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A Quantum Leap in Dermatology & Cosmetology Through AI Powered Personalized Solutions

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Abstract:
Artificial Intelligence (AI) is revolutionizing dermatology, including dermatopathology, infection identification, and cancer treatment. However, it also presents difficulties like data analysis, ethical issues, and fraud detection. Deep learning mechanism, particularly in generative AI, is increasingly used in dermatology. Ethical concerns include independence, consent, confidentiality, beneficence, nonmaleficence, and distributive justice. Dermatologists and cosmetologist must stay updated on modern technologies to improvise patient education and clinical skillsets. AI, machine learning, and deep learning methods are used in consumer and provider applications for detailed evaluation assessments and improved treatment choices for patients.

Keywords: AI-Driven Dermatology, Personalized Skin Care, Skin Analysis Technology, Cosmetic AI, Predictive Dermatology

1. Introduction:

Artificial intelligence (AI) is software that can perform tasks requiring human intelligence, such as learning, reasoning, problem-solving, perception, and communication. It can be narrow or general, aiming to replicate human cognitive abilities across all tasks. AI's potential lies in automating complex processes, analysing vast datasets, and making predictions with minimal or no human intervention. In medicine, AI could revolutionize diagnostics, treatment plans, and patient care delivery. However, ethical issues like lack of transparency, potential biases, flawed data gathering, and data privacy risks remain. The integration of AI technologies into healthcare is yet to be regulated and established. (Chen et al., 2024). Artificial intelligence (AI) has significantly impacted various aspects of daily life, including medicine, including cosmetic dermatology. The field is constantly evolving, leading to the development of promising AI modalities. For instance, 3D virtual facial reconstruction systems are being developed to optimize treatments and outcomes. Patients can now procure and safely operate home-use laser devices, receiving personalized skin care regimens through virtual platforms. Robotic systems for automation and optimizing laser treatments could also revolutionize the industry. AI is a method of making computers, software, or robots intelligent by creating algorithms to classify, analyse, and make predictions from data. (Elder et al., 2024) Artificial intelligence (AI) has shown great promise in dermatology, with applications in image recognition, breast histopathology analysis, skin cancer classification, ophthalmologic issues, cardiovascular disease risk prediction, and lung cancer detection. In dermatology, AI applications include high-speed, high-precision diagnosis, bruise feature recognition, and image documentation of bruise sites.

(Schaekermann et al., 2024a) The dermatology AI boom has impacted the creation of new technology, such as AI-driven dermatoscopes, medical records systems, and non-invasive skin biopsy technology. Machine learning models have the potential to be useful diagnostic support tools for skin bruise diagnosis in primary care, improving access to unambiguous and timely diagnosis, especially in areas with finite dermatologists. (Jeong et al., 2023)

Artificial Intelligence (AI) has the potential to transfigure medical delivery by improving patient care and provider experience. Despite its limited scale, the projected demand for healthcare and shortage of practitioners necessitates the integration of AI-based technology in clinical medicine to maintain quality care. AI applications range from clinical diagnosis to population health management through big data. (Beltrami et al., 2022) AI scaling in healthcare is currently in its first phase, used for administrative tasks and imaging. The need for AI adoption in the coming years will make it a vital aspect of diagnosis and care in and out of the hospital. Dermatology is one medical specialty where AI applications are increasingly used, with advancements in AI-based technologies such as imaging and medical speech recognition. Exposure to AI through medical education is necessary for future dermatologists to effectively utilize it. It will change healthcare through effective time management and clinical decision-making.

Artificial intelligence (AI) in dermatology has the potential to enhance skin cancer detection accuracy, potentially enhancing diagnostic processes and managing the disease. Understanding it can reduce physician concerns and promote its use in clinical settings. The development and validation of AI technologies, regulatory approval, and widespread adoption by dermatologists can enhance patient care. Technology-augmented detection of skin cancer can improve quality of life, reduce healthcare costs, and promote access to high-quality skin assessment. Dermatologists play a crucial role in responsible development and deployment of AI capabilities applied to skin cancer. (Kovarik, 2022)

However, several challenges must be addressed before it can be effectively and efficiently used in clinical practice. There is an apparent lack of established AI solutions employed by dermatology departments or patients, and ethical issues of bias and fairness in AI algorithms need to be addressed. Further research is needed on the performance of these algorithms on darker skin types and developing appropriate algorithms for primary care settings. (El Idrissi El-Bouzaidi & Abdoun, 2024) Challenges in using AI for dermatology include the need for extensive and diverse data sets, algorithmic explainability, control over how it is used in clinical practice, and inequality in access to AI technologies. Trustworthy AI can contribute to improving patient care in ophthalmology and dermatology by bridging the gap between the development and integration of AI systems. (Koka & Burkhart, 2023) This study explores the dermatological applications of deep learning, a leading artificial intelligence technology for image analysis, focusing on three primary applications: tele dermatology, enhancing clinical assessment during face-to-face visits, and dermatopathology. It discusses potential failure modes, performance assessment challenges, equity and ethical issues, and recommends standardization of metrics for reporting model performance.

2. Artificial Intelligence in Dermatology & Cosmetology

2.1 High-Quality Artificial Intelligence in Dermatology

Artificial intelligence (AI) is a rapidly developing field that uses computer systems and algorithms to perform tasks that require human intelligence. It is being integrated into everyday life through applications like face identification, streaming recommendations, voice-to-text, and ridesharing services. AI also holds great potential for clinical applications in medicine, with the concept of augmented intelligence focusing on enhancing human intelligence rather than replacing it. When developed appropriately, augmented intelligence can positively transform the practice of physicians.

2.1.1 Policies & Positions

Medical technology, such as electronic medical records, has been developed without significant input from physicians or end users. The American Medical Association (AMA) has provided policies to advance the role of Artificial Intelligence (AI) in enhancing patient care, aiming to increase the value for physicians and integrate their perspectives into healthcare AI development. (American Medical Association, 2018) The AMA emphasizes the need for high-quality, clinically validated AI that is transparent, user-centred, conforms to reproducibility standards, addresses bias, and avoids healthcare disparities. In 2019, the American Academy of Dermatology published a Position Statement on AI, reinforcing the need for collaborative development while minimizing potential disruptive effects and unintended consequences. (Kovarik et al., 2019)

2.1.2 AI for Lesion Segmentation and Severity Scoring

Atopic dermatitis is a condition that requires quantitative measurements to track patient progress and assess therapeutic efficacy. The Eczema Area and Severity Index (EASI) and the Severity Scoring of Atopic Dermatitis Index (SCORAD) have been developed to assess clinical signs of atopic dermatitis, but their reliability can be variable. Researchers have compared remote assessments using photographs with in-person ones, finding strong correlations between the two methods. (Kovarik, 2022) However, these assessments were taken by study coordinators or physicians in a controlled environment, and data on skin tone was not available for participants. A recent report by a researcher describes an AI algorithm created to automate the SCORAD assessment using photographs. The question of inter-rater and intra-rater reliability using these assessments makes ground truth and data labelling difficult. High-quality AI begins with accurately labelled training datasets derived using best practices and evidence. If the AI algorithm is trained using inaccurate eczema severity data, the outcomes will be misleading. (Medela et al. 2022) It was examined whether high-quality eczema segmentation data can be obtained reliably from dermatologists using images. They found that inter-rater reliability of eczema segmentation varied from image to image, with a poor agreement between raters on average. To improve poor inter-rater reliability in segmentation data for machine learning models, they suggested letting the algorithm identify eczema regions by itself, using algorithms that can be trained on noisy segmentation labels, improving the training of raters, and averaging the segmentation from multiple raters. (Hurault et al. 2022)

2.1.3 AI/Augmented Intelligence Innovation in Dermatology

Future AI/Augmented Intelligence innovations can enhance physician practices and patient outcomes by streamlining tasks, providing diagnostic decision support, and assisting with tasks with limited inter-rater reliability. However, the quality of the algorithm depends on the trained data labels. (Schlessinger et al., 2019) High-quality AI development is time-consuming and costly, but it holds great potential for improving patient outcomes, satisfaction, safety, cost reduction, and transforming physician practice. Therefore, it is crucial to ensure data quality and validation standards in all clinical AI applications. (Das et al., 2023)

2.2 Health Equity Assessment (HEAL) Analysis

The Health Equity Assessment (HEAL) framework is a comprehensive tool developed by an interdisciplinary team of health equity researchers, social scientists, clinicians, bioethicists, statisticians, and AI researchers. (Schaekermann et al., 2024b)The framework aims to improve the performance of health AI technology by identifying factors associated with health inequities and defining AI performance metrics. This process involves four steps:

1. Discover factors associated with health inequities and defining AI performance metrics.
2. Identifying and quantifying pre-existing health outcome disparities.
3. Measuring the performance of the AI tool for each subpopulation.
4. Compute the likelihood that the novel AI tool prioritises performance with respect to health disparities.

The literature review suggests that existing AI fairness metrics typically do not account for pre-existing inequities, and existing health equity frameworks are either qualitative or borrow quantitative metrics from AI fairness paradigms that strive for equality of AI performance but do not prioritise performance for groups experiencing worse health outcomes. The HEAL framework aims to bridge this gap by providing a four-step process for AI model developers and researchers to produce a quantitative metric that assesses prioritisation of model performance with respect to pre-existing health disparities.

The first step involves identifying factors associated with health inequities and defining metrics to quantify tool performance. This may involve reviewing scientific literature and participatory methods, such as stakeholder engagement of clinicians or people with lived experience of structural inequities or the health condition being examined. Each factor of inequity identified in this step is used as input to next step of the framework.

The second step involves identifying and quantifying pre-existing health disparities and measuring the performance of the AI tool for each subpopulation. This can be done using a retrospective dataset or in a prospective manner, requiring a trusted reference standard and case-level metadata for subgroup analysis along the factors of inequality identified in the previous steps.

The third step involves estimating the likelihood that the AI tool prioritises performance with respect to health disparities using the HEAL metric. A case study in applying the HEAL framework is provided to illustrate the effectiveness of the framework in improving AI performance.

2.3 AI Methods: A Simplified Taxonomy for Clinicians

The section shows a simple taxonomy and brief description of AI methods, highlighting their specific uses and potential oversimplifications. (Deo, 2015) It suggests that clinicians may find this granular taxonomy less useful.(Alanazi et al., 2017)

2.3.1 Supervised Method

Supervised methods learn from instances and can decipher melanoma from nonmelanoma if trained on enough expertly labelled images. However, their detailed accuracy is limited by the training set's accuracy. (Esteva et al., 2017) Classification is the quintessential supervised learning method, assigning cases into predefined groups. Decision trees and neural networks and deep learning are other classification methods, with each representing a drawback. (Eapen, 2009)

2.3.2 Unsupervised Method

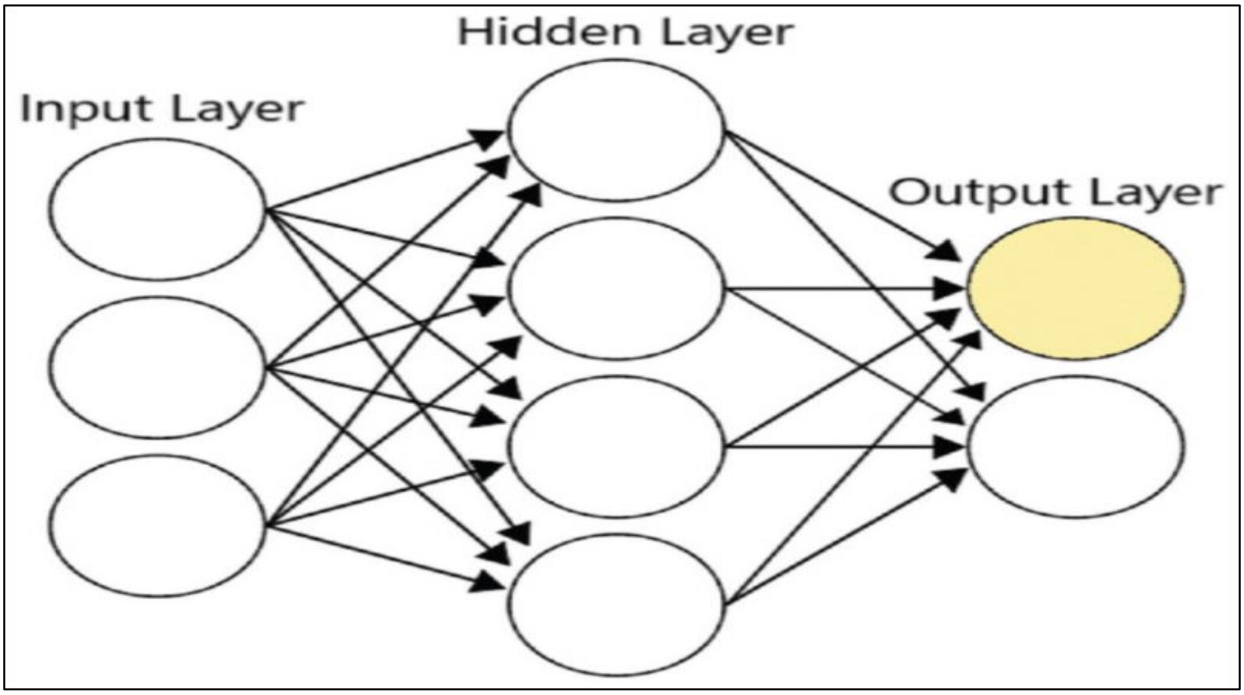
Unsupervised methods, such as clustering, identify hidden patterns based on available data attributes. For instance, clustering can identify potential clusters among psoriasis patients resembling each other. The algorithm can process demographic factors, family, and treatment history. Clusters can be profiled into likely and unlikely responses to PUVA (Psoralen + Ultraviolet A), based on clinical observations. (Yap et al., 2018) Classification can be used to assign future psoriasis patients to these clusters for treatment response prediction and protocol optimization. However, clusters may have no clinical significance, so clinical judgement is crucial especially if it does not have no clinical significance. Clustering can also be used for targeted marketing in cosmetic dermatology practice.

2.3.3 Reinforcement Learning

Reinforcement learning (RL) is a method where an agent learns from the environment by taking actions that maximize a predefined reward. This approach is limited by the amount of data available for learning. (Brinker et al., 2019) Cognitive computing and artificial general intelligence (AGI) are associated concepts, but they are distinct concepts. The utility of RL depends on the accuracy of modelling the environment, as seen in early attempts at laser hair removal modelling.

2.3.4 Neural Networks

Neutral Network (NN) is a popular machine learning technique, modelled based on neurons firing when input exceeds a certain threshold. It has input, hidden, and output layers, with many nodes representing mathematical functions. During training, data is fed through the input layer, hidden layers fire based on their thresholds, and the output layer indicates the predicted class. The process of back propagation is used to adjust the firing threshold in hidden layers to reduce prediction errors. The trained network can then predict the class for unknown data, reducing the error rate to acceptable levels. This technique is particularly important in AI, particularly in dermatology.



Source: Artificial Intelligence in Dermatology: A Practical Introduction to a Paradigm Shift

2.4 Applications of AI in Dermatology

2.4.1 Skin Malignancies

AI has been used in dermatologic malignancies to identify and decipher between benign nevi and melanoma. Researchers analyse skin lesions at the pixel level, using techniques to predict and classify malignancies. (Jansen et al., 2023) Numerous landmark papers have demonstrated high sensitivity and specificity in distinguishing between malignant and benign lesions. (O. T. Jones et al., 2022) They trained a CNN (Convolutional Neural Network) using over 100,000 biopsy-proven clinical images to determine keratinocyte carcinomas versus benign seborrheic keratoses and malignant melanomas versus benign nevi.

(Han et al., 2018) Researchers fine-tuned a CNN model to classify multiple malignancies, including basal cell carcinoma, squamous cell carcinoma, and melanoma. An annual international skin imaging competition presents publicly accessible dermatology images for melanoma-classifying models. (Marchetti et al., 2023) Studies also explore metastases, with researchers using histological tissue sections to identify metastases with high sensitivity and specificity. (Marchetti et al., 2018)

2.4.2 Inflammatory skin diseases-psoriasis, dermatitis, and others

Researchers are exploring the identification and management of inflammatory skin conditions, including psoriasis, dermatitis, and acne. (McMullen et al., 2023) Machine learning techniques are being used to identify patients with increased risk of associated psoriatic conditions, such as psoriatic arthritis. Preliminary models are being developed to optimize therapy and management for patients. (Du et al., 2023) AI techniques are also being applied to genomic studies to assist with drug target identification, drug repurposing, and screening for psoriasis biomarkers and gene expression profiling.

In dermatitis, researchers have explored using machine learning algorithms to predict atopic dermatitis severity using self-reported eczema flare scores, patient demographics, and treatment history. (Lee et al., 2023) AI models have also been used to prevent contact dermatitis by predicting skin sensitization potential and potency of substances. (Yu et al., 2022) In addition to psoriasis and dermatitis, researchers have developed acne lesion segmentation and evaluation tools that can grade acne severity from easily accessible smartphone images. (Mohan & Kasthuri, 2023) There is also exploration in identifying lichen planus and assessing the severity of hidradenitis suppurativa.(Lu et al., 2013)

2.4.3 Ulcer assessment

Skin lesions can be identified and classified by segmenting them from normal skin. Techniques simplifying images down to the pixel level have been used to measure ill-defined wound boundaries. (Toffaha et al., 2023) These techniques have been applied to hospital systems to predict pressure ulcers, with the goal of pressure ulcer prevention. Body heat maps from pressure mats have been used to identify poor in-bed position posture. (Manohar Dhane et al., 2017) These proof-of-concept works may eventually become clinical-assist tools for ulcer management.

2.4.4 Dermatopathology

Machine learning techniques are being used in dermatopathology to identify diagnoses through clinical images and electronic health record notes. Models have been developed to classify basal cell carcinoma in Mohs (specialized technique used to treat skin cancer) micrographic surgery histology slides, aid in histopathologic melanoma diagnoses, and interpret indirect immunofluorescence microscopies to classify bullous dermatoses.

2.4.5 Multi-Class Classification and Text Analysis

Technologies are increasingly focusing on multi-class classification to better replicate real-world clinical scenarios with multiple differential diagnoses from a single skin lesion. This involves a broader approach than binary classification, which aims to identify if a lesion is a specific disease or not.(Y. Liu et al., 2020) It has created a differential diagnosis system for skin lesions, creating a ranked list of the most likely diagnoses. They have classified body parts from dermatology clinical images, creating body distribution maps for different diagnoses. Natural language processing (NLP) techniques are being used to understand and interpret unstructured and freeform written data in dermatology. (Sitaru et al., 2023)Researchers have used NLP methods to examine dermatology discussion forums on social media and analyse clinical notes in electronic health records to identify specific topics discussed during clinical visits. This analysis provides insights into the lack of documentation of the disease's impact on a patient's life, which may affect management and treatment options. Recent advances in technologies, such as ChatGPT 4.0, are also being explored for their ability to guide patients, aid clinicians with administrative tasks, educate trainees, and triage surgical management of cutaneous neoplasms. (Young et al., 2023)

2.4.6 Human-AI hybrid models

The intersection of AI and dermatology is advancing rapidly, leading to the development of AI algorithms for clinical tasks. Researcher's study was the first to compare a Deep Learning (DL) algorithm against dermatologists, showing that their model matched the performance of 21 dermatologists in melanoma classification.(Jain et al., 2021) Other studies have shown that a CNN model outperformed many international dermatologists. As AI can perform diagnostic tasks, researchers are exploring ways to incorporate it into clinical workflows to assist clinicians. (X. Liu et al., 2019) AI-based assistive tools have been created to aid clinicians in interpreting clinical images, with pipelines designed for real-time AI analysis of skin lesions in clinics. Studies have shown that AI can augment the detailed accuracy of non-expert physicians in real-world setting. The AI research community may be looking to increase prospective studies and randomized trials to further assess AI's application in real-world clinical settings.(Han et al., 2022)

2.5 Challenges and Ethical Implications

AI research in dermatology faces numerous challenges, including biases, interpretability issues, regulatory hurdles, and integration difficulties. These issues need to be addressed before AI can become a ubiquitous tool in clinical practice. Robust, transparent, and equitable AI algorithms are needed to enhance patient care without introducing new problems.

2.5.1 Datasets

AI algorithms learn by identifying features and patterns in their training datasets, which can be influenced by confounders. Confounders are features that may be correlated with the algorithm's outcome through spurious associations. For example, surgical pen markers on clinical dermatology images can lead to an algorithm incorrectly learning an association between these markers and malignancy, when they only indicate which lesions were biopsied, not necessarily those that are malignant. (Winkler et al., 2019) This highlights the importance of identifying and managing confounders during the training phase of AI models to ensure their accuracy and validity. Bias in training datasets can also perpetuate pre-existing inequities in healthcare. In dermatology, early AI models trained on datasets predominantly featuring lighter Fitzpatrick skin types tend to underperform when assessed with images of darker Fitzpatrick skin types.

2.5.2 Image quality and image capturing modalities

Standardizing images in Dermatology AI research is crucial to maintain data quality, as images can come from various sources, settings, and individuals, resulting in a heterogeneous dataset. AI algorithms are sensitive to image quality, and blurry images with poor lighting can negatively impact their performance. Simple image manipulations can also change the output of an algorithm. Therefore, it is essential to establish robust image capturing standards and Digital Imaging and Communications in Medicine (DICOM) standards similar to those in other medical fields like cardiology and radiology. This ensures that the quality of images used in AI research remains consistent and accurate.

2.5.3 Implementation

The integration of AI into clinical practice presents numerous challenges, including ethical and legal issues, patient consent, data privacy, and liability in case of AI-induced medical errors. Scholars and professionals must collaborate to develop comprehensive guidance to navigate these intricacies. (C. Jones et al., 2023) Medical AI devices will evolve as they learn from new data, which may continue even after FDA approval. This continuous learning and adaptation can lead to unforeseen shifts in accuracy or effectiveness, potentially impacting patient care. (Wu et al., 2021) There is a lack of high-quality prospective randomized controlled trials of AI algorithms, which is crucial for real-world clinical situations with diverse photo quality, image capturing modalities, and demographics. Most FDA-approved medical AI devices were trained on retrospective data, which is not publicly available, preventing regulatory bodies and researchers from auditing their algorithms.

Future AI models should undergo multi-site validation on a diverse and representative population to assess their generalizability. Establishing trust among AI and stakeholders is essential for realizing AI's full potential in the field. (Nelson et al., 2020) Research shows that dermatologists and patients value the potential of augmented intelligence in dermatology and prioritize the human physician-patient relationship. Therefore, collaboration between scholars and professionals is essential to navigate these ethical and legal intricacies.

2.6 Future Directions

2.6.1 LLMs and the advent of generalist medical AI

Advanced language models, such as chatbots, have gained popularity in medicine, particularly in dermatology. Vision-Language Models (VLMs) and multi-modal models offer immense potential in dermatology. (Haug & Drazen, 2023) VLMs are large-scale models that can associate visual inputs with text data, enabling generative tasks, retrieval of information, and navigation. (Kassab et al., 2023) Recent studies have shown their impact on dermatology, with VLMs providing descriptions and diagnoses from clinical skin lesion photos. They also show accuracy in medical visual question-answering tasks. Furthermore, these models can generate accurate skin image annotations. As dermatological datasets expand and computing power increases, generalist medical AI models could provide approximate diagnoses from clinical photos, generate treatment options, and offer deeper insights into patient data by integrating demographics, visual inspection, and genetic data. Their potential applications range from patient chatbots to triage tools.(Moor et al., 2023) The inclusion of genetic data could improve the diagnosis of orphan skin conditions.

2.6.2 Federated learning and the possibility of local models

Medical data, including skin images, is challenging to access due to privacy, legal, and ethical risks. Many dermatological images are stored in data silos within healthcare institutions worldwide, and collating this data is expensive and time-consuming. This issue is particularly pronounced in resource-limited settings. To improve the performance of deep learning models, new approaches are needed to expand access to more diverse, high-quality datasets. Federated learning (FL) is a concept that allows DL models to be trained on different datasets without leaving their original locations. FL has shown similar performance in fields like radiology and oncology, but has some drawbacks, such as model memory. (Wornow et al., 2023) However, FL has the potential to enable fairer and more generalizable dermatology models by incorporating diverse demographics, capturing nuances in skin conditions across different societies. Federated learning (FM) introduces the possibility of local models, which can learn from unlabeled data and be adapted for various tasks without specific training. This fine-tuning procedure is more cost-efficient than full-scale training, making FMs more appealing within institutional contexts. Dermatology institutions can harness bespoke models tailored to their unique demographics and guidelines. However, progress towards this will require resolving data quality, aggregation, and infrastructural challenges.

2.6.3 Regulation, clinical utility, and usability in resource-poor settings

The rapid evolution of AI models in dermatology necessitates robust regulation to prevent premature adoption and foster trust. To achieve widespread adoption, AI models must be reproducible and generalizable, especially in resource-limited settings. (Meskó & Topol, 2023) Standardizing data collection processes is crucial for optimizing model training and performance. Research in the dermatology-AI space should focus on prospective and randomized clinical trials to rigorously vet models before deployment. Explainability is vital for model advancement and deployment, as emerging facial recognition (FM) models may further obscure their inner workings. (Kovarik et al., 2019) The American Academy of Dermatology Augmented Intelligence working group emphasizes the importance of research addressing explainability for model advancement and deployment.

3. Conclusion

This review explores the current state, applications, and constraints of unimodal machine learning techniques, particularly those based on text or image data. It then focuses on the prospects of multimodal models, particularly large-scale pre-training multimodal models, and their deployment in dermatology. Dermatology faces both opportunities and challenges in integrating AI into its daily operations. Despite the field's infancy and lack of specific regulatory standards, AI is expected to become a critical element in dermatologists' workflows. A global understanding of AI's workings is crucial for clinicians. A transparent, fair, safe, and responsible dermatology-AI future requires interdisciplinary efforts and leadership from the dermatology community.

The field's progress is constrained by high computational overhead and the need for accurately labelled raw data. The training data shortage in dermatological skin lesions is particularly severe due to patient privacy information. However, optimism is maintained that as technology advances and new model training methodologies become more optimized, a future dermatology assistive diagnosis system based on multimodal models could execute highly accurate self-diagnosis, easing the burden on healthcare apparatus and reducing the incidence of misdiagnoses due to doctor expertise discrepancies. The intersection of technological advancements and innovative training methods could pave the way for the next revolution in healthcare, beginning with dermatology.

4. Limitations & Future Scope

AI in dermatology faces several limitations, including the need for diverse datasets for effective model training, potential bias in algorithms, challenges in model interpretability, ethical concerns regarding privacy and security, and potential disruption in clinical workflows. Integrating AI tools into workflows requires careful planning and careful consideration of human-AI collaboration for optimal outcomes. Overcoming these limitations and ensuring responsible AI development are crucial for realizing the full potential of AI in dermatology.

The future of AI in dermatology is promising, with advanced techniques like explainable AI and federated learning enhancing transparency and collaboration. AI can also improve personalized medicine by analysing patient data to tailor treatment plans and predict disease progression. Tele dermatology powered by AI can improve access to care, especially in underserved regions. AI can accelerate drug discovery by analysing biological data and provide personalized education, improving treatment adherence. By addressing limitations and capitalizing on these opportunities, AI can significantly improve dermatological care.

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