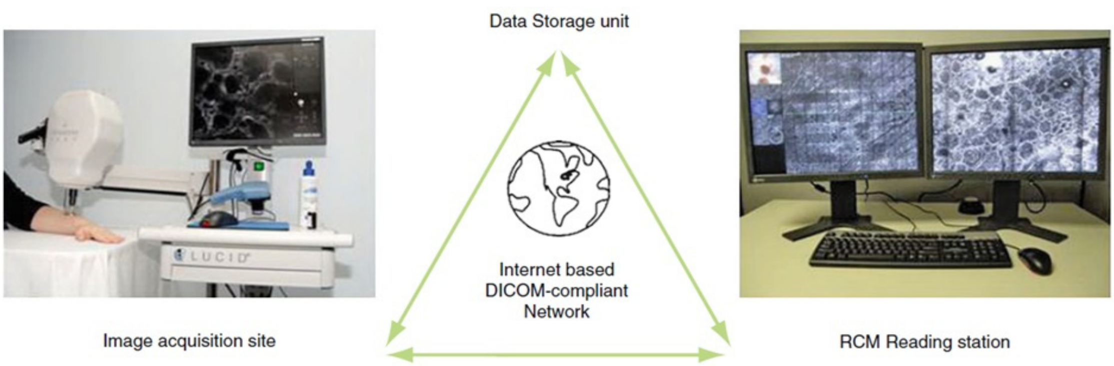

Figure 2. VivaNet® workflow: image acquisition site to remote reading rtation for RCM [36].

Confocal fluorescence microscopy (CFM) has recently provided a remedy for the limiting factors of traditional fluorescence microscopy. By targeting only the fluorochrome molecules in the specimen, CFM achieves this selectively, whereas the other method uses it to illuminate the whole specimen with white light [25]. As such, there is less noise in the background during focus since it increases sensitivity through excitation confinement. Furthermore, another border faced by traditional fluorescence microscopy is being defeated by the possibility of dispensing incomprehensive sample groundwork visualization when using CFM. The high quality of the fluorescent signals detected through an accurate laser excitation system enables the better visualization and precise measurement of cellular structures and processes in CFM. The differential refractive properties of subcellular structures provide image contrast for in vivo CFM (Figure 3) predominantly functioning in reflectance mode (RCM). Although, in contrast to fluorescence mode, there is no need for special staining; however, some contrast agents—for example, aluminum chloride, citric acid, or acetic acid—should be added to enhance the visibility of nuclei [37]. For in vivo skin evaluation, there are two types of RCM—a wide-probe confocal device with a single articulated arm, and a handheld device. Both models utilize an 830 nm diode laser. In living tissue, with near histological resolution, in vivo CFM allows for the visualization of the epidermis, the dermo–epidermal junction, and the first 200–250 µm depth of the upper dermis [37]. RCM relies on the natural refractive properties of cellular structures, eliminating the need for special staining and allowing for real-time, high-resolution imaging.

Figure 3. In vivo confocal laser scanning microscope (830 nm)—the wide-probe confocal device (VivaScope®1500; image courtesy—VivaScope GmbH, Munich, Germany) [37].

4. Artificial Intelligence in Dermatology

AI has become an integral part of our daily lives, offering solutions to tasks that typically require human intelligence, such as visual perception and decision-making [38]. Its evolution from classic methods to ML and deep learning (DL) has enabled breakthroughs across various fields [39]. In healthcare, AI has made significant strides, particularly in radiology and cardiology, with FDA-approved devices enhancing medical practice since 2016 [40].

In dermatology, AI shows promise in revolutionizing skin cancer diagnosis, using technologies like CNNs to analyze dermoscopic images [41–44]. Skin cancer, including melanoma and non-melanoma types, presents a significant health concern worldwide. Its early detection is crucial, as it significantly impacts patient outcomes, especially for melanoma. Dermoscopy, a non-invasive imaging technique, improves diagnostic accuracy for skin cancer [7,45]. However, challenges persist, including limited access to dermatologists and the underutilization of total body skin examinations [46,47].

AI offers a solution to these challenges by aiding in early skin cancer detection, potentially improving diagnostic accuracy and patient outcomes [48]. By analyzing dermoscopic images, AI algorithms can assist dermatologists in identifying suspicious lesions more effectively [41–44]. This technology has the potential to transform dermatological practice, empowering healthcare professionals to provide better care for patients. Table 1 reviews the applications of AI models in dermatology. By employing the capabilities of AI, dermatologists can enhance diagnostic accuracy and ultimately improve patient care and outcomes.

Table 1. Applications of AI models in dermatology.

Applications	AI Model	Function	Advantages	Refs.
RCM	Deep Learning Models	Automated detection and analysis of melanoma features.	Non-invasive, cellular-level imaging.	[49]
Skin Disease Identification	CNNs	Classifies various skin diseases based on RCM images.	Increases diagnostic accuracy; reduces subjectivity.	[2]
Basal Cell Carcinoma (BCC) Detection	CNNs	Automatically detects BCC in RCM images	Achieved high specificity; reduced number of biopsies needed.	[22]
Skin Cancer Analysis	CNNs	Analyzes images to detect skin cancer, including melanoma.	High sensitivity (95%) and specificity (82.5%) compared to dermatologists.	[41]
Ulcer Treatment	CNNs	Measures wound boundaries to assess ulcer impacts.	Accurate wound assessment for better treatment planning.	[50,51]
Eczema Diagnosis	Artificial Neural Networks (ANNs)	Multi-model, multi-level architecture for detecting eczema by analyzing patient data and classifying skin lesions.	Higher confidence in diagnosis and personalized treatment recommendations.	[52]
F65Melanoma Classification	ConvNeXt, ViT Base-16, and Swin V2 S	Classifies benign and malignant melanoma using dermoscopic images.	Achieved highest diagnostic accuracy among tested models.	[53]
Personalized Treatment Planning	Deep Neural Network Algorithm	Distinguishes between different skin diseases and suggests treatments.	Improved accuracy in diagnosis and treatment recommendations, including rare skin conditions.	[52]
General Dermatological Imaging	CNNs	Utilizes imaging to analyze various skin conditions like psoriasis and ulcers.	Enhanced diagnostic accuracy and efficiency.	[51,54]
Teledermatology	Various AI Models	Allows remote analysis of skin disorders through imaging.	Increased accessibility to dermatological care, especially for remote or underserved populations.	[55,56]
Appointment and Case Management	Various AI Models	Automates administrative tasks such as scheduling appointments, managing case files, and generating referral letters.	Reduces workload for healthcare professionals, increasing efficiency and patient throughput.	[55,56]
Patient–Physician Interaction	AI Programs (e.g., Hello Rache)	Analyzes and transcribes patient–physician interactions during appointments.	Saves time for healthcare professionals by automating documentation tasks.	[55]
Public Health and Education	Mobile Applications (e.g., Sunface)	Assesses user's skin to recommend skincare products and daily reminders for sunscreen application.	Improves public health through personalized skincare advice and preventative measures.	[57]

Table 1. *Cont.*

Applications	AI Model	Function	Advantages	Refs.
Research and Simulation	Various AI Models	Uses AI to simulate testing for research purposes.	More effective research with lower costs and higher efficiency.	[58]
General Dermatological Practice	Various AI Models	Enhances practice efficiency by reducing errors, personalizing care, and improving diagnostic turnaround times.	Better patient outcomes and streamlined care processes.	[58,59]

5. Dermoscopic Image Datasets

Dermoscopic image datasets play a critical role in training and evaluating machine learning models for dermatological diagnosis, with various evaluation metrics employed to assess the performance of these models. Evaluation metrics are crucial tools for measuring the performance of machine learning models. They provide an understanding into how well a model is performing and help in comparing different models or tuning parameters. Some common evaluation metrics are discussed below.

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total number of instances. It is calculated as the number of correct predictions divided by the total number of predictions.

$$\text{Accuracy} = \frac{\text{Number of Correct Prediction}}{\text{Total Number of Prediction}}$$

Precision: Precision measures the proportion of true positive predictions among all positive predictions. It is calculated as the number of true positives divided by the sum of true positives and false positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall (sensitivity): Recall measures the proportion of true positive predictions among all actual positive instances. It is calculated as the number of true positives divided by the sum of true positives and false negatives.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

F1-Score: The F1-Score is the harmonic mean of precision and recall. It provides a balance between precision and recall and is especially useful when the classes are imbalanced. It is calculated as follows:

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Specificity: Specificity measures the proportion of true negative predictions among all actual negative instances. It is calculated as the number of true negatives divided by the sum of true negatives and false positives.

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}$$

ROC Curve and AUC: Receiver Operating Characteristic (ROC) curves are used to evaluate the performance of binary classification models. They plot the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The Area Under the Curve (AUC) represents the performance of the model, with higher values indicating a better performance.

These evaluation metrics provide a comprehensive understanding of the performance of machine learning models and help in making informed decisions about model selection and optimization.

6. Publicly Available Dermoscopic Image Datasets

Dermoscopy is a vital, non-invasive tool that allows detailed imaging of skin structures below the surface, significantly improving the early detection of melanoma and other skin issues. As AI and ML are increasingly used in this field, publicly accessible image datasets have become essential. These datasets enable the training and fine-tuning of AI models, ensuring they work accurately across diverse skin types and lesion variations. They provide a standardized way to benchmark and validate models, making it easier for researchers to evaluate and compare different AI approaches. Open-access datasets also promote reproducibility, allowing scientists to validate findings and enhance research transparency. Additionally, by making high-quality data available to a broader audience, these datasets foster cross-disciplinary collaboration, supporting innovations in dermatology by welcoming diverse expertise into the field [60–65].

Dermoscopic image datasets are valuable collections of images capturing various skin conditions, obtained using an imaging technique called dermoscopy. These datasets are carefully curated and shared with researchers, doctors, and developers to advance the understanding and diagnosis of skin issues. They include diverse examples, ranging from melanoma to nevi and other skin cancers, providing a rich source of information for study and analysis. These datasets play a crucial role in the development of improved tools and methods for identifying and treating skin problems. They serve as guiding lights for researchers, offering standardized and labeled image data to test and compare different approaches, ultimately ensuring the accurate and effective diagnosis and treatment of skin conditions.

In dermatology, researchers and doctors rely on a range of datasets to train and test AI systems for tasks like diagnosing skin diseases and classifying lesions. A key resource is the ISIC (International Skin Imaging Collaboration) Dataset, which contains a diverse collection of clinical images showcasing skin issues like melanoma and nevi. Another essential dataset is the HAM10000 (Human Against Machine with 10,000 training images), packed with top-notch images of various skin problems to help fine-tune AI models for classification tasks. Additionally, datasets like the PH2 Dataset provide labeled dermoscopic images to gauge algorithm performance, while the Dermofit Dataset contains a variety of clinical and dermoscopic images of common skin conditions. Together, these datasets (Table 2) serve as the bedrock for progressing AI-driven innovation in dermatology, leading to better patient care and outcomes.

Table 2. Publicly available dermoscopic image datasets.

Dataset Name	# of Images	Lesion Types
ISIC (International Skin Imaging Collaboration) Dataset	25,000+	Melanoma, nevi, and basal cell carcinoma
HAM10000 (The Human against Machine with 10,000)	10,015	Melanoma and nevi
PH2 Dataset	200	Melanoma, nevi, and seborrheic keratosis
DermQuest Dataset	1500	Melanoma and basal cell carcinoma

A comprehensive array of datasets, including those from the International Skin Imaging Collaboration (ISIC) spanning from 2016 to 2020, serve as valuable resources for analyzing dermoscopic images in the detection of melanoma [30–32,66]. The ISIC Dataset gradually expands in size each year, with the 2020 collection containing a substantial number of 44,108 images, while the 2016 dataset holds 1279 images. Alongside the ISIC Dataset, the PH2 Dataset from the Pedro Hispano Clinic in Portugal adds 200 images

(40 melanoma and 160 of non-melanoma images) annotated for melanoma analysis [33,67]. The MEDNODE Dataset from the University Medical Center in Groningen offers 170 images, focusing on melanoma and nevi [68]. The DermIS Dataset, the largest online resource for skin cancer diagnosis, features 146 melanoma images [69]. DermQuest adds to this with 22,000 clinical images reviewed by an international editorial board [70]. The HAM10000 Dataset [71] contains 10,015 images for training and validating AI models, and the Dermofit Image Library includes 1,300 high-quality images of ten different types of skin lesions [72]. These datasets collectively empower dermatology researchers and practitioners with carefully curated resources to develop and refine algorithms aimed at improving the accuracy and efficiency of melanoma diagnosis using dermoscopic imaging techniques.

Table 3 highlights significant GitHub repositories that contribute to the field of dermatology. The dermatologist-ai project uses machine learning to classify skin lesions, enhancing diagnostic accuracy and assisting healthcare providers in making informed decisions. derm7pt offers resources for the Derm7PT assessment checklist, while MedAGI integrates AI with dermatology, providing datasets and algorithms. The dermatology repository collects essential datasets for skin disease research. DeepSkin focuses on deep learning techniques for skin lesion classification, and SkinGPT-4 uses GPT-4 to assist in analyzing and diagnosing skin conditions. Together, these repositories are valuable tools for researchers and healthcare professionals in the field of dermatology.

Table 3. Publicly available dermatological GitHub repositories.

Repository Name	Description	Access/Link
dermatologist-ai	A machine learning project focused on building an AI model to classify skin lesions.	dermatologist-ai [73]
derm7pt	Tools and resources for the Derm7PT assessment—a checklist for evaluating skin lesions.	derm7pt [74]
MedAGI	Integrating AI with medical applications, particularly in dermatology, including datasets and algorithms.	MedAGI [75]
dermatology	A collection of datasets related to dermatology for the research and analysis of skin diseases.	dermatology [76]
DeepSkin	Deep learning models and techniques for skin lesion classification.	Deepskin [77]
SkinGPT-4	AI model tailored for dermatology using GPT-4 for skin condition analysis and diagnosis.	SkinGPT-4 [78]

The motivation for this study stems from several critical factors in the field of dermatology. With the rising prevalence of skin disorders, including melanoma and other skin cancers, there is an urgent need for effective diagnostic tools and methods to improve patient outcomes. Traditional methods of skin lesion classification can exhibit significant variability in diagnostic accuracy. This inconsistency can lead to misdiagnoses and delayed treatments, which can have serious consequences for patient health. The rapid advancement of machine learning and artificial intelligence presents a unique opportunity to enhance the analysis of dermatoscopic images. By utilizing these technologies, there is potential to develop more reliable and efficient diagnostic tools. The availability of large datasets in dermatology allows for the development of models that can improve the understanding and classification of skin lesions. However, many existing datasets are underutilized or have limitations that hinder their effectiveness. There is a growing recognition of the need to integrate AI-driven solutions into clinical workflows to enhance decision-making processes for healthcare providers. This integration can lead to improved diagnostic efficiency and better resource allocation in healthcare settings.

7. Conclusions

AI is making significant progress in dermatology by assisting dermatologists in various ways. For instance, it can automatically classify skin lesions from RCM images, allowing for quicker and more accurate distinctions between benign and malignant lesions, which speeds up the diagnosis process. Additionally, RCM images can sometimes be noisy or unclear, but AI techniques help enhance these images, making it easier for doctors to spot essential details and structures in the skin.

Identifying the dermal–epidermal junction (DEJ) is crucial for accurate assessments, and AI can automate this task, benefiting both experienced professionals and those still learning the ropes [2]. Furthermore, AI tools can pinpoint important features within RCM images, like different skin layers and specific patterns that might signal various skin conditions, helping doctors concentrate on what matters most.

Some AI models even analyze past RCM data to predict whether certain skin conditions might develop in patients, supporting dermatologists in making informed treatment decisions [1]. When real RCM images are scarce, AI can create synthetic images for training other models, ensuring they perform well, despite limited data. Imagine having an AI assistant in the clinic that analyzes RCM images in real time and provides recommendations—this is becoming a reality as AI applications are integrated into decision support systems, enhancing patient evaluations.

The increased diagnostic capabilities provided by integrating artificial intelligence (AI) in teledermatology alongside RCM have contributed towards improved accuracy and efficiency in skin condition assessment. In this paper, we discuss the transformation of remote dermatological diagnostics, which has been as a result of teledermatology evolution, with an emphasis on the role played by AI and RCM technologies. RCM images can be analyzed and interpreted with high precision using AI, with the help of machine learning algorithms and neural networks, hence helping to detect skin cancers at their early stages, as well as many other dermatological conditions. This is because the design of AI-powered tools like CNNs has resulted in automatic skin lesion classification based on RCM images, thereby enhancing diagnosis and simplifying medical practice.

Clinical imaging hits a major point with reflectance confocal systems by giving fine resolution with important details like an optical biopsy for a variety of dermatological conditions. This was made possible through the teamwork of clinical researchers and scientists who found ways of connecting laboratory microscopes with everyday clinical activities [36]. By working together, clinicians and researchers will continue to improve both the usage and effectiveness of these devices. The next generation of confocal imaging systems will most probably be user friendly, offer different modalities based on particular tissue states that help in diagnosis specificity, and, at the same time, be used as a regular part of dermatological examination processes to enhance efficiency and patient care.

In conclusion, AI integration in teledermatology has transformed dermatology diagnosis. AI advancements have greatly improved diagnostic accuracy and efficiency in remote dermatology assessments through better machine learning algorithms and neural networks. Despite the progress made, some challenges persist. These challenges include the requirement for a wide variety of good-quality datasets, standardizing artificial intelligence applications, and retaining patient confidence. AI-driven tools alongside RCM have made it possible to automate skin lesion identification, facilitating the early and accurate diagnoses of a variety of dermatological conditions. Despite these advancements, challenges persist, including the necessity for diverse and high-quality datasets, the standardization of AI applications, and the crucial task of maintaining patient trust.

Advancements in AI-driven techniques for analyzing RCM images offer exciting prospects for dermatology. Continued collaboration between AI developers, dermatologists, and researchers will be essential for refining and expanding the capabilities of these tools.

Future efforts should prioritize enhancing the accuracy and efficiency of AI algorithms for tasks like lesion classification and pattern recognition, as well as aiding in diagnostic decisions. By integrating AI-driven RCM analysis into clinical workflows, dermatologists can simplify diagnoses, improve treatment planning, and, ultimately, enhance patient outcomes. Additionally, ongoing research should delve into how AI can predict disease progression, treatment responses, and tailor personalized patient management strategies. With continuous innovation and collaboration, AI-driven RCM analysis has the potential to transform dermatological diagnosis and patient care for the better in the coming years.

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References

1. Yoon, H.-J.; Keum, C.; Witkowski, A.; Ludzik, J.; Petrie, T.; Hanson, H.A.; Leachman, S.A. Enhancing Diagnosis through AI-Driven Analysis of Reflectance Confocal Microscopy. *arXiv* **2024**, arXiv:2404.16080.
2. Malciu, A.M.; Lupu, M.; Voiculescu, V.M. Artificial Intelligence-Based Approaches to Reflectance Confocal Microscopy Image Analysis in Dermatology. *J. Clin. Med.* **2022**, *11*, 429. [CrossRef] [PubMed]
3. Koller, S.; Wiltgen, M.; Ahlgrimm-Siess, V.; Weger, W.; Hofmann-Wellenhof, R.; Richtig, E.; Smolle, J.; Gerger, A. In Vivo Reflectance Confocal Microscopy: Automated Diagnostic Image Analysis of Melanocytic Skin Tumours. *J. Eur. Acad. Dermatol. Venereol.* **2011**, *25*, 554–558. [CrossRef] [PubMed]
4. Rajadhyaksha, M.; González, S.; Zavislan, J.M.; Rox Anderson, R.; Webb, R.H. In Vivo Confocal Scanning Laser Microscopy of Human Skin II: Advances in Instrumentation and Comparison With Histology11The Authors Have Declared Conflict of Interest. *J. Investig. Dermatol.* **1999**, *113*, 293–303. [CrossRef] [PubMed]
5. Robic, J.; Nkengne, A.; Perret, B.; Couprie, M.; Talbot, H.; Pellacani, G.; Vie, K. Clinical Validation of a Computer-based Approach for the Quantification of the Skin Ageing Process of Women Using in Vivo Confocal Microscopy. *J. Eur. Acad. Dermatol. Venereol.* **2021**, *35*, e68–e70. [CrossRef]
6. Gerger, A.; Wiltgen, M.; Langsenlehner, U.; Richtig, E.; Horn, M.; Weger, W.; Ahlgrimm-Siess, V.; Hofmann-Wellenhof, R.; Samonigg, H.; Smolle, J. Diagnostic Image Analysis of Malignant Melanoma in in Vivo Confocal Laser-scanning Microscopy: A Preliminary Study. *Ski. Res. Technol.* **2008**, *14*, 359–363. [CrossRef]
7. Kittler, H.; Pehamberger, H.; Wolff, K.; Binder, M. Diagnostic Accuracy of Dermoscopy. *Lancet Oncol.* **2002**, *3*, 159–165. [CrossRef]
8. Gerger, A.; Koller, S.; Weger, W.; Richtig, E.; Kerl, H.; Samonigg, H.; Krippl, P.; Smolle, J. Sensitivity and Specificity of Confocal Laser-scanning Microscopy for in Vivo Diagnosis of Malignant Skin Tumors. *Cancer* **2006**, *107*, 193–200. [CrossRef]
9. Pellacani, G.; Cesinaro, A.M.; Seidenari, S. Reflectance-Mode Confocal Microscopy of Pigmented Skin Lesions–Improvement in Melanoma Diagnostic Specificity. *J. Am. Acad. Dermatol.* **2005**, *53*, 979–985. [CrossRef]
10. Mehrabi, J.N.; Baugh, E.G.; Fast, A.; Lentsch, G.; Balu, M.; Lee, B.A.; Kelly, K.M. A Clinical Perspective on the Automated Analysis of Reflectance Confocal Microscopy in Dermatology. *Lasers Surg. Med.* **2021**, *53*, 1011–1019. [CrossRef]
11. Nori, S.; Rius-Díaz, F.; Cuevas, J.; Goldgeier, M.; Jaen, P.; Torres, A.; González, S. Sensitivity and Specificity of Reflectance-Mode Confocal Microscopy for in Vivo Diagnosis of Basal Cell Carcinoma: A Multicenter Study. *J. Am. Acad. Dermatol.* **2004**, *51*, 923–930. [CrossRef] [PubMed]
12. Pellacani, G.; Guitera, P.; Longo, C.; Avramidis, M.; Seidenari, S.; Menzies, S. The Impact of In Vivo Reflectance Confocal Microscopy for the Diagnostic Accuracy of Melanoma and Equivocal Melanocytic Lesions. *J. Investig. Dermatol.* **2007**, *127*, 2759–2765. [CrossRef] [PubMed]
13. Lupu, M.; Popa, I.; Voiculescu, V.; Boda, D.; Caruntu, C.; Zurac, S.; Giurcaneanu, C. A Retrospective Study of the Diagnostic Accuracy of In Vivo Reflectance Confocal Microscopy for Basal Cell Carcinoma Diagnosis and Subtyping. *J. Clin. Med.* **2019**, *8*, 449. [CrossRef] [PubMed]
14. Lupu, M.; Caruntu, A.; Boda, D.; Caruntu, C. In Vivo Reflectance Confocal Microscopy-Diagnostic Criteria for Actinic Cheilitis and Squamous Cell Carcinoma of the Lip. *J. Clin. Med.* **2020**, *9*, 1987. [CrossRef] [PubMed]

15. Lupu, M.; Popa, I.M.; Voiculescu, V.M.; Caruntu, A.; Caruntu, C. A Systematic Review and Meta-Analysis of the Accuracy of in VivoReflectance Confocal Microscopy for the Diagnosis of Primary Basal Cell Carcinoma. *J. Clin. Med.* **2019**, *8*, 1462. [CrossRef]
16. Lupu, M.; Tebeica, T.; Voiculescu, V.M.; Ardigo, M. Tubular Apocrine Adenoma: Dermoscopic and in Vivo Reflectance Confocal Microscopic Aspects. *Int. J. Dermatol.* **2019**, *58*, e210–e211. [CrossRef]
17. Lupu, M.; Caruntu, A.; Caruntu, C.; Boda, D.; Moraru, L.; Voiculescu, V.; Bastian, A. Non-Invasive Imaging of Actinic Cheilitis and Squamous Cell Carcinoma of the Lip. *Mol. Clin. Oncol.* **2018**, *8*, 640–646. [CrossRef]
18. Lupu, M.; Voiculescu, V.M.; Vajaitu, C.; Orzan, O.A. In Vivo Reflectance Confocal Microscopy for the Diagnosis of Scabies. *BMJ Case Rep.* **2021**, *14*, e240507. [CrossRef]
19. Lupu, M.; Voiculescu, V.M.; Caruntu, A.; Tebeica, T.; Caruntu, C. Preoperative Evaluation through Dermoscopy and Reflectance Confocal Microscopy of the Lateral Excision Margins for Primary Basal Cell Carcinoma. *Diagnostics* **2021**, *11*, 120. [CrossRef]
20. Wodzinski, M.; Skalski, A.; Witkowski, A.; Pellacani, G.; Ludzik, J. Convolutional Neural Network Approach to Classify Skin Lesions Using Reflectance Confocal Microscopy. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; pp. 4754–4757.
21. Sikorska, M.; Skalski, A.; Wodzinski, M.; Witkowski, A.; Pellacani, G.; Ludzik, J. Learning-Based Local Quality Assessment of Reflectance Confocal Microscopy Images for Dermatology Applications. *Biocybern. Biomed. Eng.* **2021**, *41*, 880–890. [CrossRef]
22. Campanella, G.; Navarrete-Dechent, C.; Liopyris, K.; Monnier, J.; Aleissa, S.; Minhas, B.; Scope, A.; Longo, C.; Guitera, P.; Pellacani, G.; et al. Deep Learning for Basal Cell Carcinoma Detection for Reflectance Confocal Microscopy. *J. Investig. Dermatol.* **2022**, *142*, 97–103. [CrossRef] [PubMed]
23. Patel, R.H.; Foltz, E.A.; Witkowski, A.; Ludzik, J. Analysis of Artificial Intelligence-Based Approaches Applied to Non-Invasive Imaging for Early Detection of Melanoma: A Systematic Review. *Cancers* **2023**, *15*, 4694. [CrossRef] [PubMed]
24. D'Alonzo, M.; Bozkurt, A.; Alessi-Fox, C.; Gill, M.; Brooks, D.H.; Rajadhyaksha, M.; Kose, K.; Dy, J.G. Semantic Segmentation of Reflectance Confocal Microscopy Mosaics of Pigmented Lesions Using Weak Labels. *Sci. Rep.* **2021**, *11*, 3679. [CrossRef] [PubMed]
25. *ISO 21073:2019*; Microscopes—Confocal Microscopes—Optical Data of Fluorescence Confocal Microscopes for Biological Imaging. International Organization for Standardization (ISO): Geneva, Switzerland, 2019. Available online: https://www.iso.org/standard/69820.html (accessed on 31 August 2024).
26. *ISO 25178-607:2019*; Geometrical Product Specifications (GPS)—Surface Texture: Areal Part 607: Nominal Characteristics of Non-Contact (Confocal Microscopy) Instruments. International Organization for Standardization (ISO): Geneva, Switzerland, 2019. Available online: https://www.iso.org/standard/67652.html (accessed on 31 August 2024).
27. Shahriari, N.; Grant-Kels, J.M.; Rabinovitz, H.; Oliviero, M.; Scope, A. Reflectance Confocal Microscopy. *J. Am. Acad. Dermatol.* **2021**, *84*, 1421–1430. [CrossRef] [PubMed]
28. Gill, M.; Alessi-Fox, C.; Kose, K. Artifacts and Landmarks: Pearls and Pitfalls for in Vivo Reflectance Confocal Microscopy of the Skin Using the Tissue-Coupled Device. *Dermatol. Online J.* **2019**, *25*, 1. [CrossRef]
29. Longo, C.; Farnetani, F.; Ciardo, S.; Cesinaro, A.M.; Moscarella, E.; Ponti, G.; Zalaudek, I.; Argenziano, G.; Pellacani, G. Is Confocal Microscopy a Valuable Tool in Diagnosing Nodular Lesions? A Study of 140 Cases. *Br. J. Derm.* **2013**, *169*, 58–67. [CrossRef]
30. Que, S.K.T. Research Techniques Made Simple: Noninvasive Imaging Technologies for the Delineation of Basal Cell Carcinomas. *J. Investig. Dermatol.* **2016**, *136*, e33–e38. [CrossRef]
31. Alawi, S.A.; Kuck, M.; Wahrlich, C.; Batz, S.; McKenzie, G.; Fluhr, J.W.; Lademann, J.; Ulrich, M. Optical Coherence Tomography for Presurgical Margin Assessment of Non-melanoma Skin Cancer—A Practical Approach. *Exp. Dermatol.* **2013**, *22*, 547–551. [CrossRef]
32. Wurm, E.M.T.; Hofmann-Wellenhof, R.; Wurm, R.; Soyer, H.P. Telemedicine and Teledermatology: Past, Present and Future. *J. Dtsch. Derma Gesell* **2008**, *6*, 106–112. [CrossRef]
33. Wurm, E.M.T.; Campbell, T.M.; Soyer, H.P. Teledermatology: How to Start a New Teaching and Diagnostic Era in Medicine. *Dermatol. Clin.* **2008**, *26*, 295–300. [CrossRef]
34. Gronbeck, C.; Grant-Kels, J.M.; Fox, C.; Feng, H. Trends in Utilization of Reflectance Confocal Microscopy in the United States, 2017–2019. *J. Am. Acad. Dermatol.* **2022**, *86*, 1395–1398. [CrossRef]
35. Longo, C.; Hemmer, P.; Pellacani, G. Tele-Reflectance Confocal Microscopy. In *Telemedicine in Dermatology*; Soyer, H.P., Binder, M., Smith, A.C., Wurm, E.M.T., Eds.; Springer: Berlin/Heidelberg, Germany, 2012; pp. 73–77. ISBN 978-3-642-20800-3.
36. Wurm, E.M.T.; Longo, C.; Hemmer, P.; Pellacani, G. Tele-Reflectance Confocal Microscopy. In *Reflectance Confocal Microscopy for Skin Diseases*; Hofmann-Wellenhof, R., Pellacani, G., Malvehy, J., Soyer, H., Eds.; Springer: Berlin/Heidelberg, Germany, 2012. [CrossRef]
37. Jayamohanan, R. Confocal Microscopy—Working Principle and Applications in Dermatology. *J. Ski. Sex. Transm. Dis.* **2022**, *5*, 81–89. [CrossRef]
38. Liopyris, K.; Gregoriou, S.; Dias, J.; Stratigos, A.J. Artificial Intelligence in Dermatology: Challenges and Perspectives. *Dermatol. Ther.* **2022**, *12*, 2637–2651. [CrossRef] [PubMed]
39. Bini, S.A. Artificial Intelligence, Machine Learning, Deep Learning, and Cognitive Computing: What Do These Terms Mean and How Will They Impact Health Care? *J. Arthroplast.* **2018**, *33*, 2358–2361. [CrossRef] [PubMed]
40. Benjamens, S.; Dhunnoo, P.; Meskó, B. The State of Artificial Intelligence-Based FDA-Approved Medical Devices and Algorithms: An Online Database. *Npj Digit. Med.* **2020**, *3*, 118. [CrossRef] [PubMed]

41. Esteva, A.; Kuprel, B.; Novoa, R.A.; Ko, J.; Swetter, S.M.; Blau, H.M.; Thrun, S. Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks. *Nature* **2017**, *542*, 115–118. [CrossRef]
42. Haggenmüller, S.; Maron, R.C.; Hekler, A.; Utikal, J.S.; Barata, C.; Barnhill, R.L.; Beltraminelli, H.; Berking, C.; Betz-Stablein, B.; Blum, A.; et al. Skin Cancer Classification via Convolutional Neural Networks: Systematic Review of Studies Involving Human Experts. *Eur. J. Cancer* **2021**, *156*, 202–216. [CrossRef]
43. Tschandl, P.; Rosendahl, C.; Akay, B.N.; Argenziano, G.; Blum, A.; Braun, R.P.; Cabo, H.; Gourhant, J.-Y.; Kreusch, J.; Lallas, A.; et al. Expert-Level Diagnosis of Nonpigmented Skin Cancer by Combined Convolutional Neural Networks. *JAMA Derm.* **2019**, *155*, 58. [CrossRef]
44. Tschandl, P.; Rinner, C.; Apalla, Z.; Argenziano, G.; Codella, N.; Halpern, A.; Janda, M.; Lallas, A.; Longo, C.; Malvehy, J.; et al. Human–Computer Collaboration for Skin Cancer Recognition. *Nat. Med.* **2020**, *26*, 1229–1234. [CrossRef]
45. Pehamberger, H.; Steiner, A.; Wolff, K. In Vivo Epiluminescence Microscopy of Pigmented Skin Lesions. I. Pattern Analysis of Pigmented Skin Lesions. *J. Am. Acad. Dermatol.* **1987**, *17*, 571–583. [CrossRef]
46. Jiang, A.; Jefferson, I.S.; Robinson, S.K.; Griffin, D.; Adams, W.; Speiser, J.; Winterfield, L.; Peterson, A.; Tung-Hahn, E.; Lee, K.; et al. Skin Cancer Discovery during Total Body Skin Examinations. *Int. J. Women's Dermatol.* **2021**, *7*, 411–414. [CrossRef] [PubMed]
47. Lakhani, N.A.; Saraiya, M.; Thompson, T.D.; King, S.C.; Guy, G.P. Total Body Skin Examination for Skin Cancer Screening among U.S. Adults from 2000 to 2010. *Prev. Med.* **2014**, *61*, 75–80. [CrossRef] [PubMed]
48. Avilés-Izquierdo, J.A.; Molina-López, I.; Rodríguez-Lomba, E.; Marquez-Rodas, I.; Suarez-Fernandez, R.; Lazaro-Ochaita, P. Who Detects Melanoma? Impact of Detection Patterns on Characteristics and Prognosis of Patients with Melanoma. *J. Am. Acad. Dermatol.* **2016**, *75*, 967–974. [CrossRef] [PubMed]
49. Faldetta, C.; Kaleci, S.; Chester, J.; Ruini, C.; Ciardo, S.; Manfredini, M.; Guida, S.; Chello, C.; Cantisani, C.; Young, J.N.; et al. Melanoma Clinicopathological Groups Characterized and Compared with Dermoscopy and Reflectance Confocal Microscopy. *J. Am. Acad. Dermatol.* **2024**, *90*, 309–318. [CrossRef]
50. De, A.; Sarda, A.; Gupta, S.; Das, S. Use of Artificial Intelligence in Dermatology. *Indian J Derm.* **2020**, *65*, 352. [CrossRef]
51. Du-Harpur, X.; Watt, F.M.; Luscombe, N.M.; Lynch, M.D. What Is AI? Applications of Artificial Intelligence to Dermatology. *Br. J. Derm.* **2020**, *183*, 423–430. [CrossRef]
52. De Guzman, L.C.; Maglaque, R.P.C.; Torres, V.M.B.; Zapido, S.P.A.; Cordel, M.O. Design and Evaluation of a Multi-Model, Multi-Level Artificial Neural Network for Eczema Skin Lesion Detection. In Proceedings of the 2015 3rd International Conference on Artificial Intelligence, Modelling and Simulation (AIMS), Kota Kinabalu, Malaysia, 2–4 December 2015; pp. 42–47.
53. Aksoy, S.; Demircioglu, P.; Bogrekci, I. Enhancing Melanoma Diagnosis with Advanced Deep Learning Models Focusing on Vision Transformer, Swin Transformer, and ConvNeXt. *Dermatopathology* **2024**, *11*, 239–252. [CrossRef]
54. Young, A.T.; Xiong, M.; Pfau, J.; Keiser, M.J.; Wei, M.L. Artificial Intelligence in Dermatology: A Primer. *J. Investig. Dermatol.* **2020**, *140*, 1504–1512. [CrossRef]
55. Anzelc, M. Can Artificial Intelligence Technology Replace Human Scribes? *Cutis* **2021**, *108*, 310–311. [CrossRef]
56. Pala, P.; Bergler-Czop, B.S.; Gwiżdż, J. Teledermatology: Idea, Benefits and Risks of Modern Age—a Systematic Review Based on Melanoma. *Adv. Dermatol. Allergol. /Postępy Dermatol. I Alergol.* **2020**, *37*, 159–167. [CrossRef]
57. Rinkunas, S. This Terrifying App Shows You What Not Using Sunscreen Will Do to Your Face. 2018. Available online: https://www.vice.com/en/article/paw3mb/facial-aging-app-sunface-uv-skin-damage (accessed on 31 August 2024).
58. Chan, S.; Reddy, V.; Myers, B.; Thibodeaux, Q.; Brownstone, N.; Liao, W. Machine Learning in Dermatology: Current Applications, Opportunities, and Limitations. *Dermatol. Ther.* **2020**, *10*, 365–386. [CrossRef] [PubMed]
59. Spatharou, A.; Hieronimus, S.; Jenkins, J. Transforming Healthcare with AI: The Impact on the Workforce and Organizations. 2020. Available online: https://www.mckinsey.com/industries/healthcare/our-insights/transforming-healthcare-with-ai#/ (accessed on 31 August 2024).
60. Codella, N.; Rotemberg, V.; Tschandl, P.; Celebi, M.E.; Dusza, S.; Gutman, D.; Helba, B.; Kalloo, A.; Liopyris, K.; Marchetti, M.; et al. Skin Lesion Analysis Toward Melanoma Detection 2018: A Challenge Hosted by the International Skin Imaging Collaboration (ISIC). *arXiv* **2019**, arXiv:1902.03368. [CrossRef]
61. Codella, N.C.F.; Gutman, D.; Celebi, M.E.; Helba, B.; Marchetti, M.A.; Dusza, S.W.; Kalloo, A.; Liopyris, K.; Mishra, N.; Kittler, H.; et al. Skin Lesion Analysis toward Melanoma Detection: A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC). In Proceedings of the 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), Washington, DC, USA, 4–7 April 2018; pp. 168–172.
62. Gutman, D.; Codella, N.C.F.; Celebi, E.; Helba, B.; Marchetti, M.; Mishra, N.; Halpern, A. Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016, Hosted by the International Skin Imaging Collaboration (ISIC). *arXiv* **2016**, arXiv:1605.01397. [CrossRef]
63. Combalia, M.; Codella, N.; Rotemberg, V.; Carrera, C.; Dusza, S.; Gutman, D.; Helba, B.; Kittler, H.; Kurtansky, N.R.; Liopyris, K.; et al. Validation of Artificial Intelligence Prediction Models for Skin Cancer Diagnosis Using Dermoscopy Images: The 2019 International Skin Imaging Collaboration Grand Challenge. *Lancet Digit. Health* **2022**, *4*, e330–e339. [CrossRef] [PubMed]
64. Senan, E.M.; Jadhav, M.E.; Kadam, A. Classification of PH2 Images for Early Detection of Skin Diseases. In Proceedings of the 2021 6th International Conference for Convergence in Technology (I2CT), Maharashtra, India, 2–4 April 2021; pp. 1–7.

65. Latha, M.; Manjula, G.; Raghavendra, Y.M.; Keerthi Kumar, M.; Rashmi, H.C. Enhancing Skin Cancer Classification on the PH2 Dataset Through Transfer Learning Technique. *Int. Res. J. Adv. Eng. Hub (IRJAEH)* **2024**, *2*, 500–507. [CrossRef]
66. Que, S.K.T.; Fraga-Braghiroli, N.; Grant-Kels, J.M.; Rabinovitz, H.S.; Oliviero, M.; Scope, A. Through the Looking Glass: Basics and Principles of Reflectance Confocal Microscopy. *J. Am. Acad. Dermatol.* **2015**, *73*, 276–284. [CrossRef]
67. Massone, C.; Brunasso, A.M.G.; Campbell, T.M.; Soyer, H.P. Mobile Teledermoscopy—Melanoma Diagnosis by One Click? *Semin. Cutan. Med. Surg.* **2009**, *28*, 203–205. [CrossRef]
68. Giotis, I.; Molders, N.; Land, S.; Biehl, M.; Jonkman, M.F.; Petkov, N. MED-NODE: A Computer-Assisted Melanoma Diagnosis System Using Non-Dermoscopic Images. *Expert Syst. Appl.* **2015**, *42*, 6578–6585. [CrossRef]
69. DermIS Dermatology Information System. 2019. Available online: https://www.dermis.net/dermisroot/en/home/index.htm (accessed on 31 August 2024).
70. Ashraf, R.; Afzal, S.; Rehman, A.U.; Gul, S.; Baber, J.; Bakhtyar, M.; Mehmood, I.; Song, O.-Y.; Maqsood, M. Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection. *IEEE Access* **2020**, *8*, 147858–147871. [CrossRef]
71. Tschandl, P.; Rosendahl, C.; Kittler, H. The HAM10000 Dataset, a Large Collection of Multi-Source Dermatoscopic Images of Common Pigmented Skin Lesions. *Sci. Data* **2018**, *5*, 180161. [CrossRef]
72. Faes, L.; Wagner, S.K.; Fu, D.J.; Liu, X.; Korot, E.; Ledsam, J.R.; Back, T.; Chopra, R.; Pontikos, N.; Kern, C.; et al. Feasibility of Automated Deep Learning Design for Medical Image Classification by Healthcare Professionals with Limited Coding Experience. *bioRxiv* **2019**, 650366. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3402015 (accessed on 31 August 2024). [CrossRef]
73. Dermatologist-Ai. Available online: https://github.com/udacity/dermatologist-ai (accessed on 31 August 2024).
74. Derm7pt. Available online: https://github.com/jeremykawahara/derm7pt (accessed on 31 August 2024).
75. MedAGI. Available online: https://github.com/JoshuaChou2018/MedAGI (accessed on 31 August 2024).
76. Dermatology. Available online: https://github.com/datasets/dermatology (accessed on 31 August 2024).
77. Deepskin. Available online: https://github.com/Nico-Curti/Deepskin (accessed on 31 August 2024).
78. SkinGPT-4. Available online: https://github.com/JoshuaChou2018/SkinGPT-4 (accessed on 31 August 2024).