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Review

Use of Artificial Intelligence in Skin Aging

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Abstract

Skin aging is a complex process that involves several extrinsic and intrinsic factors and skin health is an indicator of the well-being of an individual. In recent years, there have been numerous developments using computerized systems to aid in finding solutions and treatments to skin aging processes. Tools like artificial intelligence (AI) can aid in finding solutions and treatments for skin aging. AI can also help in monitoring or identifying early signs of skin aging. Within the field of skin aging, several innovations utilize AI to provide better patient care. There is a gap in knowledge within this field concerning current and future directions concerning skin aging and AI. In this review, we aim to highlight current and prospective applications of AI in skin aging and provide insights into future modalities in this field. Models for AI can serve to increase patient participation in skin-care decisions and eventually enhance the patient-provider experience.

Keywords
Artificial intelligence; machine learning; dermatology; skin aging

1. Introduction

Artificial intelligence (AI) is the programming of machines to imitate human thought and perform similar actions [1]. With the ability of computers to process large amounts of data, AI has found increasing use in a wide variety of medical fields, including dermatology [1]. Dermatologists heavily rely on clinical experience over many years and thousands of patient encounters to discern diagnoses. The question arises of how artificial intelligence can render similar results and encapsulate subjective clinical findings similar to dermatologists. For example, AI has been applied to dermatology in its ability to process 1.41 million training images and then accurately differentiate biopsy-proven images between both 1) keratinocyte carcinomas and seborrheic keratoses and 2) malignant melanomas and nevi when compared to board-certified dermatologists [1, 2]. The recent advancements of AI applied to medicine and dermatology open a window of opportunity for patient evaluation and management.

The application of AI in dermatology includes both diagnostic and therapeutic opportunities for home and clinical settings by both patients and providers [1, 3]. One such use includes the evaluation of skin aging [3]. Like the rest of the body's tissues, the skin ages intrinsically over time, but is also aged via extrinsic factors such as sun exposure [4]. The skin changes of aging are the focus of many dermatologic treatments and procedures. The potential to use AI to evaluate these changes and even to help guide further management provides a promising realm for advancement in combating the physiologic process of aging. This review highlights key areas of artificial intelligence's existing and future applications regarding skin aging in dermatology, including machine learning, diagnostic and evaluation purposes, and its role in diagnosis, management, and therapeutic developments.

2. Artificial Intelligence and Machine Learning

Artificial intelligence is a technique for teaching a computer, software, or robot to think intelligently. Its use entails developing algorithms to classify, analyze, and predict data. AI is becoming more complex; artificial neural networks, machine learning, and deep learning are being used to uncover complex associations in many fields of medicine [1]. Artificial neural networks (ANN) are designed to simulate signaling in the brain, similar to human neuronal networks that generate thoughts and actions. The networks are made up of multiple nodes that mimic biological neurons [1]. These nodes receive input data and use it to perform simple operations, and their outcomes are then passed on to other nodes in a linear or feedback loop fashion [1]. The ability of these networks to incorporate vast amounts of information and perform complex tasks rapidly continues to gain popularity in its potential in the medical field and dermatology, especially.

ANN can be trained by machine learning techniques. This is possible through specific techniques, such as supervised, unsupervised, and reinforcement learning, that generate algorithms to solve problems [5]. In supervised learning, networks can make classifications and recognize patterns based on a training dataset and a test dataset [1]. The role of the training dataset is to shape the test dataset to associate inputs with desired outputs for its eventual application in analyzing new data [5]. For example, a study by Kendale et al. sought to train a network to identify patients who experienced postinduction hypotension after receiving anesthesia to establish predictability for patients at risk for this complication in the future [5]. This model was based on analyzing factors such as patient medical history, vital signs, medications, and comorbidities [5, 6]. This is made possible by the network's use of the training dataset to analyze and categorize risk factors into a predictive algorithm. The network then compares its original guess to the "correct" answer and adjusts future responses to align with desired outcomes pre-defined by the original dataset [1, 5, 6]. This is frequently employed in pattern recognition systems, in addition to unsupervised learning practices. This system possesses greater independence and is characterized by pattern recognition modalities categorizing data solely on similarities and differences [1]. In dermatology, one example of this practice is the use of AI to classify suspicious skin lesions as benign or malignant [1]. Based on the corresponding histopathology of lesions in the dataset, the computer is "taught" which lesions are malignant or benign [1]. Additionally, algorithms continue to be developed via computer-based image analysis to assess the extent and progression of various dermatoses [7]. This not only lends interest to the diagnostic capability of AI systems, but also to their ability to evaluate disease progression.

In unsupervised learning, a single dataset identifies patterns and algorithms within itself and is often used to generate novel ways of classifying patients, therapeutics, and other medical groupings [5]. For example, unsupervised learning systems in anesthesia have been used to identify which patient cohorts with asthma would benefit most from glucocorticoid therapy by analysis of their specific genomics [5]. AI mechanisms similar to this model pose therapeutic potential in their application to dermatologic conditions. For example, medical dermatologic condition treatment could be optimized in identifying which biologic therapies may benefit certain patient subsets. Additionally, the outcomes of cosmetic dermatology interventions could be predicted based on patient-specific factors associated with skin aging.

AI reinforcement learning is similar to the concept of operant conditioning in psychology, where a task is either performed correctly or incorrectly, and subsequent learning results from labeling outcomes as a success or mistake [5]. Application of this type of machine learning has been demonstrated in a rapidly adapting system developed for anesthetic control based on patient vital signs. Such a system has controlled propofol infusion rates by constantly monitoring and adjusting medication to maintain a target range of patient bispectral index and mean arterial pressure [5]. Real-time adjustment and encoding of patient characteristics to produce optimal variation in therapeutics pose potential benefits in many areas of medicine.

Deep learning is another AI technology that enables the network to learn without human intervention [1]. Deep learning deciphers higher-level information from raw input data by using layers of neural network algorithms [1]. In image-recognition systems, for example, one layer identifies features like sharp edges or light contrasts in photos, another layer identifies shapes, and a third layer determines what the image shows [1]. This layering technique allows for the prompt integration of multiple evaluation modalities to generate accurate results. Traditional AI computer systems lacked the ability to adapt, learn, or self-correct. However, with the introduction of machine learning, these systems can improve accuracy over time by analyzing larger data sets and adapting to mistakes, as in the example of successful differentiation between two similarly appearing skin lesions by AI technology [1]. Other AI studies have demonstrated high accuracy, sensitivity, and specificity rates in identifying lesions by adapting specific frequency settings on consumer-level images, suggesting the potential for broad use among practitioners [1]. With the myriad of contributors to skin aging such as UVR, environmental exposures, immune and biochemical homeostasis, machine learning holds vast potential in its application to this area of dermatological care [8].

3. Artificial Intelligence in Dermatology

With the emergence of AI utilization in many fields in medicine, attention has turned towards dermatology, specifically as a field with both vast medical and cosmetic potential for its use. AI systems can be trained to utilize large data quantities of skin images to develop diagnostic capabilities in dermatology. Multiple studies conducted on AI evaluation of smartphone, dermoscopic, or histopathologic images have shown that AI can diagnose certain skin conditions with accuracy comparable to experienced dermatologists [1]. With this capability, AI could assist clinicians in differentiating between benign and malignant pigmented skin lesions or diagnosing non-melanotic skin cancer [1]. This technology has yet to be adapted to and adopted in a real-world setting, but as AI systems become more polished, they could be used in the clinical diagnostic realm [1].

On the clinical side, AI has been proposed to improve clinical decision-making for non-dermatologic physicians and providers. For example, Du-Harpur et al. suggested the use of AI as an aid for physicians who are not dermatologists to assist in the risk-stratification of skin lesions to make assist with clinical decisions [9]. Currently, there are few dermatological diagnostic decision aids available as the process of lesion diagnosis is often visually based by pattern recognition that dermatologists are specifically trained in. With the use of AI, convolutional neural networks could assist non-dermatologist physicians with lesion triage to make recommendations on the possibility of a lesion being malignant. These recommendations include guidance on whether to reassure the patient, refer routinely to a dermatologist, or refer urgently to a dermatologist [9].

A 2021 systematic review evaluated 19 artificial intelligence-based skin cancer classifiers and found that these systems showed superior or equivalent performance compared to clinicians [10]. These consisted of AI's related to dermoscopic images (n = 11), clinical images (n = 6), and histopathological whole slide images (n = 2) [10]. One included an algorithm to discriminated between malignant melanoma and melanocytic nevi, becoming the most comprehensive binary dermoscopic reader study to date [11]. In comparison of management decisions based upon test images, the neural network outperformed 136 of 157 dermatologists across various experience levels [11]. In follow up studies with increased difficulty of the test set, neural network classification was significantly superior to junior and board-certified dermatologists for the first time [12]. Multiple other studies also demonstrated superior performance of AI systems in comparison to dermatologists in the differentiation of benign vs malignant lesions [13-15]. While the results from this review are impactful, it was noted that many of the studies were conducted in an experimental setting based on single images alone of lesions with no other clinical correlations [10].

Further, A notable limitation in dermatologic AI is the restriction of image evaluation to two dimensions when evaluating three-dimensional skin texture [1]. Skin curvature often results in uneven illumination in imaging that causes variability and lack of image standardization [1]. Many factors contribute to an image, such as zoom, lighting, angles, and clarity, which may alter the perception of artificial intelligence algorithms when attempting to identify skin pathologies or aging changes. Researchers have attempted to reduce uneven illumination by recognizing that pigmented skin lesions are in the high spatial frequency components of an image. In contrast, uneven illumination is in an image's low spatial frequency component [1, 16]. Thus, they designed a network to remove low spatial frequency components to correct for uneven illumination to improve accuracy in the diagnosis of benign vs. malignant lesions. Moreover, this study achieved 86% accuracy, 94% sensitivity, and 68% specificity [1, 16]. In the determination of skin aging progression, similar modalities could be designed to focus algorithmic monitoring in areas of the skin most affected by skin aging processes to eliminate interference by areas less susceptible to skin aging. In 2018, the Antera 3D model was evaluated for suitability in assessing skin pores [17]. Mean pore volume, area, and maximum depth were found to be repeatable parameters and the system was verified as a reliable tool, creating a promising development from two-dimensional analysis [17].

Factors to consider when assessing the feasibility of complex neural networks and AI systems include the financial capability of clinical entities. A malignant melanoma detection system developed by Ningrum et al. successfully ran an AI model using dermoscopic images on a medium class computer without the need for cloud computing [18]. Compared to previous studies, high computational computers were not needed to generate similar success related to malignant lesion identification [19-24]. Their aim was to create a system suitable for deployment on devices with limited resources, thus making AI attainable for a broader clinician population. Stiff et al. recently proposed real-life application of AI use in a clinical setting. In reviewing numerous AI systems and their application to melanoma diagnosis, they characterized AI has an adjuvant to clinical practitioners, not a replacement [25]. They support AI's potential to augment medical decision making and access to medical care, in combination with the value that a provider brings in terms of diagnosis, patient confidant, and counsellor. Perhaps this increased access could be utilized in primary care settings in underserved areas with little access to dermatological care.

In addition to purely diagnostic functions, AI has also begun to aid in management of skin conditions [3]. For example, the PROVEN Beauty quiz (https://www.provenskincare.com/) asks consumers questions about their skin, including age, skin type, concerns such as fine lines and wrinkles, topical prescription use, ethnic background, and lifestyle practices such as diet, exercise, water intake, and geographical location. This information is then linked to a database called the Beauty Genome Project. This project possesses a database of more than eight million customer reviews, over 100,000 skin care products with 20,000 ingredients, and over 4000 published articles related to skincare ingredients. An algorithm is generated based on the consumer information and the database to develop a customized skin care regimen for the quiz taker based on their answers. The algorithm can generate 527 unique routine combinations based on recommendations, including cleansers, moisturizers with SPF protection, and night creams.

The use of AI in recognition and management of dermatologic conditions is on the horizon for real-world application. AI is becoming more widely accepted in its role of improving physician practice rather than serving as a substitute for provider knowledge and capability [26]. A 2022 web-based survey study reported that AI can improve the overall accuracy of dermatologists in image discrimination of malignant lesions. Clinicians may integrate their own knowledge related to patient age and past medical history to provide optimal patient care [26]. A recent cross-sectional study aimed to assess dermatologic provider attitudes towards the implementation of AI in their clinical practice [27]. Overall, respondents were generally positive in embracing AI and the top three areas thought to be most promising included malignant lesion identification, benign lesion identification, and pigmentation disorders [27]. While many studies have emerged in recent years related to diagnostic lesion classification, the use of AI for skin aging evaluation and intervention has not been explored as extensively.

4. Application of Artificial Intelligence in Skin Aging Evaluation

Skin aging is a complex process involving changes on both the macro and microscopic levels [3]. Changes occur on the molecular level, with alterations in skin DNA methylation (DNAm) relating to skin aging [28]. AI has been used to evaluate the degree of skin aging concerning DNAm. On the macroscopic level, AI can process facial features to estimate patient age. Large sets of facial imaging datasets allow AI to identify certain characteristics among aging patients and connect them with patient age. Difficulties behind discerning the physiology of the aging process include complex processes involving different aging mechanisms of facial tissues, skin, fat, muscles, and bones that vary from person to person. For example, Sajid et al. detected facial asymmetry correlation in age-grouped subjects and used this information to improve facial recognition. They determined that deeply learned asymmetrical features have more discriminative results compared to existing methods. This study additionally found that integrating knowledge from age estimation with a proposed facial recognition algorithm considerably boosts face image recognition accuracy [29].

Similarly, Bobrov et al. created a novel system that predicts a subject's age with a mean error of 2.3 years using imaging of the subject's eye corners called the PhotoAgeClock [30]. Machine learning has been utilized in aging to generate multiple age predictors frequently referred to as the "aging clocks" based on the rationale that estimation of biological age gives insight into the physiological state of an organism [30]. The practicality of this AI intervention serves as a reliable, non-invasive tool for assessing visual biomarkers of skin aging and gives valuable insight into the state of the human body and health [30]. With this information, evaluating skin aging processes will become individualized, allowing for the development of unique management strategies to restore skin health and homeostasis.

Skin imaging analysis studies have even compared two commercially available image analysis softwares. In a study by Wang et al, VISIA® from Canfield and IPP® from Media Cybernetics were found to have acceptable correlation in measuring various skin conditions such as skin spots, wrinkles, vascular features, porphyrin, and pore size on the forehead, cheek, and periorbital skin areas [31].

Additionally, a recent study validated a facial analysis system aimed at recognizing skin aging characteristics among photos of users such as, wrinkles, moisture, eyelid drooping, dark circles, and skin firmness [32]. Then, smart devices such as iPads and iPhones utilized an application to analyze the images. The application had excellent test-retest probability and was found to be adaptable in many situations with variable lighting, background, skin types, ages, and genders. In comparison to physicians, agreement by the application was reached in 69% of rankings. They remark that previously developed devices for skin analysis are costly and are most commonly used in dermatologic clinical and research settings [32, 33]. However, this system allows broad user access in the form of a smartphone application with low cost to the user.

AI can similarly analyze the skin to help guide treatment. With more sophisticated imaging systems, algorithms have been designed to detect fine wrinkles by the specific localization of subtle textural variations in the skin [3, 34-36]. Studies have also used deep learning models to classify patients regarding wrinkle severity and even evaluate two photos of the same person to label their skin aging process as static or dynamic. This information is then used to make recommendations for cosmetic interventions such as the use of specific facial fillers and techniques for optimal management that is personalized to the subject [3, 37]. There exist few platforms to measure dermatologic conditions on established scales actively. However, Yoelin et al recently developed two novel AI algorithms that utilize a validated facial wrinkle scale for the glabellar region of the forehead to accurately rate the severity of rhytids [38]. With further validated scales, the consumer market for anti-aging algorithms prompts interest.

Another important realm of the evaluation of aging is on the molecular level, specifically with methylated DNA (DNAm). Horvath found that the measurement of DNAm in cells reflects the molecular age of tissues, showing different ages of tissues within the same organism [39]. The development of a multi-tissue predictor of age allows the measurement of the cumulative effects of an epigenetic maintenance system [39]. This novel epigenetic clock poses future use as a laboratory assay to detect skin aging across multiple samples from a single patient. The study of DNAm age across many different tissues and cell types has shown it correlates not only with patient chronologic age, but also with external factors such as infection and inflammation [28].

Identifying environmental factors contributing to skin aging could also open a realm of preventative and therapeutic measures in the context of AI. While photoaging by UV radiation is one of the primary mechanisms attributed to skin aging, other deleterious exposures might contribute to skin aging pathogenesis [40]. On the molecular level, the skin holds many functions such as its ability to act as a barrier via the immune system and complex extracellular matrix that degrades with skin aging [40]. Additionally, the skin's role as a thermoregulator dissipates over time with the loss of eccrine sweat glands and cutaneous vascular function, which comorbid medical conditions might contribute to skin aging [40]. Furthermore, DNAm age is correlated with mortality risk, showing it could play a role in determining health status [28]. With these findings across multiple tissue types, the methylated skin age might give insight into the homeostasis of other internal organ systems and tissues. With the multifactorial nature of skin aging, AI has the potential to be utilized in identifying prominent contributors to these processes. Perhaps more extensive studies could generate AI algorithms to identify common skin molecular markers in a range of aging patients to identify and predict aging status.

Due to the variability of DNA methylation seen among certain disease states and accumulation of UVR or other environmental exposures, chronologic age might not be a reliable indicator of skin aging molecularly [39]. Using machine learning on DNAm datasets, Boroni et al. developed an algorithm specifically for skin DNAm age. This algorithm could detect DNAm age differences in skin disease conditions such as actinic keratosis and squamous cell carcinoma, which had lower DNAm ages than healthy skin [28]. The algorithm could also detect the decreased skin age of fresh skin biopsies treated with the known senomorphic agent Rapamycin [28]. The use of DNAm age measurement using AI could aid in assessing skin age and health as well as measuring the therapeutic or damaging effects of treatment. It was additionally found that methylation patterns differ and become more heterogenous between individuals with the advancement of age, contradicting previously held beliefs that the process of aging is similar in all people [28, 41]. With these findings, it is further elucidated that skin aging is a process unique to each individual and should not be generalized. Thus, the need for individualized skin aging detection and management systems arises to discover beneficial therapeutics specific to certain patient cohorts and demographics.

An area of dermatology that has gained attention in recent decades is skin of color. Often, topics regarding the aging of skin operate under the assumption that the molecular and biological composition of skin does not vary based on race, ethnicity, or genetic origin [42]. It is widely recognized that other dermatologic conditions carry predispositions based on race due to genetic factors [43]. Skin aging should be met with the same context because although all humans are subject to this degenerative process, people of different demographics will possess variability in skin aging that warrants sufficient investigation and consideration.

Gender differences can also account for variability in skin aging. Estrogen has a profound effect on skin physiology, promoting skin thickness, wound healing, collagen generation, and keratinocyte production in women experiencing normal to high rates of estrogen production [44]. Postmenopausal women experience skin dryness, decreased elasticity, increased rapidity of wrinkling, and aging [44]. Thus, artificial intelligence algorithms should be developed in the context of gender when applied to skin aging for optimal reliability.

Ethnic differences in skin properties also contribute to skin aging. African American skin is reported to have a greater thickness, number of cell layers, lipid content, sebum production, melanosome size, distribution, and induction than Caucasians. Midface aging is implicated especially in African Americans by increased laxity of the eyelids, ocular proptosis, and descent of malar fat pads causing infraorbital shadowing that is often burdensome to this population [44]. Additionally, Asian skin is thought to have more water and ceramide content than African American and Caucasian skin, and photoaging is manifested as pigmentary changes with greater intensity than in other racial populations [44]. These differences become apparent during the skin aging process, a concept that should not be discredited during future AI developments.

With the historical lack of diversified clinical images and diagnostic tools for skin conditions in skin of color populations, Rezk et al. are in the development process of an AI-based skin cancer detection system, specifically for underrepresented skin tones [45]. Their model aims to improve the generalizability of skin cancer detection and assist physicians and general practitioners in evaluating skin lesion severity and triage [45]. Similar systems are warranted in the context of skin aging in diverse populations that incorporate biological skin aging data with demographic data to account for age, gender, and ethnical group classifications. With AI systems that attempt to estimate ages based on images, it has been observed that estimation accuracy decreases with age progression due to factors such as gender, ethnical group, stress levels, eating, and sleeping habits [29]. Limitations in these models exist because skin pigment may be detected without the additional knowledge of racial and ethnic background in evaluating skin age.

Ultimately, cultural considerations for patient outcomes are widely lacking regarding medical interventions to combat skin aging in diverse populations. Thus, future AI interventions must account for demographic characteristics in their databases in order to render accurate and encompassing results for patients of different backgrounds, genders, and races. Skin aging prevention and treatment pose the most success for individual patients if AI has the ability to generate beneficial recommendations in the context of demographic and genetic factors. Perhaps an optimal AI system is complex in nature and can integrate patient images adjunct to demographic information, personal medical history, and molecular assay analysis to provide a holistic approach to the aging process.

5. Application of Artificial Intelligence in Skin Aging Management

AI networks can be used to identify targets for skin aging treatments. While the literature has numerous examples of the use of AI for skin aging detection and subsequent recommendations of products, there is little reported on the role AI could play in the future of developing skin aging therapeutics. Many influential factors contribute to the dysregulation of cutaneous homeostasis and skin aging, such as UVR exposure, skin health maintenance, chemical exposures, biomechanical alterations in the skin, and immune surveillance [8]. Combinations of these factors vary from individual to individual, warranting the exploration of AI in this area as a means for regaining homeostasis of the skin with specific interventions and therapeutics. For example, using a neural network system with a large database, Yeh et al. processed information regarding protein-protein interaction, gene regulation, and human skin gene expression data to identify possible pathways and biomarkers of skin aging [46]. Using drug-target interaction data, they also proposed two drug treatments based on the identified biomarkers, one for young adulthood to middle age and another for middle age to old age [46].

With increasing knowledge of processes contributing to skin aging and AI systems developed to detect skin aging processes in individuals, therapeutic AI systems can provide unique treatment options. Kennedy et al. also used AI to analyze known peptide effects on the extracellular matrix to identify a candidate peptide for anti-aging found in the pea proteome [47]. They verified the approach by testing the peptide, and a month of treatment resulted in anti-wrinkle and collagen stimulatory effects as demonstrated by increased collagen and elastin expression as well as decreased average roughness in a patient’s skin [47]. Ozols et al. took a different approach and developed a neural network to predict cleavage sites on proteins for various cutaneous proteases [48]. They combined the results with the ultraviolet radiation (UVR) susceptibility of proteins, determined by amino acid composition [48]. They found that fibrillar collagens were likely only susceptible to proteases, while elastic fibers were susceptible to both UVR and proteases [48]. The development of this proteome susceptibility calculator has the potential to identify targets of protein and osmotic damage in skin aging that can be opposed by the development of therapeutics to target these pathways. Future AI interventions can help identify both targets for potential anti-aging treatment as well as vulnerabilities of relevant proteins susceptible to damage within the skin. The multiplicity of factors contributing to skin aging makes the identification of a single, efficacious therapeutic very difficult. However, with AI's ability to delineate pathways that most contribute to skin aging pathogenesis, the advancement of novel therapeutics can arise.

Skin microbiome and aging is an emerging field. Carrieri et al. used machine learning with cutaneous microbiome data from healthy skin samples to create a system that predicts skin characteristics such as skin hydration and age [49]. Further, the system attempts to explain its characteristic predictions by showing the microbiome variations that resulted in the prediction [49]. Establishing links between microbiome alteration and cutaneous manifestations could aid in developing microbiome-based therapeutics in skin aging.

The ability of AI to judge aging via skin imaging could aid in determining the effectiveness of anti-aging treatments. A particular study found that a deep learning AI system using smartphone camera images was able to grade the results of a 1-month anti-aging treatment in a manner comparable to patient self-assessments [50]. A popular skin anti-aging product was tested for efficacy defined subjectively by the user as well as by an automatic, AI-based system. A photo was taken of the user for 28 consecutive days, and final results were compared to subjective findings of self-perceived facial signs, and global agreement was reached [50]. Such a system could provide a standardized evaluation of skin aging treatment efficacy for numerous products, revolutionizing the consumer market of skin aging products.

Augmented reality applications take this concept a step further with the incorporation of photo and video imaging software. Vichy Skin Consult is another AI website with the capability of using consumer images and videos to detect, quantify, and predict skin appearances using its “virtual mirror” application [3]. Developed with dermatologists and skin aging atlases, the AI can detect conditions like dyschromia, dryness, and fine wrinkles [3]. Recommendations are then generated based on focused areas of improvement, such as infraorbital lines, elasticity, deep rhytides, lack of radiance, hyperpigmentation, and pores [3]. Neutrogena also offers their Skin360 application for mobile device cameras to evaluate dark spots, under-eye circles, wrinkles, textural changes, and fine lines to generate a “Skin360” score. Based on these five categories, the user is given suggestions for products and the ability to track improvement with product use visually over days, weeks, and months to provide follow-up skin evaluations. Additionally, the app provides options for lifestyle habit tracking that influence skin health, such as diet, sleep, exercise, and stress [3]. A summary of AI interventions relating to skin aging can be found in Table 1. The use of AI for skin aging management can be utilized both by developing target pathways for therapeutics and in individualizing skin evaluation techniques via photos to generate unique therapeutic combinations specific to the user.

Table 1 Examples of skin aging AI interventions.

Author	Year	Purpose of AI Use	AI Intervention
Elder et al.	2020	Management	PROVEN beauty quiz adjunct to Beauty Genome Project database to generate recommendations for consumer specific products based on quiz answers
Sajid et al.	2018	Skin aging analysis	Recognition of images based on age group estimations adjunct to deep learning measures of asymmetric facial dimensions to estimate age of a given image
Bobrov et al.	2018	Skin aging analysis	Use of “aging clocks” to predict a subject’s age based on high resolution images of eye corners to give insight to one’s health
Hovarth	2013	Tissue aging analysis	The use of DNA methylation array datasets to predict age of tissues in the development of epigenetic clock evaluators
Yeh et al	2021	Therapeutic Development	Identification of target pathways and biomarkers in skin aging for potential drug development in two aging groups

Kennedy et al.	2020	Therapeutic Development	Evaluation of a peptide's effects on reduction of wrinkles by increased collagen and elastin expression to identify therapeutic targets
Ozols et al	2021	Therapeutic Development	Identification of novel therapeutic target pathways with the prediction of protease cleavage sites mediating skin aging damage
Carrieri et al	2021	Therapeutic Development	Detect changes in skin microbiome composition to target pathways of skin aging
Flament et al.	2021	Aging product efficacy	Monitor efficacy of anti-aging products with consecutive photos of skin to assess for improvement in facial signs of aging
Elder et al.	2020	Management	Augmented reality application of user images to predict skin changes and recommend products in focused target areas of skin aging
Elder et al.	2020	Management	Camera mobile device application to generate a score based on five categories and suggest products as well as track progress with product use over time

6. Conclusion

Artificial intelligence possesses a wide variety of potential applications in medicine, especially in dermatology. AI systems are being studied for usage in the diagnostics and evaluation as well as the management and therapeutics of skin aging. It has been used to determine skin chronologic and molecular age to success, which can help assess health status or treatment effectiveness. AI has also facilitated in the identification of skin aging biomarkers and even potential treatments, expanding the possibilities for management. Using multiple variables contributing to skin aging, such as demographics and genetic backgrounds, in association with visual AI evaluation of aging, will generate the future of skin aging prediction and management. As it is further developed, AI technology can significantly improve our understanding and treatment of skin aging in its ability to process large quantities of information generated from various types of machine learning to generate algorithms applicable to individuals and groups. AI has the potential for the use of multiple machine learning systems in evaluation, management, and therapeutic development regarding skin aging.

Author Contributions

Dr. NY was responsible for project development. Ms. VJ, Mr. MC and MS wrote the draft of the manuscript. Ms. VJ and Dr. NY were responsible for final editing of the manuscript.

Competing Interests

The authors have declared that no competing interests exist.

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