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MULTIMODAL ARTIFICIAL INTELLIGENCE IN AESTHETIC DERMATOLOGY: CURRENT APPLICATIONS, CHALLENGES, AND FUTURE PERSPECTIVES – A NARRATIVE REVIEW

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ABSTRACT

Background The rapid evolution of artificial intelligence (AI) technologies has transformed many areas of medicine, including dermatology, where AI-assisted diagnostic systems have demonstrated considerable effectiveness in identifying skin diseases. In contrast, aesthetic dermatology presents additional challenges due to the subjective nature of cosmetic assessments and the absence of universally accepted evaluation standards.

Objective This review aims to examine the current role of artificial intelligence in dermatology, with particular emphasis on its application in aesthetic medicine. Furthermore, it evaluates the shortcomings of conventional assessment methods and discusses future opportunities for integrating AI-driven solutions into clinical practice.

Methods A narrative review of the literature was conducted to assess the implementation of AI technologies in both medical and aesthetic dermatology. Traditional evaluation approaches, including patient-reported outcome measures and instrument-based skin analysis systems, were reviewed and compared with emerging AI-supported methodologies. Particular attention was given to the limitations of current AI models, dataset quality, and the lack of standardized assessment frameworks.

Results Artificial intelligence has achieved notable success in dermatological diagnostics, especially in the detection and classification of skin cancers. Nevertheless, aesthetic dermatology continues to rely heavily on subjective evaluation techniques that often lack reproducibility and standardization. Although AI-based tools are increasingly being introduced into this field, their clinical utility remains constrained by limited dataset diversity, potential algorithmic bias, and variability in assessment protocols.

Conclusions The successful implementation of AI in aesthetic dermatology requires the development of standardized evaluation criteria, the creation of comprehensive and ethnically diverse datasets, and improved education of healthcare professionals regarding both the capabilities and limitations of AI technologies. Addressing these challenges may enhance diagnostic consistency, optimize treatment outcomes, and facilitate the broader adoption of AI-driven solutions in aesthetic practice.

KEYWORDS

Artificial Intelligence, Aesthetic Dermatology, Aesthetic Medicine, Machine Learning, Skin Analysis, Diagnostic Accuracy, Personalized Medicine

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1. Introduction

1.1. Current Applications of Artificial Intelligence in Dermatology

Over the past decade, artificial intelligence (AI) has emerged as one of the most transformative technologies in healthcare, significantly influencing the field of dermatology. Advances in machine learning and deep learning have enabled the development of highly accurate diagnostic systems capable of analyzing dermatological images and supporting clinical decision-making. A pivotal study published in Nature demonstrated that deep convolutional neural networks could classify skin cancers with a level of accuracy comparable to that of experienced dermatologists, highlighting the potential of AI as a valuable diagnostic aid and expanding access to dermatological expertise beyond conventional clinical settings [1].

The integration of AI into dermatological practice has accelerated in recent years, particularly through image-based diagnostic tools designed to assist healthcare professionals in primary care and non-specialist environments [2]. Furthermore, AI-powered mobile health (mHealth) applications have gained increasing popularity, providing the general population with accessible tools for preliminary skin assessments and early risk identification [3–5]. Such technologies have shown considerable potential in facilitating the early detection of skin cancers, inflammatory dermatoses, and infectious skin diseases, thereby contributing to improved clinical outcomes, reduced disease burden, and lower transmission rates in communicable dermatological conditions [6,7].

Beyond diagnostic applications, AI has demonstrated promising results in disease severity assessment and treatment monitoring. Recent studies have reported successful implementation of AI algorithms for evaluating conditions such as atopic dermatitis, psoriasis, and alopecia areata, enabling more objective and reproducible assessments compared with traditional clinical evaluation methods [8–10]. The ability of AI systems to process large volumes of data, recognize complex patterns, and provide real-time analytical support positions this technology as an increasingly important component of modern dermatological practice.

Despite these advances, the application of AI in aesthetic dermatology presents unique challenges. Unlike medical dermatology, where diagnoses are typically established according to well-defined clinical criteria and may be confirmed through histopathological examination, aesthetic dermatology focuses primarily on cosmetic concerns such as wrinkles, pigmentation disorders, skin texture irregularities, and laxity. These characteristics are inherently subjective and are influenced by multiple factors, including age, sex, ethnicity, cultural perceptions of beauty, and individual patient expectations [11,12].

Additionally, medical dermatology benefits from numerous validated assessment instruments, including the Eczema Area and Severity Index (EASI), Psoriasis Area and Severity Index (PASI), and Severity of Alopecia Tool (SALT), which facilitate standardized evaluation and treatment monitoring. In contrast, aesthetic dermatology lacks universally accepted and validated assessment scales, resulting in considerable variability in clinical evaluations and treatment outcome measurements. Consequently, current assessment methods often rely heavily on subjective physician judgment, patient satisfaction surveys, or device-based measurements that may not fully capture aesthetic outcomes.

Artificial intelligence offers a potential solution to these limitations by enabling more objective, consistent, and data-driven evaluation processes [13]. Through the analysis of large and diverse image datasets, AI algorithms can identify subtle visual features and correlations that may not be readily detectable through human observation alone. Such capabilities may improve diagnostic consistency, enhance treatment planning, and facilitate longitudinal monitoring of aesthetic outcomes.

Although the implementation of AI in aesthetic dermatology remains at a relatively early stage, growing research interest suggests substantial opportunities for future development. This review aims to examine the current landscape of AI applications in aesthetic dermatology, critically evaluate the limitations of conventional assessment approaches, and discuss the challenges, opportunities, and future directions for integrating AI technologies into routine clinical practice.

2. Current Assessment Methods in Aesthetic Dermatology and Their Limitations

Aesthetic dermatology has experienced remarkable growth over the past decades, driven by technological innovations and increasing patient demand for minimally invasive procedures targeting concerns such as wrinkles, hyperpigmentation, skin laxity, and overall skin rejuvenation. Alongside these developments, numerous approaches have been proposed to evaluate treatment outcomes and characterize skin conditions, including patient-reported questionnaires, instrumental measurements, and clinician-based assessments [12,14,15]. Despite their widespread use, each of these methods possesses inherent limitations that restrict their ability to provide comprehensive, objective, and reproducible evaluations.

One of the most commonly utilized questionnaire-based approaches is the Baumann Skin Type Indicator, which classifies individuals into sixteen skin types based on standardized questions related to hydration, sensitivity, pigmentation, and aging characteristics. The primary advantage of this method lies in its simplicity, accessibility, and low implementation cost. However, its reliance on self-reported responses introduces substantial subjectivity, potentially affecting reliability and reproducibility. Furthermore, the categorical nature of the classification system may oversimplify the complex and dynamic characteristics of human skin, limiting its ability to capture subtle clinical variations.

Instrumental assessment methods provide a more objective alternative by quantifying specific skin parameters. Devices such as the Mexameter, Sebumeter, Cutometer, and Tewameter are frequently used to evaluate pigmentation, sebum production, skin elasticity, and transepidermal water loss, respectively. These technologies offer precise and reproducible measurements, making them valuable tools in both clinical practice and research settings. Nevertheless, their assessments are typically limited to localized skin areas and individual parameters, which may not accurately reflect overall facial appearance or global aesthetic outcomes. Consequently, important aspects of facial aging and cosmetic improvement may remain underrepresented [15].

Another commonly employed approach involves assessments performed by trained clinicians or expert evaluators. Such evaluations allow for a more holistic interpretation of aesthetic outcomes by considering multiple facial features simultaneously. However, these assessments are inherently subjective and are influenced by individual experience, perception, and aesthetic preferences. Moreover, many clinician-based grading scales utilize relatively broad scoring categories, reducing sensitivity to subtle yet clinically meaningful treatment-related changes.

A major challenge within aesthetic dermatology is the absence of universally accepted and validated assessment standards. Unlike medical dermatology, where disease severity can be quantified using established instruments such as the Eczema Area and Severity Index (EASI), Psoriasis Area and Severity Index (PASI), or Severity of Alopecia Tool (SALT), aesthetic dermatology lacks comparable standardized frameworks for evaluating conditions such as wrinkles, pigmentation disorders, skin laxity, or facial aging [16]. This lack of standardization complicates both clinical decision-making and the comparison of outcomes across studies.

The complexity of aesthetic assessment is further amplified by substantial interindividual variability in aging patterns. Facial aging manifests through multiple interconnected processes, including volume loss, tissue descent, wrinkle formation, pigmentary alterations, and changes in skin texture. Importantly, these processes vary considerably according to ethnicity, age, sex, genetic background, and environmental exposure. For example, pigmentation disorders may be more prevalent in certain ethnic populations, whereas wrinkle formation and skin laxity may predominate in others. Existing assessment methods are often insufficiently adaptable to capture these diverse manifestations consistently and accurately across different populations [17].

The absence of standardized and objective evaluation systems has several important consequences. First, it limits the ability to directly compare the efficacy and safety of different aesthetic interventions, thereby hindering the development of robust evidence-based treatment guidelines. Second, the inability to accurately quantify treatment-related changes restricts the advancement of precision medicine approaches, which aim to tailor interventions according to individual patient characteristics and predicted outcomes. Finally, inconsistent assessment methodologies create significant barriers to the collection and analysis of large-scale datasets, which are essential for developing and validating advanced artificial intelligence models capable of supporting clinical practice in aesthetic dermatology.

Consequently, there is an increasing need for innovative assessment approaches that combine objectivity, reproducibility, scalability, and clinical relevance. Artificial intelligence has emerged as a promising solution to address these limitations and may play a pivotal role in establishing more standardized and data-driven evaluation frameworks within aesthetic dermatology.

3. Imaging Hardware Devices and Artificial Intelligence Algorithms

Recent technological advances in digital imaging have significantly expanded the capabilities of aesthetic dermatology. High-resolution imaging systems, three-dimensional (3D) facial scanners, and AI-supported analysis platforms are increasingly being incorporated into clinical practice to improve the assessment of skin quality, facial morphology, and treatment outcomes. These technologies generate large amounts of multimodal data, including two-dimensional (2D) and 3D photographs, skin surface topography, pigmentation profiles, and volumetric measurements. When combined with machine-learning algorithms, these datasets may facilitate more objective, reproducible, and personalized aesthetic evaluations.

Several commercially available imaging systems have been developed specifically for aesthetic dermatology and facial analysis. While these platforms differ in their technological approaches, they share a common goal of improving diagnostic accuracy, treatment planning, and longitudinal outcome assessment.

3.1. Canfield Imaging Systems

Canfield Scientific has developed a range of imaging platforms widely used in aesthetic medicine, including Vectra H2, Vectra XT, Vectra WB360, IntelliStudio, Visia Skin Analysis, and Reveal Imager. These systems combine high-resolution photography with advanced image-processing techniques to evaluate facial skin characteristics and anatomical structures.

One of the key technologies employed by Canfield is Red/Brown Subsurface Analysis (RBX®), which separates vascular and pigmented skin components, allowing clinicians to visualize erythema and pigmentation independently. Additional imaging modes enhance the assessment of skin texture, contour irregularities, and volumetric changes. Modern Vectra systems also incorporate markerless tracking and three-dimensional reconstruction, enabling quantitative evaluation of facial volume, wrinkle depth, pore distribution, and skin texture.

The integration of AI-driven image analysis allows for automated detection of facial features and simulation of treatment outcomes, including volume augmentation and contour modification. Despite these technological advantages, evidence demonstrating superior clinical outcomes compared with conventional assessment methods remains limited. Furthermore, the high acquisition and maintenance costs of these systems may restrict accessibility and contribute to disparities in the availability of advanced aesthetic technologies.

3.2. Quantificare Imaging Systems

Quantificare has developed several imaging solutions designed for aesthetic analysis, including LifeViz Mini Face, LifeViz Infinity Face, LifeViz Body, LifeViz Body & Breast, and LifeViz Micro Skin Microstructure. These systems utilize 3D photographic reconstruction to evaluate facial and body morphology with high spatial accuracy.

Quantificare platforms enable detailed analysis of facial proportions, wrinkle morphology, pore characteristics, pigmentation patterns, vascular changes, and skin texture. In addition, volumetric analysis tools can quantify treatment-induced changes, making them valuable for monitoring outcomes following dermal filler injections, fat grafting procedures, and skin-tightening interventions.

Several systems incorporate facial proportion analysis based on mathematical concepts such as the golden ratio, although the clinical relevance of such measurements remains controversial. While 3D visualization may improve communication between clinicians and patients and facilitate treatment planning, further studies are required to determine whether these technologies translate into improved clinical outcomes, patient satisfaction, or treatment efficacy.

3.3. Miravex Antera 3D

The Antera 3D system developed by Miravex utilizes a patented multidirectional illumination technique to reconstruct high-resolution three-dimensional images of the skin surface. This technology enables detailed quantitative analysis of skin topography, including wrinkle depth, pore size, texture irregularities, pigmentation, vascularity, and volumetric changes.

By mapping skin structures onto a digital 3D model, Antera 3D provides clinicians with objective measurements that can be used for treatment planning and longitudinal monitoring. Such capabilities are particularly valuable in aesthetic medicine, where subtle changes may be difficult to detect through visual inspection alone.

Despite its advantages, the performance of Antera 3D across different ethnic groups, skin phototypes, and age categories has not been fully established. Additional comparative studies involving diverse patient populations and alternative imaging technologies are needed to determine its relative clinical utility and generalizability.

3.4. Integration of Artificial Intelligence With Imaging Systems

The growing adoption of advanced imaging devices has created opportunities for integrating artificial intelligence into aesthetic dermatology. Machine-learning and deep-learning algorithms can analyze large volumes of imaging data, identify complex patterns associated with aging and skin quality, and generate objective assessments that may reduce observer variability.

AI-driven systems have the potential to automate the evaluation of wrinkles, pigmentation, erythema, facial asymmetry, skin laxity, and volumetric changes while simultaneously monitoring treatment outcomes over time. Moreover, combining imaging data with demographic, clinical, and lifestyle information may facilitate the development of personalized treatment recommendations and predictive models for aesthetic outcomes.

However, the effectiveness of AI algorithms depends heavily on the quality, diversity, and standardization of the datasets used for training. Many currently available systems are based on limited populations and may not adequately represent variations in ethnicity, age, sex, and skin phototype. Consequently, concerns regarding algorithmic bias, reproducibility, and external validity remain important barriers to widespread implementation.

Table 1. Examples of Imaging and AI-Based Technologies Used in Aesthetic Dermatology

Technology	Main Application	Parameters Evaluated	Advantages	Limitations
Canfield (Visia, Vectra)	Facial analysis and treatment simulation	Wrinkles, pores, pigmentation, texture, volume	High-resolution 2D/3D imaging, treatment simulation	High cost, limited outcome validation
Quantificare (LifeViz)	3D facial and body assessment	Volume, skin texture, pigmentation, facial proportions	Quantitative volumetric analysis	Limited evidence on clinical impact
Miravex (Antera 3D)	Skin surface analysis	Wrinkles, texture, pigmentation, vascularity	Detailed topographic assessment	Limited validation across diverse populations
AI-based image analysis	Automated assessment and prediction	Multiple skin and facial aging parameters	Objectivity, scalability, personalization	Dataset bias, lack of standardization

3.4. FotoFinder

FotoFinder Systems has developed several imaging platforms designed to support dermatological diagnostics and longitudinal skin monitoring. Among the most widely utilized systems are the Automated Total Body Mapping (ATBM) Master, which enables comprehensive skin imaging and automated lesion tracking, and Meesma, a high-resolution handheld imaging device used for detailed visualization of skin structures. These technologies facilitate the assessment of skin texture, pigmentation patterns, vascular changes, and lesion evolution over time. In addition, the ATBM Master incorporates automated disease severity assessment tools, including Psoriasis Area and Severity Index (PASI) scoring for extensive body surface evaluations [18].

One of the most notable AI-driven applications developed by FotoFinder is Moleanalyzer Pro, a deep-learning-based decision support system for skin lesion classification. The algorithm has been evaluated in several landmark studies, including the "Man against Machine" and "Man against Machine Reloaded" investigations conducted at Heidelberg University [19]. In these studies, convolutional neural networks demonstrated diagnostic performance comparable to that of experienced dermatologists in melanoma detection. In the original study, the algorithm achieved an area under the receiver operating characteristic curve (AUROC) of 0.86, performing at a level similar to that of 58 participating dermatologists [20].

The current version of Moleanalyzer Pro is based on a modified implementation of Google's Inception-v4 architecture and has been trained using large dermoscopic image datasets, including images from the International Skin Imaging Collaboration (ISIC) archive. Validation has also been performed using independent datasets, including images from Memorial Sloan Kettering Cancer Center and the ISIC Challenge databases [21]. Such external validation is essential for assessing the generalizability and robustness of AI models across different clinical settings.

Beyond skin lesion analysis, FotoFinder has expanded AI applications into hair and scalp diagnostics through TrichoScale DX, an automated trichoscopic assessment platform capable of analyzing hair density, growth characteristics, and scalp conditions in both clipped and non-clipped hair. While these technologies may enhance diagnostic efficiency and standardization, concerns remain regarding excessive reliance on algorithmic outputs and the potential reduction of clinical oversight in decision-making processes.

3.5. Aram Huvis

Artificial intelligence has also been increasingly applied to trichology and scalp assessment. The AI-Scalp Grader developed by Aram Huvis represents one such example. This automated diagnostic system utilizes high-magnification trichoscopic images acquired through dedicated imaging devices to evaluate scalp health and classify scalp conditions objectively.

The platform assesses scalp status using the Scalp Photographic Index, which incorporates multiple parameters including dryness, seborrhea, erythema, folliculitis, and dandruff severity [22]. Through image analysis and machine-learning algorithms, the system generates standardized scores that may assist clinicians in treatment selection and monitoring.

Clinical investigations have demonstrated that scalp-care regimens selected according to AI-generated assessments may improve scalp conditions and treatment outcomes [23]. Nevertheless, evidence regarding the long-term clinical utility of these systems remains limited. Furthermore, variations in hair color, hair density, ethnicity, and scalp morphology may influence algorithm performance, highlighting the need for validation across diverse patient populations before widespread adoption.

3.6. Clinical Experience, User Feedback, and Current Challenges

The growing implementation of advanced imaging systems and AI-supported analysis platforms has generated valuable insights from clinicians and patients. Reports from routine clinical practice suggest that these technologies improve patient education, facilitate treatment planning, and enhance communication by providing objective visual representations of skin conditions and anticipated treatment outcomes.

Among commercially available platforms, systems such as Canfield VISIA are frequently recognized for their detailed skin quality assessments, while Quantificare LifeViz platforms are widely appreciated for volumetric analyses used in facial rejuvenation and filler procedures. Similarly, AI-supported tools such as FotoFinder Moleanalyzer Pro have received positive evaluations for assisting in the early detection of malignant skin lesions and improving diagnostic confidence.

Despite these advantages, several challenges continue to limit broader implementation. High acquisition and maintenance costs represent a significant barrier, particularly for smaller practices. In addition, the complexity of some systems may require substantial clinician training and workflow adaptation. Data privacy and cybersecurity concerns have become increasingly important as large quantities of patient images and biometric information are collected, stored, and processed by AI-based systems.

Another important consideration is the risk of over-reliance on algorithmic recommendations. Although AI technologies may provide valuable decision support, they should not replace clinical expertise, patient-specific judgment, or comprehensive dermatological evaluation. Most experts currently advocate for a collaborative approach in which AI functions as an adjunctive tool rather than an autonomous diagnostic system.

Overall, advanced imaging technologies and AI-based analytical platforms represent promising developments in aesthetic dermatology. However, evidence regarding their impact on long-term clinical outcomes, treatment efficacy, cost-effectiveness, and patient satisfaction remains limited. Future research should focus on comparative effectiveness studies, validation across diverse ethnic and demographic populations, and the establishment of standardized evaluation frameworks. Addressing these challenges will be essential for ensuring the responsible and equitable integration of artificial intelligence into aesthetic dermatology and cosmetic medicine.

4. Multimodal Data Integration: Combining Sensor Measurements, Imaging Data, and Patient Metadata

The integration of multimodal data has emerged as one of the most promising strategies for improving the performance of artificial intelligence systems in medicine. Multimodal AI refers to the ability of machine-learning models to simultaneously analyze and integrate multiple sources of information, including medical images, physiological measurements, clinical records, demographic characteristics, and patient-reported outcomes. By combining complementary data streams, AI systems can generate a more comprehensive representation of a patient's condition than would be possible using a single data source alone.

In dermatology, multimodal approaches have already demonstrated significant potential. Deep-learning algorithms trained on dermoscopic images have achieved high levels of accuracy in the detection and classification of skin lesions, particularly melanoma and other skin cancers. However, dermatological diagnosis rarely relies solely on visual information. In routine clinical practice, dermatologists routinely consider additional patient-specific factors such as age, sex, ethnicity, medical history, family history, medication use, environmental exposures, and symptom duration when making diagnostic decisions.

Recognizing this complexity, recent studies have explored the integration of clinical images with patient metadata to improve AI-assisted diagnostic performance [24]. Smartphone-acquired photographs, dermoscopic images, and demographic information have been successfully combined to develop deep-learning models capable of more accurate skin lesion classification. Evidence suggests that incorporating patient-specific characteristics such as age, gender, and clinical history significantly improves algorithm performance compared with image-only models [25,26]. By mimicking the contextual reasoning used by clinicians, multimodal systems may better replicate real-world diagnostic processes.

The value of multimodal learning extends beyond disease diagnosis. In aesthetic dermatology, where treatment decisions are highly individualized, integrating multiple data sources may provide a more nuanced understanding of skin health and aging. Modern skin assessment technologies generate a broad range of quantitative measurements, including hydration, sebum production, pigmentation, elasticity, transepidermal water loss, vascularity, and surface texture. Devices such as the Multi Probe Adapter System (MPA), Corneometer CM 825, Mexameter, Cutometer, and Tewameter provide objective measurements of these parameters and are increasingly used in both clinical practice and research.

When combined with facial imaging, patient demographics, lifestyle factors, treatment history, and genetic predispositions, these sensor-derived measurements create a rich multimodal dataset suitable for training advanced machine-learning models. Such comprehensive datasets may enable more accurate prediction of treatment responses, improved monitoring of skin aging, and the development of personalized treatment strategies tailored to the unique biological characteristics of each patient.

Despite its considerable potential, multimodal data integration presents several technical and operational challenges. One major obstacle is the lack of interoperability among imaging devices, sensors, electronic health record systems, and software platforms. Different manufacturers often utilize proprietary data formats and storage structures, making data aggregation and standardization difficult. As a result, the development of large, harmonized datasets suitable for AI training remains a significant challenge.

Data quality represents another critical issue. Multimodal systems require consistent, high-quality data across multiple domains. Missing information, inconsistent image acquisition protocols, variations in device calibration, and incomplete patient records may negatively affect algorithm performance and limit model generalizability. Establishing standardized data collection procedures will therefore be essential for ensuring reliable AI development.

Patient privacy and data security are equally important considerations. Multimodal datasets often contain highly sensitive information, including facial photographs, biometric measurements, medical histories, and potentially genetic data. Consequently, robust governance frameworks must be implemented to ensure compliance with privacy regulations and ethical standards. Techniques such as anonymization, federated learning, secure cloud infrastructures, and encrypted data storage may help protect patient confidentiality while still enabling large-scale AI research.

The successful integration of multimodal data has already demonstrated clinical value in other medical specialties. In oncology, for example, artificial intelligence models combining histopathological images, radiological findings, genomic information, and clinical variables have improved risk stratification, prognostic prediction, and treatment selection [28,29]. These successes illustrate the potential of multimodal AI to transform clinical decision-making and provide a framework for future developments in dermatology.

Looking forward, multimodal AI is likely to become a cornerstone of precision dermatology and aesthetic medicine. By integrating imaging data, skin sensor measurements, patient demographics, lifestyle information, treatment history, and potentially genomic biomarkers, future AI systems may deliver highly personalized assessments and treatment recommendations. Such models could identify subtle biological patterns associated with aging, treatment responsiveness, and disease progression that may not be apparent through conventional assessment methods.

Ultimately, multimodal data integration represents a critical step toward more objective, accurate, and individualized care in aesthetic dermatology. Although technical, ethical, and regulatory challenges remain, the convergence of imaging technologies, sensor platforms, and artificial intelligence offers substantial opportunities to enhance diagnostic accuracy, optimize treatment planning, and advance the implementation of precision medicine in dermatological practice.

5. Artificial Intelligence Applications in Aesthetic Dermatology

5.1. Current Applications of Artificial Intelligence in Aesthetic Dermatology and Their Limitations

The implementation of artificial intelligence in aesthetic and cosmetic dermatology remains in its early stages but has attracted substantial scientific and commercial interest. Recent advances in machine learning, deep learning, and computer vision have enabled the development of systems capable of analyzing facial images, assessing skin quality, predicting treatment outcomes, and supporting clinical decision-making. These technologies have the potential to improve objectivity, standardization, and personalization in aesthetic practice. Nevertheless, several scientific, technical, and ethical challenges continue to limit their widespread adoption.

One of the most significant barriers to the development of robust AI systems in aesthetic dermatology is the lack of large, representative datasets. Most currently available algorithms are trained on image collections that do not adequately reflect the diversity of the global population. Variations in age, sex, ethnicity, skin phototype, and environmental exposure significantly influence skin characteristics and aging patterns. Consequently, algorithms trained on limited datasets may exhibit reduced accuracy when applied to underrepresented populations.

A growing body of evidence has highlighted the importance of diversity in dermatological AI development. A recent study emphasized the challenges associated with constructing representative datasets across different ethnic groups and skin types, noting the persistent underrepresentation of minority populations in dermatological research [30]. Biological differences, including variations in skin barrier function, melanin distribution, inflammatory responses, and aging characteristics, may substantially influence algorithm performance. For example, differences in corneocyte layer thickness, pigmentation patterns, and wrinkle formation among various ethnic groups may affect image interpretation and predictive accuracy. These findings underscore the need for more inclusive datasets capable of supporting equitable and generalizable AI systems.

Another major limitation relates to variability in data acquisition. Image quality may be influenced by differences in camera systems, lighting conditions, image resolution, patient positioning, and imaging protocols. Similarly, measurements obtained from skin sensors and imaging devices may vary depending on calibration methods and hardware specifications. Such inconsistencies introduce noise into training datasets and may negatively affect model performance and reproducibility. Furthermore, aesthetic evaluations often rely on subjective assessments by clinicians or patients, introducing additional variability that can complicate the development of reliable AI models.

Despite these challenges, AI-based systems have already demonstrated promising results in dermatological image analysis. Recent studies evaluating smartphone-based applications have reported diagnostic performances comparable to those of experienced clinicians in identifying pigmented skin lesions [31]. However, while algorithms may perform well in lesion recognition and classification tasks, human experts continue to outperform AI systems when integrating contextual information, evaluating treatment options, and making complex clinical decisions. This observation reinforces the concept that AI should function as a decision-support tool rather than a replacement for clinical expertise.

In aesthetic dermatology specifically, emerging AI applications extend beyond lesion classification. Recent algorithms have been developed to assess facial aging, quantify wrinkles, analyze pigmentation disorders, evaluate skin texture, and estimate facial symmetry. Some systems are capable of predicting treatment outcomes following procedures such as botulinum toxin injections, dermal filler placement, laser therapies, and skin-tightening interventions. AI-assisted facial analysis may also contribute to personalized treatment planning by identifying anatomical features associated with optimal aesthetic outcomes.

However, the increasing use of AI raises important ethical and regulatory concerns. Aesthetic dermatology frequently involves highly sensitive personal information, including identifiable facial images and detailed biometric measurements. Ensuring the privacy, security, and responsible use of these data is essential for maintaining patient trust and regulatory compliance. Robust governance frameworks, transparent consent procedures, and secure data storage solutions are therefore critical prerequisites for broader AI adoption.

Transparency of algorithmic decision-making represents another important challenge. Many deep-learning systems operate as “black boxes,” producing predictions without clearly explaining the underlying reasoning process. This lack of interpretability may reduce clinician confidence and limit clinical implementation. To address this issue, increasing attention has been directed toward explainable artificial intelligence (XAI), which seeks to provide interpretable explanations for algorithm outputs. Recent research has demonstrated that integrating XAI into dermatological diagnostic systems significantly improves clinician trust, acceptance, and willingness to incorporate AI into clinical workflows [32]. By visualizing relevant image features and providing rationale for predictions, explainable models may facilitate safer and more transparent human–AI collaboration.

Although current applications demonstrate considerable promise, the successful integration of AI into aesthetic dermatology will depend on overcoming several remaining challenges. Standardized imaging protocols, diverse and representative datasets, rigorous clinical validation studies, transparent algorithm design, and comprehensive ethical frameworks will all be necessary to ensure reliable implementation. Future systems should be developed with a focus on fairness, interpretability, and clinical utility, ensuring that technological innovation translates into meaningful improvements in patient care.

Ultimately, artificial intelligence has the potential to transform aesthetic dermatology by enabling more objective assessments, personalized treatment strategies, and data-driven clinical decision-making. However, realizing this potential will require continued collaboration among clinicians, engineers, researchers, industry stakeholders, and regulatory authorities to ensure that AI technologies are developed and implemented responsibly, effectively, and equitably.

5.2. Future Strategies for the Integration of Artificial Intelligence in Aesthetic Dermatology

The successful implementation of artificial intelligence in aesthetic and cosmetic dermatology will depend not only on advances in computational methods but also on the establishment of robust clinical, technical, and regulatory foundations. Although AI technologies have already demonstrated considerable promise, several critical prerequisites must be addressed before they can be fully integrated into routine aesthetic practice.

Standardization of Aesthetic Assessment

The first and perhaps most important requirement is the development of standardized assessment methodologies. Unlike medical dermatology, where validated scoring systems such as EASI, PASI, and SALT provide objective measures of disease severity, aesthetic dermatology lacks universally accepted evaluation frameworks. Current assessments frequently rely on subjective clinical judgment, patient satisfaction questionnaires, or device-specific measurements that are difficult to compare across studies and clinical settings.

Future efforts should focus on establishing standardized aesthetic metrics capable of quantifying parameters such as wrinkle severity, pigmentation irregularities, skin laxity, facial symmetry, texture, and overall facial aging. Equally important is the harmonization of measurements obtained from different imaging systems and skin assessment devices. Comparative studies evaluating correlations among clinician assessments, patient-reported outcomes, and instrument-derived measurements will provide a foundation for the development of reliable and reproducible standards [33].

The creation of standardized evaluation protocols would facilitate objective comparisons among treatments, improve clinical research quality, and provide high-quality datasets necessary for training robust AI models.

Development of Large, Diverse, and Representative Datasets

A second critical requirement is the creation of comprehensive datasets that adequately represent the diversity of the global population. Skin aging patterns, pigmentation characteristics, wrinkle formation, and treatment responses differ significantly according to ethnicity, age, sex, geographic location, and environmental exposures [17].

To minimize algorithmic bias and maximize generalizability, future datasets should include individuals from diverse demographic backgrounds and encompass multiple skin phototypes, age groups, and ethnic populations. Furthermore, datasets should integrate information from various imaging devices, skin sensors, clinician evaluations, and patient-reported outcomes. Such diversity would enable AI systems to learn robust patterns that remain applicable across different clinical environments and patient populations [34,35].

Large-scale international collaborations will likely be necessary to collect sufficiently diverse datasets and ensure equitable representation of historically underrepresented groups.

Open Science and Collaborative AI Development

The history of artificial intelligence demonstrates that scientific progress is often accelerated by open access to data, algorithms, and validation frameworks [36]. Greater transparency and collaboration within the aesthetic dermatology community could substantially enhance AI development by enabling independent validation, reproducibility, and comparative benchmarking.

However, unlike many other AI domains, dermatological datasets frequently contain identifiable facial photographs and highly sensitive biometric information. Consequently, balancing data accessibility with patient privacy represents a significant challenge. Emerging approaches such as federated learning, synthetic data generation, privacy-preserving machine learning, and generative AI models may provide solutions that facilitate collaborative research while maintaining confidentiality [37–39].

The use of synthetic datasets generated by advanced generative models may be particularly valuable in expanding training datasets while reducing privacy concerns and improving representation of underrepresented populations.

Education and Clinical Adoption

The successful integration of AI into aesthetic dermatology will also depend on education. Healthcare professionals must understand both the capabilities and limitations of AI technologies to use them effectively and responsibly. Misinterpretation of algorithmic outputs or excessive reliance on automated systems may negatively affect clinical decision-making and patient care.

Educational initiatives should therefore focus on improving AI literacy among dermatologists, aesthetic physicians, nurses, and other healthcare professionals involved in cosmetic treatments. Training programs should address fundamental AI concepts, model interpretation, ethical considerations, data privacy, and practical implementation strategies.

At the same time, AI developers must acquire a deeper understanding of aesthetic dermatology, including clinical workflows, patient expectations, facial aging mechanisms, and treatment planning principles. Close collaboration between clinicians and engineers will be essential to ensure that future AI systems address genuine clinical needs rather than purely technical objectives.

International Collaboration, Regulation, and Governance

Given the global nature of both artificial intelligence and aesthetic medicine, international cooperation will play a pivotal role in shaping future developments. Recent publications have proposed guidelines for the development, validation, and reporting of AI systems in dermatology [40,41]. Similar initiatives specifically focused on aesthetic dermatology are needed to establish best practices for research, clinical implementation, and regulatory oversight.

Future progress may benefit from the creation of multidisciplinary working groups involving dermatologists, aesthetic physicians, data scientists, engineers, industry representatives, ethicists, and regulatory authorities. Such organizations could coordinate efforts related to dataset standardization, clinical validation, ethical governance, regulatory approval pathways, and post-market surveillance of AI systems.

The establishment of internationally accepted standards would facilitate responsible innovation while ensuring patient safety, algorithm transparency, and clinical effectiveness.

Toward Precision Aesthetic Medicine

Ultimately, the convergence of standardized assessment methods, multimodal datasets, advanced machine-learning algorithms, and international collaboration may pave the way for precision aesthetic medicine. Future AI systems may be capable of integrating facial imaging, skin sensor measurements, demographic characteristics, lifestyle factors, genetic information, and treatment history to generate highly individualized treatment recommendations.

Such systems could assist clinicians in predicting treatment responses, optimizing procedure selection, monitoring outcomes, and identifying patients at increased risk of adverse events. By enabling more objective and personalized care, AI has the potential to transform aesthetic dermatology from a largely subjective discipline into a data-driven and evidence-based specialty.

Realizing this vision will require sustained collaboration among researchers, clinicians, technology developers, and policymakers. Nevertheless, the foundations being established today suggest that artificial intelligence will become an increasingly important component of aesthetic dermatology in the coming decades.

5.3. Generative Artificial Intelligence and Foundation Models in Aesthetic Dermatology

Recent advances in generative artificial intelligence (Generative AI) and foundation models have introduced new opportunities for transforming clinical practice in aesthetic dermatology. Unlike traditional machine-learning systems designed to perform specific tasks, foundation models are trained on large-scale multimodal datasets and can process diverse forms of information, including text, images, clinical data, and structured patient records [42,43]. These capabilities enable a broader range of applications that extend beyond conventional image classification and diagnostic support.

Large language models (LLMs) and multimodal AI systems have demonstrated remarkable abilities in information synthesis, clinical reasoning, image interpretation, and decision support [43,44]. In dermatology, these technologies may assist clinicians in generating differential diagnoses, summarizing patient histories, creating treatment recommendations, and supporting medical documentation. When combined with facial imaging systems and skin assessment devices, foundation models may provide comprehensive analyses of skin health and aesthetic concerns by integrating visual findings with patient-specific clinical information.

One particularly promising application is personalized treatment planning. By analyzing facial morphology, skin quality parameters, demographic characteristics, lifestyle factors, and previous treatment responses, AI systems may assist clinicians in identifying individualized treatment strategies [25,26,44]. Such approaches align closely with the principles of precision medicine, which seeks to optimize clinical outcomes through patient-specific interventions rather than standardized treatment protocols.

Generative AI may also improve communication between clinicians and patients. Advanced image-generation models can simulate potential treatment outcomes and visualize expected changes following procedures such as dermal filler injections, botulinum toxin treatments, laser therapies, skin resurfacing, and facial contouring [45]. These visualizations may facilitate shared decision-making, improve patient understanding of realistic treatment goals, and enhance informed consent processes. However, it is essential that such simulations be presented as predictive estimations rather than guaranteed outcomes.

Another important application involves the generation of synthetic datasets. The development of robust AI systems requires large amounts of high-quality training data, yet the collection and sharing of facial photographs raise significant privacy concerns. Generative models may create realistic synthetic images that preserve important clinical characteristics while reducing the risk of patient identification [46,47]. Synthetic data could therefore help expand training datasets, improve representation of underrepresented populations, and facilitate collaborative research while maintaining patient confidentiality.

Foundation models may also support automated documentation and workflow optimization. By integrating information from clinical consultations, imaging devices, and electronic health records, AI systems could generate structured clinical notes, treatment summaries, follow-up recommendations, and patient education materials [43,48]. Such automation may reduce administrative burden and allow clinicians to dedicate more time to patient care.

Despite these opportunities, several important limitations remain. Generative AI systems may produce inaccurate or misleading outputs, a phenomenon commonly referred to as “hallucination” [49]. In aesthetic medicine, incorrect recommendations or unrealistic treatment simulations could negatively influence patient expectations and clinical decision-making. Furthermore, many foundation models operate as complex black-box systems, limiting transparency and making it difficult to explain specific recommendations or predictions.

Ethical and legal considerations also remain substantial. The use of facial images, biometric information, and predictive treatment simulations raises concerns regarding privacy, informed consent, intellectual property, and professional liability [49,50]. Regulatory frameworks governing the clinical use of generative AI in aesthetic medicine are still evolving, and further guidance will be required to ensure safe and responsible implementation.

Looking ahead, the combination of multimodal foundation models, advanced imaging technologies, and large-scale clinical datasets may fundamentally reshape aesthetic dermatology. Future AI systems could function as intelligent clinical assistants capable of integrating visual, clinical, and contextual information to support diagnosis, treatment planning, patient communication, and outcome prediction [42–50]. While substantial scientific, ethical, and regulatory challenges remain, generative AI represents one of the most promising frontiers for the future development of precision aesthetic medicine.

6. Conclusions

Artificial intelligence is poised to become a transformative force in aesthetic and cosmetic dermatology. Recent advances in machine learning, computer vision, multimodal data integration, and imaging technologies have created new opportunities for objective skin assessment, personalized treatment planning, and longitudinal outcome monitoring. Although AI has already demonstrated remarkable success in medical dermatology, particularly in skin cancer detection and disease classification, its application in aesthetic dermatology remains at an early stage of development.

One of the major challenges limiting wider adoption is the absence of standardized and universally accepted methods for evaluating aesthetic outcomes. Current assessment approaches often rely on subjective clinical judgment, patient-reported outcomes, or device-specific measurements, resulting in limited reproducibility and comparability across studies and clinical settings. The development of standardized assessment frameworks will therefore be essential for generating reliable datasets and enabling meaningful clinical validation of AI systems.

The future success of AI in aesthetic dermatology will also depend on the availability of large, diverse, and representative datasets that adequately capture variations in age, ethnicity, sex, skin phototype, and environmental influences. Such datasets are necessary to reduce algorithmic bias, improve generalizability, and ensure equitable performance across diverse patient populations. Furthermore, the integration of multimodal data—including imaging, skin sensor measurements, clinical records, demographic characteristics, and patient-reported outcomes—has the potential to substantially improve the accuracy and clinical utility of AI-driven systems.

Equally important are the ethical, legal, and regulatory considerations associated with AI implementation. Protecting patient privacy, ensuring transparency of algorithmic decision-making, and maintaining appropriate clinical oversight will be critical to fostering trust among both healthcare professionals and patients. Emerging approaches such as explainable artificial intelligence and privacy-preserving machine-learning techniques may play a key role in addressing these concerns.

Looking ahead, AI should not be viewed as a replacement for clinicians but rather as a powerful decision-support tool capable of augmenting human expertise. By combining objective measurements with advanced analytical capabilities, AI has the potential to reduce subjectivity, enhance treatment precision, improve patient communication, and facilitate evidence-based clinical decision-making. As standardized methodologies, collaborative datasets, and regulatory frameworks continue to evolve, artificial intelligence is expected to become an integral component of precision aesthetic medicine.

Ultimately, the successful integration of AI into aesthetic dermatology will require close collaboration among clinicians, researchers, engineers, industry stakeholders, and regulatory authorities. Such multidisciplinary cooperation will be essential to ensure that technological innovation translates into meaningful improvements in patient care, treatment outcomes, and the overall advancement of aesthetic dermatology.

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