IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 18 May 2023, accepted 3 July 2023, date of publication 13 July 2023, date of current version 19 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3295001

SURVEY

Artificial Intelligence in Cosmetic Dermatology: A Systematic Literature Review

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This work was supported by the Specific League Funds from Mahidol University.

ABSTRACT Over the last ten years, the field of dermatology has experienced significant advancements through the utilization of artificial intelligence (AI) technologies. The adoption of such technologies is multifaceted, encompassing tasks such as screening, diagnosis, treatment, and prediction of treatment outcomes. The majority of prior systematic reviews in this domain were centered on medical dermatology, with the aim of detecting and managing serious skin diseases such as skin cancer. However, the adoption of AI in cosmetic dermatology, which focuses on improving skin conditions for cosmetic purposes, has not been comprehensively reviewed. Therefore, the objective of this systematic review article is to analyze the existing and recent research revolving around applications of AI in the field of cosmetic dermatology. The study encompasses articles published between 2018 and 2023, where a total of 63 publications are deemed relevant based on the established inclusion criteria, divided into five categories based on utilization domains, namely cosmetic product development, skin assessment, skin condition diagnosis, treatment recommendation, and treatment outcome prediction. This systematic review article provides not only valuable insights for researchers interested in exploring new research areas related to aesthetic medicine but also applicable guidance for practitioners seeking to implement AI technologies to address real-world challenges in cosmetic services.

INDEX TERMS Artificial intelligence, machine learning, deep learning, computer vision, cosmetic dermatology, sensitization testing, skin condition diagnosis, skin assessment, treatment recommendation.

I. INTRODUCTION

Dermatology is a medical subspecialty that focuses on the scientific investigation, diagnosis, treatment, and prevention of disorders affecting the integumentary system, including skin, hair, and nails. Dermatological conditions are varied in terms of causes, severity, and symptoms [1]. Despite the fact that dermatological disorders have been a longstanding concern for humans, it was only in the 18th and 19th centuries that skin disorders were investigated through a broader medical lens. The progress of dermatology during that period was concurrent with the advancements made in the field of science. The field of dermatology experienced a significant surge in growth subsequent to the scientific revolution of the 19th century and has continued to undergo further development in the present day [2].

Artificial intelligence (AI) pertains to the emulation of human intelligence in machines that are programmed to simulate human thought processes and behaviors [3]. AI technologies have been adopted in medicine to assist repetitive tasks that rely on human experts, such as screening, diagnosis, treatment, and analyses in epidemiology [4]. Machine learning (ML) is a subfield of AI that involves the development of algorithms and statistical models that enable machines to learn from data without being explicitly programmed. In essence, it emulates the cognitive processes of human learning by utilizing experiential data to inform decision-making. The task can be executed under the supervision of an expert, in a semi-supervised manner, or without any supervision (i.e., unsupervised learning). Recently, the progress in computational hardware technologies has played

The associate editor coordinating the review of this manuscript and approving it for publication was Nikhil Padhi.

a significant role in the emergence of deep learning (DL) as a subfield of machine learning (ML) [5]. DL utilizes deep neural network architectures to automatically extract features from input data, thereby foregoing the traditional domain-expert-dependent feature engineering processes [6]. Numerous studies have indicated that DL exhibits superior performance in the field of medicine [7], [8], specifically in dermatology [9], [10] when compared to traditional ML methods. However, compensating for the absence of guided feature engineering processes, the superior accuracy of deep learning is contingent upon the extensive scale of the underlying training datasets [11]. Consequently, it is crucial that deep learning algorithms possess the ability to comprehend patterns in disparate data derived from diverse sources and formats. This is essential not only to guarantee the availability of adequate training data but also to enable the algorithms to capture the wide variety of diseases that afflict patients from different geographical regions and backgrounds [12].

According to Borade and Kalbande [13], a significant number of dermatologists have relied on conventional diagnostic techniques in the past, which can be laborious and time-consuming. In addition, the field of skincare demands a high level of precision and expertise from many professions, necessitating specialized knowledge and abilities. For instance, certain dermatological conditions may present with a similar appearance, posing a challenge for even experts in their classification. The aforementioned issues necessitate the utilization of automated procedures that possess the ability to furnish dermatologists and relevant healthcare professionals with the requisite information necessary for their decision-making processes. The current trend indicates a significant rise in the adoption of AI and ML methodologies within the dermatology domain, owing to the vast accumulation of medical data. These technologies have been utilized as an assistant to dermatologists for various tasks such as disease diagnosis, evaluation of the severity of conditions, and development of treatment recommendations [14]. Certain studies even discovered that AI algorithms exhibit a high level of accuracy when functioning as clinical assistants, and in certain cases, their accuracy surpassed that of human dermatologists [15].

Common obstacles encountered in the field of dermatology often involve decision-making processes that entail skin or hair pictures, which are frequently presented as computer vision tasks that can be addressed by ML techniques. ML approaches utilized in dermatology have the ability to acquire knowledge from various types of image data, including clinical, dermoscopic, histopathological, and self-captured images. Such ability to intelligently process and extract useful information from patient or specimen images has proved useful not only for clinical dermatology but also teledermatology [16], where consultant sessions are performed remotely and online. The proliferation of teledermatology and self-assessment via smartphone applications can be attributed to the restricted availability of dermatologists and advanced healthcare services [17]. Furthermore, the exigencies of the COVID-19 pandemic served as a catalyst for the expedited implementation of teledermatology, where the utilization of online dermatological consulting was observed to emerge as a viable solution during the period of social distancing [18].

Considerable research has been carried out regarding the utilization of AI within the realm of dermatological disorders. The majority of prior studies have utilized AI in medical dermatology, specifically in the context of diagnosing and treating dermatological diseases that, if left untreated, may have detrimental effects on patients' well-being or even result in mortality [19]. Therefore, several review articles have focused on the utilization of AI and ML methodologies to address challenges in medical dermatology. For instance, Wells et al [20] examined the utilization of AI in dermatopathology. Furthermore, Zhang et al. [21] and Mosquera-Zamudio et al. [22] conducted a systematic review of scholarly articles that explore the use of DL to analyze melanoma images. Recently, Jeong et al. [23] analyzed the research trends, findings, and constraints pertaining to applying DL in medical dermatology.

Cosmetic dermatology is distinct from medical dermatology in that it focuses on addressing skin conditions that are not attributable to illness, including but not limited to wrinkles, age spots, acne, freckles, and melasma [24]. Although non-fatal and not posing a direct threat to a patient's physical health, these beauty-related dermatological conditions may have psychological implications for individuals, including diminished self-esteem and confidence, as well as enduring adverse long-term mental effects [25]. In recent years, research in cosmetic dermatology has also integrated AI and ML techniques to aid dermatologists in the diagnosis [26], [27] and prescription of treatment [28], as well as enhancing cosmetic product development [29] and engaging with potential consumer bases [30]. However, to our knowledge, there has been no systematic review, synthesis, or consolidation of research on the applications of AI and ML in cosmetic dermatology. Hence, the objective of this article is to employ the standard methodology of systematic literature review [31] to collect and compile recent and relevant research that pertains to utilizing AI technologies in tackling challenging issues in cosmetic dermatology, with the aim of bridging the aforementioned contribution gap.

The contribution of this systematic review is to examine the utilization of AI and ML techniques in cosmetic dermatology research, encompassing the entire spectrum of dermatological procedures, including the upstream development of cosmetic products, middle-stream diagnosis and treatment activities carried out by dermatologists, and downstream aspects focusing on ensuring customer satisfaction. The subsequent sections of this review paper are structured as follows. Section II explains the review methodology, which entails the specification of the search terms used to query scholarly documents, research questions, and inclusion and exclusion criteria. Section III provides a comprehensive representation of the chosen papers from various demographic angles. Section IV comparatively discusses the chosen papers, which are divided into categories based on the different stages in cosmetic dermatological services. Section V sheds light on the relevant potential future challenges and research topics. Finally, Section VI concludes this systematic review article.

II. REVIEW METHODOLOGY

This systematic literature review uses a methodology that follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [32]. Specifically, the research questions are first established. Then, a search strategy is determined, including the selection of databases and search keywords and filtering keyword-matched papers using inclusion and exclusion criteria. Finally, all selected articles are analyzed on their objective, techniques, strengths, and limitation. Pertaining to recent literature on AI applications in cosmetic dermatology, three research questions are raised:

(Q1) What are the specific tasks in cosmetic dermatology where AI approaches are employed?

(Q2) What AI methodologies are employed within the cosmetic dermatology domain?

(Q3) How well does AI demonstrate proficiency in tasks related to cosmetic dermatology? Could AI effectively aid dermatologists in their diagnosis and treatment procedures, as well as reduce human involvement in non-clinical cosmetic tasks?

A. SEARCH STRATEGY

We used the SCOPUS, IEEE Xplore, and PubMed databases as our resources. The following query is used to retrieve the initial set of papers:

(dermatology OR skin) AND (cosmetic)
AND (artificial intelligence OR machine learning
OR deep learning)

Duplicated and non-English papers are removed. Furthermore, papers published before 2018 are removed to retain only recent papers.

B. SELECTION METHOD

Keyword-matched papers from the preceding stage must undergo a manual check for inclusion in further reviewing processes. First, the papers go through a screening process based on their titles, whereby only those papers that are deemed relevant to the fields of AI and dermatology are retained, while those that are not are excluded. The primary objective of the title screening process is to eliminate unrelated papers while maintaining the recall. Nevertheless, the possibility of false positives persists, wherein papers may contain AI and dermatology components but do not specifically pertain to the utilization of computational intelligent technologies in addressing challenges in cosmetic dermatology. Consequently, the remaining papers undergo additional screening based on their abstract content, whereby only those papers that specifically address the applications of AI in cosmetic dermatology are selected for further review. The articles that successfully pass the initial abstract screening procedure are subjected to an in-depth review and comparative analysis.

The scholarly articles reviewed in this study are limited to journal articles and conference proceedings. This review excluded posters, abstracts, extended abstracts, review papers, letters, and preprints. Furthermore, this review encompasses AI utilization in cosmetic dermatology, including not only the diagnosis and treatment procedures but also all aspects pertaining to cosmetic businesses, ranging from the development of cosmetic products and measurement of skin sensitization to the evaluation of customer satisfaction. The scholarly articles being reviewed must necessitate the utilization of either AI or ML in a certain portion of their research addressing challenges in cosmetic dermatology. In this study, AI is not typically attributed to rule-based decision algorithms, classical mathematical models, formulas, or mere statistical techniques. Furthermore, the investigation pertaining to the implementation of AI in the field of clinical or medical dermatology is also deemed ineligible for inclusion. Recall that the differentiation between cosmetic dermatology and medical dermatology is based on the evaluation of the outcome of the symptom. Medical dermatology encompasses conditions that are classified as illnesses or diseases and those that have the potential to cause mortality, such as malignant tumors or cancer. If a medical condition pertains to aesthetics or lacks a direct association with well-being or mortality, such as conditions like acne, wrinkles, melasma, and hair loss, it falls under the category of cosmetic dermatology. To summarize, the exclusion criteria utilized are as follows:

(EC1) not being a full research paper,
(EC2) not related to dermatology,
(EC3) mainly focused on medical dermatology,
(EC3) not using AI approaches in any part of the studies.

III. SELECTION RESULTS

The number of articles in each screening stage is shown in the diagram in Figure 1. This diagram was generated by [33].

The search string was queried on 30 December 2023. Initially, the publications databases returned 937 articles. The 253 papers that were published before 2018 were removed. In the titles and abstracts screening stage, 546 papers that did not meet our inclusion and exclusion criteria were excluded. The full text of all remaining 174 papers was found. After the full texts were screened, we finally obtained 63 articles, which were 49 journal articles and 14 conference papers.

The papers were classified into five categories based on the target tasks in cosmetic dermatology, which AI was applied to address, including the cosmetic product development process, skin assessment, skin condition diagnosis, treatment recommendation, and treatment outcome prediction. The number of papers in each category is shown in Table 1. The number of selected articles in each category by year of publication is shown in Figure 2.

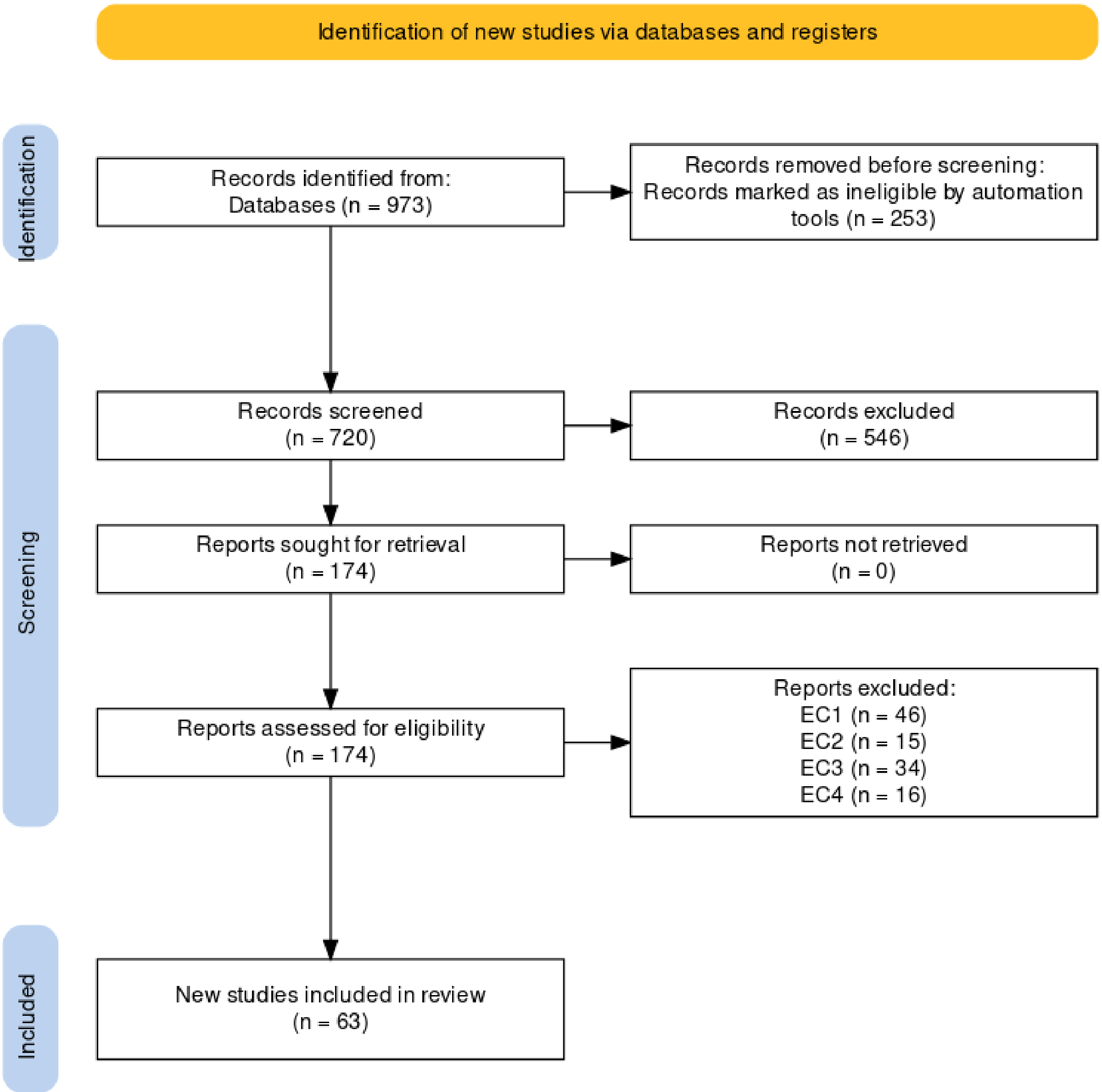

FIGURE 1. The PRISMA flow diagram of the study.

TABLE 1. Number of papers of each category.

	Category	Number of papers
A	Cosmetic Product Development	12
B	Skin Assessment	6
C	Skin Condition Diagnosis	32
D	Treatment Recommendation	4
E	Treatment Outcome Prediction	9

This review article focused on examining and comparing the performance of AI techniques employed in the selected literature. It is noteworthy that the predominant AI methodologies utilized in the field of cosmetic dermatology are those falling under the umbrella of machine learning (ML). As such, the subsequent sections of this review article will be dedicated to expounding upon ML techniques for specificity rather than referring to them as AI in a broader sense. We divided ML into two main classes, including conventional ML and DL approaches. Deep learning (DL) is a ML technique that autonomously extracts and evaluates valuable features from raw data. Conversely, traditional ML necessitates expert proficiency in feature selection and engineering tasks. In addition, research has shown that, with sufficiently large data, DL performance was shown to surpass that of traditional ML in a variety of predictive tasks [34]. However, if the training dataset is small, traditional ML with guided feature engineering was reported to outperform DL [35]. Popular conventional ML methods utilized in cosmetic dermatology research include

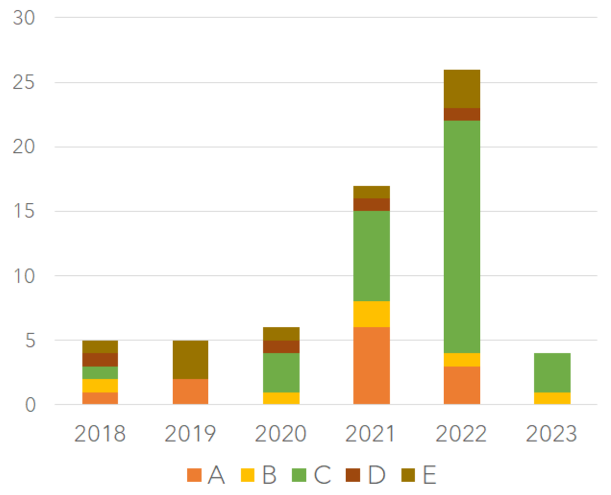

FIGURE 2. Number of papers of each category by year.

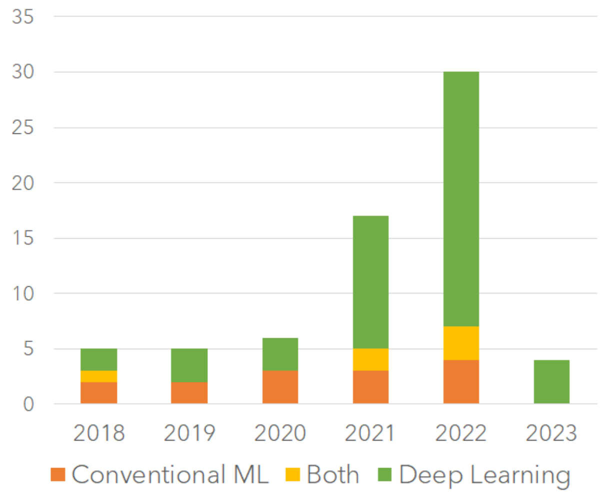

FIGURE 3. Distribution of the numbers of papers utilizing conventional ML, DL, and both by year.

Support Vector Machine (SVM), Discriminative Analysis (DA), Naive Bayes (NB), Decision Trees (DT), k-Nearest Neighbors (kNN), k-Means, Principal Component Analysis (PCA), and Neural Networks (NN). The widely used DL methods are based on Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). In addition, while DL technologies have only recently emerged [5], it is noteworthy that the utilization of deep learning methodologies in cosmetic dermatology has gained significant traction in recent years, as evident from the steep upward trajectory of research publications incorporating DL techniques, as depicted in Figure 3.

Among the 63 articles that were selected, a significant number of them had first authors affiliated with institutions located in Asia. India is the country from which the majority of papers originated, with a total of 11 papers. China, South Korea, and Taiwan follow closely behind with 10, 9, and 6 papers, respectively. Figure 4 illustrates the presentation of papers categorized by country.

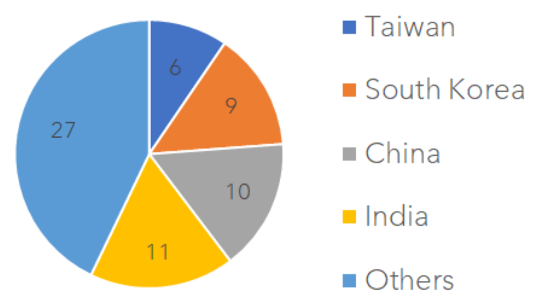

FIGURE 4. Number of papers by country.

IV. ANALYSIS OF REVIEWED PAPERS

This review study involved the comparative analysis of 63 articles, with a focus on the utilization of ML in the field of cosmetic dermatology. The investigation aimed to assess the current state-of-the-art contribution and novelty of such computational intelligent technologies.

A. COSMETIC PRODUCT DEVELOPMENT

Developing cosmetic products is a crucial element in cosmetic dermatology [36]. This process involves three distinct subtasks, namely generating, making, and testing products [37]. During the generation stage, a recipe is formulated based on specific requirements. Then, the developed formulae are created in a laboratory setting. Finally, it is imperative to conduct testing procedures to guarantee the safety and the absence of any adverse consequences. Indeed, recent research has discovered the use of ML to automate and improve the efficiency and efficacy of cosmetic product development processes, as detailed in the following subsections.

1) COSMETICS DEVELOPMENT

Cosmetics development involves both generating formulae and creating actual products for testing. In the generation stage, experts must create new recipes according to the requirements. Normally, this process is carried out manually. In order to streamline this laborious task, Sunkle et al. [37] proposed an integrated automated recommendation system that utilizes a knowledge graph incorporating previous formulation recipes and contextual information. Their method produces a cosmetic formulation template predicated on the input specifications. This approach may be employed to suggest a template to the specialist as an initial reference. Furthermore, Zhang et al. [38] transformed the cosmetic formulation into an optimization problem. All conditions were mathematically expressed as a variable and defined as Mixed-Integer Nonlinear Programming (MINLP) problems. The objective function was defined to be the overall sensorial rating. The optimization problem was numerically solved using generalized disjunctive programming reformulation and model substitution. Linear Regression, Artificial Neural Networks (ANN), and Support Vector Regression (SVR) were employed to predict the sensorial rating. In a recent study, Yeh et al. [39] employed a deep neural network to forecast drug-target interactions based on established relationships. Their proposed method involved narrowing down potential candidates for multi-molecule drugs aimed at mitigating the effects of skin aging in humans. The achieved accuracy of the test was 93%.

2) SENSITIZATION TESTING

In the cosmetics sector, sensitization tests are employed to evaluate the sensitizing potential of chemicals and medical devices on the skin. The aforementioned tests are designed to evaluate the capacity of a given material or product to induce a delayed hypersensitivity response. Traditionally, there are generally four ways to conduct sensitization experiments: *in vivo*, *in vitro*, *in chemico*, and *in silico* [40]. *In vivo* refers to studies carried out inside a living thing, typically an animal, whereas *in vitro* refers to experiments carried out in a lab environment employing cells, tissues, or biological substances outside of a living thing. *In chemico* refers to tests carried out in a lab setting apart from a biological environment. Lastly, *in silico* is testing without any laboratory, the test was done completely by computation, and this is where ML was mostly employed. It is worth noting that the conventional method for testing sensitization through *In vivo* experiments often involves animal testing. This approach can be both financially burdensome [41] and ethically controversial [42]. The ethical implications surrounding cosmetic testing on animals have been a topic of controversy, particularly following the 2013 ban by the European Union on the use of animals for testing cosmetic products and ingredients [43]. Therefore, the ethical concerns and financial pressures associated with animal testing may have a substantial impact on the adoption of ML techniques to optimize skin sensitization testing procedures [44], [45], [46], [47], [48], [49], [50], [51].

Several ML models have been devised to evaluate skin sensitization through well-defined methodologies. However, the primary factor contributing to inaccuracies was the presence of imbalanced data – the number of sensitizers is typically greater than that of non-sensitizers. Li et al. [52] aimed to tackle this problem by applying a data-rebalancing approach before training an SVM model. The best-proposed model for hazard prediction, namely hazard-DA, reached 90.63% accuracy on the test set. For potency prediction, the potency-DA model yielded 68.75% accuracy on the test set. The utilization of Quantitative Structure-Activity Relationship (QSAR) has been widely employed as a means of predicting toxicity through *in silico* methods. The study established a correlation between the chemical composition of a substance and its level of toxicity. Recent studies have reported the use of diverse machine-learning classification algorithms in the QSAR modeling processes [53]. Akturk et al. [54] employed the QSAR model to predict the comedogenic compounds present in cosmetic commodities, which underlie the problem of acne cosmetica. The study examined KStar, Random Forest, and NNge as classification algorithms, and the Random Forest model yielded the most favorable outcomes. The descriptor packages, Mold2 and alvaDesc, modeled with Random Forest yielded satisfactory results with an accuracy of 75.86% and 79.31%.

Instead of using QSAR, Sharma et al. [55] developed a skin sensitization method predicting the allergenicity of chemicals. They employed many classification algorithms, including Logistic Regression (LR), k-Nearest Neighbors (kNNs), Decision Tree (DT), Gaussian Naive Bayes (GNB), XGBoost (XGB), Support Vector Classifier (SVC), and Random Forest (RF). The chemical compounds were obtained from the IEDB database. Features were selected by removing the low variance and highly correlated, redundant features. Finally, a Support Vector Machine classifier with a linear kernel was trained with these dimension-reduced features. The obtained feature set consists of fourteen 2D features, six 3D features, and 22 fingerprint features. For the experiment, Random Forest based model using all features performed the best (accuracy of 83.39%). Wilm et al. [56] highlighted the lack of interpretability associated with utilizing non-intuitive descriptors as features in a model. They introduced a novel compatible model, Skin Doctor CP:Bio, which utilizes a concise set of ten highly interpretable features. Their proposed method, using Random Forest, achieved an efficacy of 82% with a significance level of 0.20. Recently, Jeon et al. [57] used a graph convolutional network in their study to evaluate skin sensitization. This study evaluated the potency and categorized it into three distinct classes based on its strength: strong, weak, and non-sensitizer. The model for assessing hazards, which utilized GCN, KeratinoSens, and h-CLAT features, yielded the most optimal outcomes, exhibiting an accuracy of 88%. However, they found that the model based on potency alone yielded an accuracy of only 64%.

In addition to conducting *in silico* testing, researchers have employed ML algorithms to analyze laboratory results obtained from *in vitro* testing. The Genomic Allergen Rapid Detection (GARD) method was employed as a means of conducting cell-based testing for skin sensitization. The study employed an in vitro model that consistently demonstrated a predictive accuracy of approximately 90% for the classification of the test data. Forreryd et al. [58] provided additional information to the preceding study regarding the classification efficacy by examining a sizable external test dataset comprising 70 observations with Support Vector Machine (SVM). The results indicated an accuracy of 79%. Furthermore, they presented a conformal prediction framework that enables the regulation of the error rate by adjusting the confidence threshold. The findings indicated that their proposed approach achieved an accuracy of 88% using a confidence level of 0.85.

Skin toxicity refers to the capacity of a substance to induce a localized response and/or systemic toxicity upon dermal exposure [59]. The reduction in skin thickness has been identified as a potential indicator of skin toxicity. However, the conventional approach of assessing epidermal layers through manual examination by a pathologist poses challenges in terms of efficiency and scalability. To facilitate such delicate processes, Hu et al. [60] utilized DL and image processing methods to measure the epidermal thickness. The estimation was significantly correlated with a pathologist's semi-quantitative evaluation and mildly agreed with one performed by other pathologists. For toxicity prediction, the method yielded 0.8 sensitivity. Furxhi et al. [61] predicted Nano-Particles *in vitro* toxicity using ML techniques on the Safe and Sustainable Nanotechnology datasets. Eight classifiers in different categories of algorithms were selected. The result showed that Random Forest and Neural Networks performed best among the classifiers chosen for the evaluation. Jun and Shin [62] utilized convolutional neural networks and convolutional long short-term memory (ConvLSTM) to predict the artificial skin images for testing. The evaluation was conducted by comparing the projected images with the real ones in a 3D culture setting.

The reviewed papers in this section emphasize ML algorithms used to predict skin sensitivity and toxicity of cosmetic chemicals, especially in the absence of animal testing. The article discusses different approaches, focused mostly on *in silico* type testing. Since ML algorithms require sufficient and representative data to achieve high accuracy, the lack of these elements could be a huge challenge. Specifically, the lack of datasets and data imbalance were shown to hinder the ML algorithms' ability to learn. Various classification algorithms, both DL and traditional ML ones, were used to validate the hypotheses in the studies. Additionally, ML techniques were also employed to increase the efficacy and efficiency of *in vitro* methods, such as the genomics allergen rapid detection method. These articles reviewed in this section also highlight the requirement for additional studies in order to create precise models that can be used as economical and humane alternatives to animal testing.

B. SKIN ASSESSMENT

The skin assessment task involves assessing primitive skin properties, such as color, oiliness, and hydration, as well as the compatibility between the patient's skin and treatments or products. Individuals undergoing the skin assessment process do not necessarily have unwanted skin conditions but rather seek to better comprehend their skin properties for selecting fitting cosmetic products or treatments. While the traditional skin assessment procedure is carried out by dermatology experts, recent literature has shown that such redundant tasks could be assisted with AI technologies.

Skin hydration is one of the essential characteristics for adjusting a recommended cosmetic treatment or a product suggestion. Chirikhina et al. [63] employed contact capacitive imaging and high-resolution ultrasound imaging techniques to estimate the water content in the skin. The study involved conducting experiments on multiple facial regions, such as the volar forearm, cheek, chin, eye corner, forehead, lips, neck, and nose. The skin Epsilon value was utilized as a reference standard for measuring water content. Several deep learning algorithms were evaluated for the classification of contact capacitive images, including AlexNet, GoogLeNet, VGG16, ResNet-50, InceptionV3, MobileNetV2, DenseNet 201, SqueezeNet, InceptionResNetV2, and Xception. Regardless of the training time, DenseNet201 exhibited the highest level of accuracy. Two novel feature-based techniques were introduced for obtaining high-resolution ultrasound images. First, an analysis was conducted on the color-based features, including the mean, standard deviation, median, and luminosity value of the RGB channels. This analysis used various ML algorithms, namely Logistic Regression, K-Nearest Neighbor (KNN), Neural Networks (NNs), and Random Forest. Second, a texture-oriented approach was employed, utilizing a set of five conventional textural characteristics in conjunction with an additional five outputs derived from single-layer pretrained convolutional networks, which were projected onto a lower dimensional space using principal component analysis (PCA).

Zegour et al. [64] proposed a method for assessing skin hydration levels using High-resolution Magnetic Resonance Imaging (MRI). The T2 sequence data extracted from MRI were utilized as the model features. The segmentation algorithms employed in the study were DenseNet and U-net. The utilization of the Hausdorff distance metric facilitated the comparison between an algorithmic output and a particular variant of human-derived segmentation. The findings indicated that ML techniques yielded hydration assessment that was notably closer to manual expert assessment.

The outermost layer of the skin system, known as the skin barrier, serves as a protective wall that shields the body from external hazards and maintains the body's homeostasis by regulating water loss [65]. A traditional approach to assessing the efficacy of the skin barrier function is estimating transepidermal water loss, which can be time-consuming. To speed up this process, Koseki et al. [66] introduced an ML algorithm that utilizes topological data analysis to forecast skin barrier function by analyzing skin images. Microscopic skin images were utilized to identify the structural characteristics of the skin through the application of topological data analysis. They found a strong correlation between the topological characteristics and the transepidermal water loss.

Borade et al. [67] conducted a study to examine the skin's sebum production and determined whether it exhibits characteristics of oily or dry skin. The experiment involved an examination of SVM, VGG-16, and ResNets in the classification of preprocessed skin images. The findings indicated that ResNets yielded a 98% accuracy, surpassing the performance of the other models. Furthermore, Kothari et al. [68] categorized skin images into four distinct types, namely normal, dry, oily, and combination. A face detection technique based on Multi-Task Cascaded Convolutional Neural Network (MTCNN) was applied to each facial image, which partitioned it into four distinct regions, namely the forehead, left cheek, right cheek, and nose. Subsequently, the Convolutional Neural Network (CNN) was trained to estimate the oiliness level for each image and proceeded to classify them based on their respective types.

Skin thickness is another important integral attribute determining skin composition and function. Measuring the thickness and density of skin layers in individuals poses a significant challenge due to the considerable variability observed across different sites, genders, ages, and regions [69]. The conventional approach to determining thickness involves the extraction of a skin sample through a biopsy, followed by microscopic examination, which is considered to be an invasive procedure [70]. To mitigate this issue, Vyas et al. [71] introduced a technique for estimating skin thickness that is non-invasive. According to the authors, the lack of available true skin thickness data in the past prevented an accurate determination of the estimation method's true accuracy. Nonetheless, the authors were able to obtain the gold standard established by dermatologists and use them to calculate the prediction error directly. Furthermore, the problem of estimating skin thickness using a Lytro camera was addressed by Ko et al. [72], where they proposed a novel approach that incorporates texture information and employs Conditional Generative Adversarial Networks (CGANs) to produce a skin depth map with enhanced precision.

Understanding skin properties such as hydration, thickness, and oily/dry classification is crucial for developing effective cosmetic treatments and product recommendations. The reviewed articles in this section have shown that skin moisture and thickness can be precisely measured by non-invasive imaging methods such as touch capacitive imaging, high-resolution ultrasound imaging, and high-resolution magnetic resonance imaging. These techniques can also be used to precisely classify skin as oily or dry using DL algorithms. Such advancements in AI technologies provided a strong basis for creating treatment plans and the opportunity to create more specialized goods and treatments that cater to the particular demands of different skin types.

C. SKIN CONDITION DIAGNOSIS

In contrast with the skin assessment discussed in the previous section, skin condition diagnosis mainly involves assessing and identifying the types and severity of unwanted cosmetic conditions. Such a process is crucial for predicting effective treatment and management. However, even for expert dermatologists, it could be challenging to diagnose certain conditions based on symptom appearances alone, as numerous skin conditions can present similar features. Addressing this problem, ML approaches can be particularly useful, as they can learn to capture patterns in large datasets and identify relationships that may not be immediately apparent to human dermatologists. In the field of medical dermatology, automated ML-powered disease diagnosis has become applicable, especially in skin cancer detection and classification [73], [74], [75], [76].

Likewise, in cosmetic dermatology, researchers have demonstrated that ML approaches could be used to improve the accuracy and speed of diagnosis, leading to better patient outcomes. Articles in this category were divided into five subcategories: (1) single condition diagnosis, a binary classification problem of determining whether the patient has a particular condition or not; (2) condition classification, a multi-class classification problem of identifying which condition a patient has among the predefined classes of cosmetic conditions; (3) localization, to identify the location and type of the condition; and (4) severity estimation which may involve a regression problem or a multi-class classification problem to grade the level of severity of a specific condition.

1) SINGLE CONDITION DIAGNOSIS

In this subsection, articles that aimed to diagnose specific cosmetic conditions were reviewed. By focusing specifically on the diagnosis of cosmetic conditions, we aimed to explore the current state of research and highlight some of the potential benefits associated with using ML in this context. Previously, computer vision techniques were wildly used to extract properties from lesion images for dermatological disease diagnosis. This problem can be framed as an image classification task where conventional ML models are trained to spot images containing the target skin conditions. Nowadays, convolutional neural networks (CNN) and other DL approaches have become more utilized because of the fact that they generally provide better classification efficacy compared to traditional ML approaches in medical image classification tasks [77].

Huang et al. [78] employed a CNN model based on ResNet-50 to distinguish photos of subjects with rosacea, a chronic inflammatory disease, from other skin conditions. The model yielded 89.8% in accuracy. They also classified rosacea lesions into three subtypes: Erythematotelangiectatic Rosacea (ETR), Phymatous Rosacea (PhR), and Papulopustular Rosacea (PPR). Sameera et al. [79] used CNN to evaluate the probability of the existence of three facial spots, wrinkles, dark spots, and puffy eyes. Their model can simultaneously differentiate these characteristics and exhibit various potential applications, owing to its utilization of specialized convolution and pooling operations, as well as parameter shifting. Consequently, an overall accuracy of 94.11% was achieved. Liu et al. [80] used four DL architectures, namely DenseNet, ResNet, Swin Transformer, and MobileNet, to diagnose images of subjects with and without melasma. The research investigated the effect of different photo-taking modes used by VISIA, a device for measuring a patient's dyschromia from images [81]. Each subject was taken five shots, including Normal, UV Spots, Porphyrins, Brown Spots, and Red Areas modes. The experimental results showed that DenseNet121 performed the best. They also discovered that the Brown Spots mode gave the best performance among all five modes (Accuracy 0.944), and the best combination was Brown Spots together with Normal and UV Spots modes (accuracy 0.974). Aditya et al. [82] diagnosed patients who had symptoms that indicate Alopecia Areata, an autoimmune disorder that causes hair loss in patches on the scalp, by taking images of patients' back heads to create training data for five ML models, including SVM, CNN, KNN, Random Forest, and Gaussian Naive Bayes. CNN was reported to perform best.

In addition to skin images, other various health and histopathological data were utilized as inputs for the classification tasks. Alagić et al. [83] employed an artificial neural network (ANN) to analyze skin health data, which included parameters such as pH value, sebum, and transepidermal water loss. These features were utilized to distinguish individuals who are in good health from those who have skin conditions. The dataset comprises various dermatological conditions such as acne, dry skin, decreased elasticity, and wrinkles. Dubey et al. [84] diagnosed the scalp by performing an optical coherence tomography. This non-invasive imaging technique uses light waves to create high-resolution images of internal tissues and structures. The A-line and B-scan features were extracted from the OCT. Seven models, including classical ML models and neural networks, were used in the pilot experiment. The multilevel ensemble model gave the highest performance using eight features. Jansen et al. [85] diagnosed Seborrheic Keratosis, a type of benign skin condition commonly found in senior patients. The data comprised images of tissue slides from three dermatological research centers. ResNet-34 was used as a classification model. Wang et al. [86] investigated the skin disease from metagenomic sequencing data of acne, which is a kind of lipid in the face skin. The data were analyzed using Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), and Multiset Canonical Correlation Analysis (MCCA). Each method provided information pertaining to lipids that influence the diagnosis results.

To summarize the literature reviewed in this section, the majority of research utilizing AI to identify a single cosmetic skin condition relied on computer vision and ML technologies to train predictive models using annotated historical data. While traditional computer vision methods relied on hand-crafted color and texture features, the advent of DL applications enabled the elimination of the feature engineering process while achieving cutting-edge performance. The single-condition diagnosis research classified skin images into two classes, with a condition or without a condition. One major limitation of this approach is that it needs proper prior information on which condition this patient may have. In fact, some condition is very similar and hard to distinguish by physical observation. Such issues pose challenges for ML models trained specifically for diagnosing particular conditions in that they may be unable to tell apart closely-resemble skin conditions. Furthermore, cosmetic patients may have varied conditions. Therefore, the ability to detect only one condition may not suffice in practice. As a result, these issues behoove the ability to automatically tell apart different types of cosmetic conditions, especially those that appear similar to each other, which will be elaborated on in the next section.

2) CONDITIONS CLASSIFICATION

Identifying various skin conditions can be difficult due to their similar visual presentations. The articles within this particular subcategory examine the utilization of AI in discriminating between similar beauty-related conditions that bear a resemblance to one another. The majority of research presents such issues as multi-class classification tasks, which permit the direct application of traditional and advanced ML-based image classification techniques. The task of classifying skin images into respective skin conditions has been previously accomplished through the utilization of traditional ML techniques, including Support Vector Machines and K-Nearest Neighbor algorithms. For example, Abas et al. [87] employed a methodology wherein RGB facial images featuring acne were transformed into Grayscale, followed by applying an entropy-based filter to isolate the regions of the image that exhibit acne. The segmented image was analyzed, and various features were categorized into six distinct skin conditions, one of which was acne. The experimental investigation involved using Binary Tree, Discriminant Analysis, k-NN, and Naive Bayesian techniques, where an accuracy of 85.5% was attained.

Recently, DL models, especially CNN-based ones, such as AlexNet, GoogleNet, and DenseNet, have been popularized in the medical areas. For example, Yang et al. [88] used DenseNet-96 and ResNet-152 to classify the 12,816 cropped benign and pigmented facial skin lesion photos collected at the Hospital for Skin Diseases of the Chinese Academy of Medical Sciences from 2004 to 2016 into six classes based on their skin conditions, including acquired nevi of Ota, melasma, cafl-au-lait spots, freckles, seborrheic keratoses, and nevi of Ota. The automated classification result was compared with the three expert dermatologists. The results showed that ResNet-152 outperformed the other methods. While these DL algorithms often are accompanied by pre-trained models that can be directly fine-tuned and applied to image classification tasks, recent literature in cosmetic dermatology has found that revising the architectures of these DL algorithms could improve the predictive efficacy. For instance, Huong et al. [89] focused on the problem of limited training data by proposing to ensemble pre-trained CNN with SVM and KNN. The performance of classifying four skin disease classes of transfer-learned AlexNet, AlexNet-SVM, and AlexNet-KNN was evaluated and compared. The modified model outperformed the non-modified one and also reduced the computational time. López-Leyva et al. [90] addressed this problem through the development of a method aimed at classifying ten distinct categories of skin lesions. Their method relied on the Fourier spectral information of images within a color model. The Edinburgh Dermofit Library utilized a 26×1 vector to represent each image, consisting of Fourier spectral indicators that pertain to both the original size image and the cropped version. Subsequently, the vector that was represented was inputted into a Two-Layer Feed-Forward Neural Network (TLFN) with the purpose of accurately categorizing the lesion according to its respective type. Overall, the proposed method exhibited a 99.33% accuracy, 94.16% precision, 92.9% sensitivity, and 99.63% specificity. Jain et al. [91] proposed the Optimal Probability-based Deep Neural Network (OP-DNN) for the purpose of classifying skin images into four distinct categories, namely Basal Cell Carcinoma, Seborrheic Keratosis, Melanoma, and Squamous Cell Carcinoma. The study involved extracting seven distinct color and texture features from each image, namely mean, standard deviation, skewness, contrast, correlation, energy, and extropy. The OP-DNN methodology was designed to expedite the training process of conventional DNNs by leveraging the WOA optimization algorithm instead of refreshing weight values at each cycle. The results indicated that the OP-DNN approach achieved a marginally superior level of accuracy and precision compared to the baseline method while also exhibiting a notable reduction in training time. Ito et al. [92] employed the Google Cloud AutoML technology to classify scar images into four distinct categories, namely immature scar, mature scar, hypertrophic scar, and keloid. The outcomes of the classification were compared with the expert medical judgment. In a recent study conducted by Borade et al. [93], the authors expanded their analysis beyond images in the RGB color space to include three additional color spaces: YUV, YCbCr, and HSV. The study employed five traditional ML techniques, namely Support Vector Machine (SVM), k-Nearest Neighbor (kNN), Naive Bayes (NB), Multilayer Perceptron (MLP), and Random Forest (RF) to categorize images of four distinct dermatological conditions, namely acanthosis nigricans, melasma, alopecia areata, and acne.

Kim and Song [94] identified several limitations associated with the utilization of CNN-based models in the classification of facial skin conditions. These limitations include the challenge of accurately identifying minor skin issues, the need to classify over 20 distinct conditions, the presence of variations within the same condition, the potential for confusion between similar conditions, and the possibility of false segmentation on non-facial regions. The authors proposed effective strategies for overcoming each constraint, and the empirical findings demonstrated a 32.58% higher diagnostic efficacy in comparison to the traditional Convolutional Neural Network (CNN).

Apart from cosmetic skin conditions, Jeong et al. [95] employed the EfficientNet to categorize ten distinct scalp symptoms, namely normal, drying, oily, sensitivity, atopy, seborrheic, trouble, dry dandruff, oily dandruff, and hair loss. Their classification technique formed an integral component of AI-ScalpGrader, which comprised a handheld scalp imaging device, a smartphone application, and a cloud-based administration platform. The system provided accuracy values ranging from 87.3% to 91.3%.

The capacity to categorize skin images into various skin conditions could potentially assist in initial self-diagnosis and could be integrated into a decision support system for dermatologists. However, the ability to precisely identify the location and dimensions of each lesion could offer vital supplementary insights, especially in cases where the lesions are diminutive or consist of diverse skin conditions. For example, some grading systems necessitate the quantification of papules and pustules, which are indicative of inflamed acne, in order to evaluate the corresponding severity levels [96]. It is imperative for automated systems to possess the ability to identify and quantify any and all instances of inflammatory lesions present on a patient's facial image. This issue necessitates a redefinition of the diagnosis task as a lesion detection task that is cognizant of location, type, and size information to provide requisite information at a more granular level.

3) CONDITIONS LOCALIZATION AND DETECTION

The task of diagnosing cosmetic conditions through image classification can pose a challenge due to the presence of extraneous information in the background of the images. In addition, specific therapies for skin conditions that present as isolated, non-adjacent spots necessitate knowledge regarding the precise locations and dimensions of the lesions, which do not accompany the image classification task. The ability to localize and confine the lesions in the input image before performing further analyses could mitigate such issues. Indeed, the process of localizing a condition is a crucial aspect of both diagnosis and the estimation of its severity, as it eliminates extraneous information from the images. The task can be accomplished through the application of conventional image processing methodologies, including edge detection, thresholding, and clustering. Object detection is a more specific task that combines both localization and classification together. This section examines scholarly articles that endeavor to identify cosmetic conditions, beginning with the pure localization approach and progressing to the utilization of object detection methodologies.

The detection of facial wrinkles through automated techniques poses a significant challenge to cosmetic condition detection tasks. Yap et al. [97] conducted a survey on the topic of automated facial wrinkles detection, including various types of research, including handcraft-based image processing techniques, stochastic models, and mathematical filters. The conclusion highlighted that while there has been a notable surge in the application of DL methods for image inpainting, there is a scarcity of research that has specifically explored its potential for addressing facial wrinkles.

Rew et al. [98] utilized the Deeplab-v3+ and Inception-ResNet-v2 models to perform pixel segmentation on skin wrinkles. Then, LightGBM and MP algorithms were employed to enhance the segmentation procedure's efficacy. Their proposed segmentation scheme yielded a mean accuracy of 85.4%, a mean intersection over union of 74.9%, and a mean boundary F1 score of 85.2%, improving over the panoptic-based semantic segmentation method by 1.1%, 6.7%, and 14.8%, respectively. Ismail and Sung [99] introduced a deep-learning framework designed to identify the locations and types of acne lesions and wrinkles in facial and half-body images. Various deep-learning networks, namely the Faster RCNN and the Residual Network, were explored. The convolutional feature map was generated by utilizing 50 layers of a residual neural network to extract the characteristics of the image. The mAP score of the detection model was found to be 47.96%. Shih et al. [100] employed a weakly supervised algorithm to localize the area of Vitiligo to evaluate the treatment system. Specifically, Wood's lamp was utilized to capture and photograph both the impacted and unaffected regions in order to establish a repository of training images. Then, a CNN model was used to perform an initial segmentation of the affected region from large-scale images, such as those of the head and face. Next, physician-validated and authorized images depicting the impacted region were utilized alongside a substantial quantity of images captured by Wood's lamp to enable self-learning and classification. Finally, facial recognition technology was employed to rectify the camera's shooting angle, thereby mitigating image distortion arising from disparate shooting angles.

In addition to detecting skin lesions, Gallucci et al. [101] employed U-Net, an image segmentation technique, to segment and detect hair from images for quantifying hair numbers. Furthermore, they utilized the said method in conjunction with the detection of skin lesions. The experiment involved a comparison between U-net and several other models, namely Lenet-5, VGG-16, ResNet-50, and DenseNet-121. The employment of U-Net yielded the highest correlation with the manual count by experts.

In addition to identifying the location of the lesions, object detection methodologies were also used to classify the localized lesions into respective condition types. Phan et al. [102] designed an LED therapy device that incorporates an automated algorithm for diagnosing acne vulgaris. The proposed model was derived from a modified version of ResNet-50 architecture, which was integrated with YOLO-v2. Once the location of acne was automatically identified on the input self-image, the information will be transmitted to the intelligent LED therapy device for further processing. Wen et al. [103] conducted a comparative analysis of the efficacy of utilizing CNN as the underlying framework for detecting acne vulgaris. A number of object detection algorithms were evaluated, namely MobileNet-v1, YOLO-v4, and Inception-v2. They also implemented an automated severity evaluation tool that was made publicly available through the WeChat application for self-monitoring of acne. In addition to acne detection, Maknuna et al. [104] suggested a scar lesions detection model for the WSI of HE-stained tissue. Mask R-CNN was used to detect scar lesions. Then, ResNet-101 was used as a backbone of the region proposal network. The detected region of interest was fed to the image clustering model, k-Means, to partition the structure and character of the scar.

You Only Look Once (YOLO) [105] has emerged as an efficient object detection algorithm and has also been used for skin condition recognition by framing the problems as object detection tasks. Liao et al. [106] experimented with distinguishing acne, freckle, and wrinkle images with YOLO-v3, YOLO-v4, and with and without Mask R-CNN. The results showed that using Mask R-CNN as a face segmentation algorithm before using YOLO to detect the symptoms performed slightly better than using only the YOLO model. The highest obtained accuracy was 60.38% by using Mask R-CNN and YOLO-v4 with 500 training images. Ding et al. [107] conducted a comparable experiment utilizing YOLO-v4, YOLO-v5, Single-Shot Multi-box Detection (SSD), and Faster R-CNN. As anticipated, YOLO-v5 demonstrated superior performance in all skin conditions, with the exception of melasma, when compared to other methods.

The literature examined in this section presents the diagnosis of cosmetic conditions as a task of localization or object detection. This involves obtaining not only detailed locations of the lesions but also identifying the specific types of conditions. The utilization of lesion localization and object detection techniques enables the advancement of automated skin condition diagnosis to a finer granularity. Automated lesion localization methods have significantly reduced the necessity for a manual cropping process, facilitating streamlined and informed diagnosis.

4) SEVERITY ESTIMATION

In addition to ascertaining a patient's skin condition, it is also crucial to consider its degree of severity. Severity estimation is a technique employed to assess the degree of criticality of a given condition or its level. The ability to acquire this knowledge automatically diminishes the duration of dermatologists' involvement in evaluating the severity of a condition and facilitates the selection of more fitting treatments [108]. The degree of severity can be assessed either through continuous scoring, which poses a regression problem, or through discrete categorization of the condition, ranging from normal to extremely severe [109], [110].

There has been a growing interest in utilizing smartphone-generated selfie images to automatically assess the severity of various skin conditions, owing to their ease of acquisition. However, it should be noted that the accuracy of the estimation may be influenced by factors such as lighting conditions, facial expressions, and individual variations in skin type. To address these particular problems, Jiang et al. [111] conducted an investigation wherein they modified the Convolutional Neural Network (CNN) classifier to a CNN regressor. This allowed them to obtain a score for various skin facial conditions, such as wrinkles, folds, lines, and pores. The dataset utilized in the study comprised a diverse range of age groups spanning from 18 to 80 years old, distinct cohorts including Asian, Caucasian, and African American, and various lighting conditions such as outdoor natural daylight, indoor natural daylight, indoor artificial diffused light, and indoor artificial direct light. Additionally, the dataset contained diverse facial expressions characterized by slight smiles, slight pouts, or disapproval. The obtained scores were compared with the evaluation provided by the proficient evaluator. The findings indicate a lack of complete concurrence between the automated approach and the evaluation of the specialist. However, they do suggest that the outcome was marginally affected by the lighting situation and facial expression.

Subsequently, the aforementioned research team proceeded with the advancement of an automated grading system for facial conditions utilizing self-portrait photographs, where Flament et al. [112] yielded a superior correlation between the automated outcome and the evaluation provided by the expert. In addition, Flament et al. [113] employed an algorithm derived from [111] and [112] to examine images of selfies. A total of 465,587 images of European women and 79,016 images of Chinese women were utilized in the study, where the researchers assessed the severity of nine skin conditions and examined their correlation with the age of the subjects. In a recent study, Flament et al. [114] evaluated the accuracy of grading the severity of various skin conditions using images captured through selfies. The study utilized a sample of 1,041 self-portrait images captured by women in the United States, featuring diverse age ranges, Fitzpatrick skin types, geographical locations, and ancestral backgrounds. The severity of seven facial skin conditions was estimated utilizing algorithms as described in [111] and [112]. The results generated through automation were compared with the severity levels assessed by proficient dermatologists from the United States. The findings of the study indicated a robust correlation between the automated and dermatologist results for five out of seven conditions, namely Forehead wrinkles, Periorbital wrinkles, Nasolabial fold, Ptosis of the lower part of the face, and Diffused redness. On the contrary, there exists a moderate and weak correlation between the pores present on the skin of the cheeks and the darkest skin tones. The findings indicated that neither age nor ancestry exerted any influence on the observed correlations.

In addition to easily obtainable selfie images, ML solutions have been devised to aid in the assessment of severity grading on high-quality images captured by professional cameras. The detection and evaluation of facial wrinkles, pores, and acne were conducted by Seck et al. [115] using the high-resolution 3D surface texture obtained from the light stage. Furthermore, the study conducted by Wang et al. [116] sought to develop a tool for evaluating the severity of acne vulgaris. To achieve this objective, the researchers introduced a convolutional neural network (CNN) model, which they named lightweight Acne-RegNet. This model is capable of accurately categorizing lesions and providing a corresponding severity score. The comparative analysis involved the proposed models and other lightweight deep-learning models such as MobileNet-V3, SENet, EfficientNet-B0, and ghostNet. The Acne-RegNet exhibited superior performance compared to other models, achieving an accuracy of 94.11% on the test dataset. Furthermore, they continued to examine a visual condition that impacts precision. The findings indicated that the utilization of a front-facing camera had a negative impact on the algorithm's efficacy. The study also found that the accuracy was not significantly affected by the device brand or the light conditions, including outdoor, indoor, and flash.

In addition to facial skin conditions, ML techniques were employed to assess the severity of various cosmetic conditions. Wang et al. [117] examined Microtia, a congenital ear malformation, through the utilization of nine CNN-based models, namely AlexNet, Inception-v3, DenseNet-121, ResNet-18, ResNet-50, ResNet-101, ShuffleNet-v2, MobileNet-v2, and MnasNet. The objective was to determine the efficacy of these models in accurately classifying the degree of Microtia based on ear images. The images were assessed and categorized into four distinct levels, namely normal ears, grade I microtia, grade II microtia, and grade III microtia. Man et al. [118] introduced a novel approach, SACN-Net, for assessing the extent of hair damage based on SEM images. The study's findings indicated that SACN-Net outperformed other established CNN-based models, as evidenced by an accuracy rate of 98.38%. Chang et al. [119] proposed the ScalpEye system, a handy scalp hair imaging microscope with a mobile device application that connects to the AI training server. The scalp hair imaging microscope took images, then proceeded to the DL model and reported severity scores for the four common scalp hair symptoms: Dandruff, Folloculitis, Hair Loss, and Oily Har. The reported severity levels are: minor, normal, middle, and high. For the DL model, the authors tried Faster R-CNN Inception-v2, SSD Inception-v2, and Faster R-CNN Inception-ResNet-v2-Atrous. The experimental result showed that Faster R-CNN InceptionResNetV2Atrous was the best algorithm for all four symptoms, with average precision ranging from 97.41% to 99.09%. Still, its training time was significantly higher than the others.

The reviewed papers presented in this section show that deep convolutional neural networks and their variants have emerged as commonly employed algorithms in severity assessment tasks. The experiment on estimating a specific condition's severity involves the implementation and comparison of numerous ML algorithms trained on image datasets whose samples were annotated with appropriate severity levels. The evaluation of their performance was primarily conducted through a comparative analysis of their graded outcome and that of an expert. Later on, after the condition type and severity grade were indicated, the next natural research question would be whether such predictive diagnosis methods could be used to infer dermatologists' treatment options. Indeed, this process is framed as a treatment recommendation task which will be discussed in the next section.

D. TREATMENT RECOMMENDATION

Patient-centered medicine is an approach that aims to consider the treatment effectiveness and patient satisfaction by tailoring it to the specific disease and patient, considering individual variability in clinical presentation, medical history, genes, environment, and lifestyle. Especially in cosmetic dermatology, which relates to personal preferences, the treatment paradigm has shifted from disease-centered to patient-centered health care [120]. To accomplish this, the development of intelligent technologies is needed to overcome these challenges and fulfill this goal [121].

Huang et al. [122] invented Alluring, a cloud-based system for dermatological analysis of skin and scalp, which utilized skin images to provide treatment recommendations. The system comprises a handheld device equipped with a camera for capturing dermatological images. A skin image is processed by a comprehensive analysis for various factors, including moisture, oil, sensitivity, color, pore size, and pore distribution, utilizing YOLO-v2. Subsequently, the outcome of the analysis was utilized to suggest a dermatological product and facilitate customers to make a purchase within the application.

In addition to utilizing skin images, genetic information was also employed. Liu et al. [123] developed a method for recommending cosmetic products by integrating genetic data related to consumer skin health, product data, demand factors based on phenotype, and data on the relationship between ingredients and their functions. The data pertaining to skin-health products were transformed into numerical data and subsequently classified using three ML algorithms, namely Random Forest, Logistic Regression, and Support Vector Machine. The empirical findings demonstrated that Support Vector Machine exhibited better time efficiency compared to other methods, while Random Forest (RF) marginally outperformed other classifiers in terms of classification efficacy. The utilization of genetic data and the consideration of trade-offs between phenotypic demands resulted in an improvement in the recommendation performance.

Ray et al. [30] proposed a scheme for recommending cosmetic products that utilize Convolutional Neural Networks (CNN). The study employed image analysis techniques to predict various categories of consumer facial images based on skin health. This was achieved by extracting relevant features such as shape, texture, and color from the photographs. The algorithm that was proposed attained a success rate of 97.38% accuracy in recommending items on the test data. Zhang et al. [124] utilized knowledge graphs to develop a recommendation system for cosmetic sequences. The construction of the knowledge graph for skincare products was achieved through a combination of manual screening and multi-label classification techniques applied to an open dataset. A ranking algorithm was developed with the aim of suggesting the optimal product based on the specific needs of consumers and their individual skin types.

ML techniques were employed to evaluate skin images, genetic data, and other pertinent factors for the purpose of providing personalized treatment recommendations in the field of aesthetic dermatology. This methodology facilitated the development of a therapeutic regimen that is both effective and tailored to specific customer requirements while considering the unique clinical manifestations, medical background, genetic makeup, surroundings, and lifestyles. These techniques aim to enhance the accuracy and efficiency of the system in aligning customers with the optimal products and treatments based on their individual requirements, skin characteristics, and dermatological conditions.

E. TREATMENT OUTCOME PREDICTION

Following the process of diagnosing the condition, the subsequent step involves selecting an appropriate treatment plan. In the context of clinical dermatology, the responsibility of selecting treatments primarily falls upon the dermatologist. Cosmetic cases are different as they do not pose any harm to the patient, and there exists a plethora of treatment options that patients may opt for. Dermatologists are presented with a wide range of treatment options, and patients may play a role in selecting a treatment modality based on their personal preferences and financial considerations. The treatment outcome prediction task involves forecasting a patient's responses after receiving a particular treatment. The prediction of treatment outcomes holds significant importance at this stage as it could guide dermatologists and patients toward narrowing down appropriate treatment plans. This section will delve into the articles examining AI techniques for predicting treatment outcomes.

The utilization of simulated postoperative images derived from preoperative images can serve as a valuable tool for patients in making informed decisions regarding their treatment options. Shah et al. [125] have demonstrated the ability to generate a precise three-dimensional facial image subsequent to the Rejuvenation procedure. The model has been utilized as an input for generating 3D facial scan images. Facial landmarks were identified as injection sites for dermal fillers. Their study introduced a model that forecasts the quantity of dermal filler required for facial application by utilizing a multi-layered neural network architecture comprising two concealed layers. Their approach yielded an accuracy of 62.5%, surpassing that of the baseline methods 3D-Div by 51.5% and 3D-Vor by 55.8%. Shah et al. [126] proposed enhancement to their simulation model for postoperative rejuvenation image prediction using ML techniques. In this study, a deep neural network model, Rejuv3DNet, and a kernel regression-based (KR) model were developed and demonstrated accuracy rates of 62.5% and 66.7%, respectively. In addition, they produced the initial 3D facial dataset that includes 3D facial images before and after receiving treatments. Lin et al. [127] utilized cosmetic laser therapy to modify the melanin and hemoglobin components of the skin, resulting in the desired outcome of the treatment. In their study, ML algorithms were employed to retouch freckles and adjust skin tone by considering variations in melanin and hemoglobin levels based on the training data.

While the aforementioned articles focus on simulating the posttreatment outcomes, other studies in treatment outcome prediction also investigated the possibility of using AI techniques to quantify the treatment success chances. Akben [128] employed a decision tree-based fuzzy informative approach to predict the success of various wart treatments. The utilization of an automated prediction model has been proposed as a computer-assisted tool for medical professionals. The variables used in their study consisted of the patient's gender, age, duration of time before treatment, quantity and classification of warts, surface area, and the induration diameter of the initial test. These features were utilized to forecast the outcome of the treatment as a dichotomous variable, namely, positive or negative. The findings indicated that the duration between onset and treatment provided the most information gain, followed by age, as determined through a comparative analysis with established classification techniques, including SVM, KNN, Random Forest, and Logistic Regression. The Decision Tree approach demonstrated the highest level of accuracy of 94.4%.

Erdoğan et al. [129] constructed the post-operation evaluation of the FUE hair transplantation procedure. Their algorithm was implemented as part of KEBOT, a comprehensive device designed for hair transplantation. The KEBOT system comprised an operational infrared-based depth camera that was utilized to produce a three-dimensional model of the user's head. The acquired data was processed to extract information. Subsequently, the DL algorithm was employed to conduct an analysis that commenced with object detection, followed by hair thickness estimation, and culminated in metrical analysis. The investigation focused on RetinaNet, M2Det, YOLO-v4, and EfficientDet during the object detection stage. The hair thickness was estimated through the utilization of SegNet, UNet, and ERFNet for hair segmentation. Finally, the surgeon was presented with the post-operative prediction in order to strategize the surgical procedure. Shi et al. [130] created SkincareMirror, a personalized appearance prediction after using skincare products. SkincareMirror was developed for applications by males and females, regardless of their knowledge pertaining to skincare products. The study conducted on the cosmetic product website revealed that users exhibited different behavioral patterns when using SkincareMirror. Specifically, the results indicated that users who utilized SkincareMirror tended to click on a greater number of products, albeit spending comparatively less time reading through the product descriptions. The results also indicated that the male cohorts who did not have skincare knowledge exhibited higher levels of satisfaction with the system in comparison to the remaining groups.

Some cosmetic treatments, especially plastic surgery, can completely alter a patient's appearance. K and Krishnaveni [131] pointed out that this change may affect the face recognition and identity identification system. Hence, pairing posttreatment images with pretreatment images is also an essential task. They compared the performance of two common feature extraction techniques: Extended Uniform Circular Local Binary Pattern (EUCLBP) and Scale Invariant Feature Transform (SIFT). The findings indicated that the optimal outcome was achieved through the combined utilization of SIFT and EUCLBP, as opposed to individual models. Bahçeci Şimşek and Şirolu [132] studied the changes of patients who did upper eyelid blepharoplasty surgery and compared the result with and without a Meller's muscle-conjunctival resection (MMCR). In the experiment, upper eyelid blepharoplasty surgery patients were divided into two groups, with and without MMCR. After six months, the full-face image was analyzed by measuring the change from the preoperative image compared between the two groups.

In the cosmetic businesses, customer satisfaction held a significant important attribute. In this direction, The study conducted by Kim et al. [133] investigated the emotional responses of customers during the use of cosmetic cream through the analysis of EEG data. The study was conducted by assessing the electroencephalogram (EEG) activity of participants during the administration of four distinct categories of topical skincare products. Subsequently, participants were administered a questionnaire to assess their level of satisfaction with the cream. The proposed features were extracted from the EEG signal and processed in a CNN-based model to predict satisfaction. The findings revealed that the stacked CNN model yielded an accuracy of 75.4%, surpassing all other selected models for the experiment.

Reviewed papers in this section demonstrated the applications of ML models for predicting treatment outcomes, success rates, and postoperative changes. These models could be used to assist patients and dermatologists in making informed decisions about treatment options and to help dermatologists select suitable courses of treatment for their patients. Additionally, research in this field may result in the development of advanced simulation tools, such as those that can simulate the outcomes of several cosmetic procedures simultaneously or those that can take a wider range of patient preferences and characteristics into account.

V. DISCUSSION

In the discussion section, a summary of the findings from the reviewed articles is presented. The discussion is structured into three distinct segments, namely trend, limitation, and opportunity.

The review analysis presented in the previous section reveals an apparent trend of heightened adoption of ML techniques in the domain of cosmetic dermatology. Historically, traditional ML models served as the primary means of analysis. However, modern practices have shifted to utilizing DL methods due to their various advantages in medical domains [134]. Numerous studies have conducted a comparative analysis between conventional ML and DL methodologies. Analyzing facial images has historically posed a challenge due to the quality and quantity of input data. However, recent advancements in DL techniques offer potential solutions to these issues. Currently, there is a significant research emphasis on utilizing self-portrait photographs as input, as evidenced by recent studies [111], [112]. Furthermore, the exponential growth in the population of smartphone users has brought automatic self-diagnosis and product recommendations to the forefront of attention. As a result, AI-powered dermatology applications have been witnessed to continue rising [135]. Numerous scholarly articles have extensively utilized ML methodologies as an integral component of their respective application or website systems [102], [116], [130].

The issue of insufficient data persisted as a constraint in the adoption of ML techniques for diagnosis and assessment of the severity of cosmetic dermatological conditions. Due to ethical concerns, a majority of research studies have been limited to small and specific datasets. Furthermore, such concerns also influence the sharing of data for research purposes. The absence of diverse data may lead to overfitting of the model and a deficiency in its ability to generalize. For example, the utilization of color and skin texture as extracted features to indicate skin health in various models resulted in a constructed model that exhibited satisfactory performance solely for the learned data, which was predominantly derived from limited skin types. Some research has attempted to solve this problem by varying the skin types for machines to learn, but this was still done in a limited variation.

Another significant critique regarding the utilization of ML, particularly DL, approaches in the field of cosmetic dermatology pertains to their opaque nature, commonly referred to as 'black boxes.' Despite achieving satisfactory levels of accuracy, the model's incapacity to provide a clear explanation for its decision-making process during the prediction of diagnoses, evaluations, or treatments could potentially result in unforeseen consequences during practical application [136]. Explainable artificial intelligence (XAI) has the potential to address this concern and presents a promising avenue for further investigation within this domain.

VI. CONCLUSION

The utilization of artificial intelligence and machine learning is a significant factor in numerous functions within the field of cosmetic dermatology. This systematic literature review was undertaken to provide a comprehensive summary of the contemporary research utilizing machine learning in this domain in accordance with the PRISMA protocol. The 63 papers that underwent review were categorized into five distinct groups according to their respective tasks, namely: cosmetic product development, skin assessment, skin condition diagnosis, treatment recommendation, and treatment outcome prediction. The utilization of machine learning approaches in the domain of cosmetic dermatology was highlighted, with a focus on identifying trends, limitations, and future opportunities. The primary contribution of this article is a methodical examination of existing recent studies aimed at the utilization of artificial intelligence (AI) technologies in cosmetic dermatology. We expect this study to provide an overview for researchers seeking to explore contribution gaps in this area as well as medical and IT practitioners looking to utilize intelligent technologies to address real-world challenges in cosmetic industries.

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