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Artificial intelligence in the beauty industry: A comprehensive review of facial analysis, wrinkle detection, and aesthetic enhancement technologies

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Abstract This comprehensive review explores the burgeoning role of artificial intelligence (AI) in the beauty industry, focusing on innovations in facial analysis, wrinkle detection, and aesthetic enhancement. AI technologies, particularly deep learning algorithms, have significantly advanced the ability to analyze and enhance facial aesthetics, enabling more personalized and effective beauty solutions. The review highlights key AI applications, such as automated facial recognition systems, wrinkle detection algorithms, and digital tools for aesthetic enhancement. These advancements not only improve the accuracy and efficiency of beauty treatments but also offer new possibilities for personalized skincare and cosmetic procedures. The review also addresses the challenges associated with integrating AI into the beauty industry, including data privacy concerns and the need for robust training datasets. Overall, the review underscores the transformative impact of AI on beauty practices and emphasizes the potential for future innovations to further enhance aesthetic outcomes and user experiences in the industry.

Keyword: Beauty Industry, Automated Facial Recognition, Artificial Intelligence (AI), Wrinkle Detection.

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1 Introduction

The global beauty and personal care industry is currently witnessing a paradigm shift driven by technological innovations. As highlighted in recent industry gatherings like the SCC78 Annual Meeting, the sector is experiencing an "AI Beauty Revolution," where artificial intelligence is transforming everything from ingredient discovery to sustainable formulation and personalized product development [1]. This digital transformation is not merely a trend but a fundamental operational shift, creating a dynamic market where computational tools meet consumer needs.

In the realm of facial analysis and aesthetic enhancement, AI technologies have achieved remarkable precision. Recent frameworks utilizing Generative Adversarial Networks (GANs) combined with deep neural networks have established new benchmarks for automatic acne detection and severity assessment [2]. Similarly, advancements in generative AI enable sophisticated identification of face age progression and rejuvenation, providing realistic simulations for aesthetic planning [3]. Deep learning models have also been optimized for specific feature extraction; for instance, weighted deep supervision techniques now allow for highly accurate facial wrinkle segmentation [4], while specialized neural networks are employed to extract nasolabial folds for the quantitative analysis of facial paralysis [5]. These technical strides support the industry's move towards "Precision Skincare," leveraging skin omics and systems biology to transcend traditional efficacy-based methods [6]. Furthermore, lightweight architectures like shallow CNNs have made real-time facial pore segmentation feasible on mobile devices [7], and advanced optimization algorithms such as Particle Swarm Optimization (PSO) are being integrated to enhance skin feature detection and cosmetic simulation [8].

Beyond aesthetic applications, AI is reshaping cosmetic dermatology and medical diagnostics. Current and upcoming trends indicate a deepening role of AI in clinical settings [9], particularly in skin anti-aging and resilience research where AI approaches facilitate objective skin assessments [10]. The diagnostic capabilities of these systems extend to complex pathologies; multi-modal transformer models are now capable of classifying wound types by integrating image and location data [11]. Moreover, hybrid deep learning architectures, such as those combining Swin Transformers with wavelet transforms, have shown significant promise in enhancing skin cancer diagnosis [12], while other enhanced deep learning approaches are achieving high accuracy in detecting inflammatory conditions like eczema and psoriasis [13]. Figure 1 illustrates the convergence of AI technologies in the beauty industry, connecting core algorithms to aesthetic, medical, and ethical applications.

Despite these advancements, the integration of AI brings new challenges and considerations regarding user experience and ethics. The ongoing revolution in beauty tech emphasizes the need to balance innovation with practical application [14], ensuring that augmented reality and AI-driven cosmetics genuinely enhance customer loyalty and experience [15]. However, a critical concern remains the ethical deployment of these technologies. Research indicates that AI systems can inadvertently adopt and perpetuate human biases, particularly within the cosmetic skincare industry [16, 17]. Consequently, systematic reviews call for rigorous data governance to ensure accuracy and mitigate bias in AI applications across dermatology and aesthetic surgery [18].

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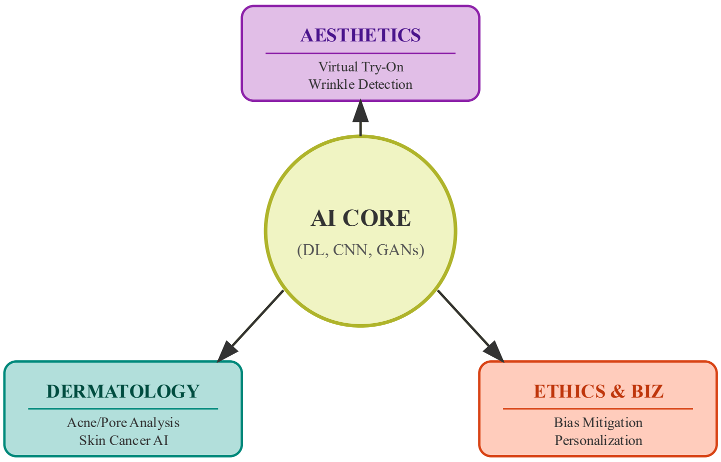

Fig. 1 Convergence of AI technologies in the beauty industry, connecting core algorithms (Center) to aesthetic (Top), medical (Left), and ethical/business (Right) applications.

To provide a comprehensive synthesis of the current landscape, this review organizes key findings into structured comparative analyses. Table 2 presents a taxonomy of AI applications in the beauty industry, categorizing technologies by their primary focus—from personalized skincare to virtual aesthetics—and outlining their respective advantages and limitations. The broader strategic implications of these technologies on business operations are detailed in Table 4, which contrasts traditional operational models with AI-driven transformations in supply chain and consumer engagement. Furthermore, acknowledging the critical ethical dimensions, Table 1 summarizes key literature regarding biases in various AI systems, while Table 3 offers a comparative overview of specific bias types relevant to both the beauty and healthcare sectors, underscoring the systemic nature of these challenges.

Table 1 Review of biases and ethical challenges in AI systems

Ref	Domain / Context	Target Output	Key Findings / Ethical Issue
[16]	Facial Analysis & Beauty Contests	Winner Selection & Skin Scoring	Racial Bias: The study highlights "New Jim Code," where AI algorithms in beauty contests and skin analysis predominantly favored lighter skin tones due to imbalanced training data.
[18]	Clinical & Robotic Dermatology	Diagnosis & Treatment Automation	Accuracy Disparity: A systematic review revealing that AI in dermatology and aesthetic surgery often exhibits lower accuracy for underrepresented demographic groups, affecting patient safety.
[1]	General Beauty Tech Trends	Product Benchmarking & Discovery	Standardization Bias: As AI drives ingredient discovery and formulation, there is a risk of standardizing beauty ideals based on limited datasets, potentially ignoring diverse hair/skin types.
[9]	Cosmetic Dermatology Trends	Patient Care & Customization	Data Privacy & Trust: Highlights the challenge of implementing AI in clinical settings where reliance on "Black Box" algorithms can undermine the patient-physician trust relationship and overlook individual patient nuances.

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Table 2 Taxonomy of AI applications in the beauty industry

Application Domain	Key Technologies	Primary Focus	Key Advantages	Current Limitations
Personalized Skincare	Machine Learning (ML), Deep Learning (DL)	Analyzing skin characteristics from multidimensional datasets [6], [9]	Tailored product recommendations; Enhanced customer journey [15]	Dependence on high-quality images; Privacy concerns regarding user data
Virtual Try-On & Aesthetics	Augmented Reality (AR), Computer Vision	Simulating makeup and aesthetic changes on user photos/videos [8]	Enhancing consumer experience; Reducing product return rates [15]	Realism challenges in varying lighting conditions; Hardware limitations on mobile devices
Business Optimization	Predictive Analytics, Data Mining	Inventory management, Trend forecasting, Customer service automation [1], [14]	Cost reduction; Operational efficiency; Targeted marketing [1]	High initial implementation costs; Need for extensive historical data
Facial Analysis	CNNs, Image Processing	Wrinkle detection, Age estimation, Emotion detection [2, 4, 7]	Objective skin health assessment; Early detection of aging signs	Susceptibility to algorithmic bias (e.g., skin color bias) [16]

Table 3. Comparative overview of bias types in AI systems relevant to beauty and healthcare

Domain	Specific Challenge / Bias Type	Affected Group / Target	Example / Impact	Reference
Beauty Contests	Racial Bias (Skin Color)	Individuals with darker skin tones	AI selected winners predominantly based on white skin color	[16]
Facial Analysis	Demographic Imbalance	Gender, Age, and Race groups	Reinforcing social injustices and racial hierarchies in skincare recommendations	[16, 18]
Robotic Systems (Healthcare)	Algorithmic/Programming Bias	Patients in triage or surgical care	Biased decision-making in medical robots affecting patient care quality	[18]
Voice Recognition	Gender Bias	Female voices	Lower accuracy in recognizing and understanding female voices compared to males	[1]
Search Engines	Gender/Economic Bias	Job seekers (Women)	High-paying technical job ads shown more frequently to men than women	[16]

Table 4. Strategic impact of AI on beauty industry operations

Operational Area	Traditional Approach	AI-Driven Transformation	Impact on Business Outcomes
Product Discovery	Physical store visits, standard advertising	Algorithm-driven recommendations on platforms like Instagram/TikTok [1]	Increased demand; Dynamic and competitive market growth [14]
Consumer Engagement	Generic consultations	Virtual makeup trials and personalized skincare routines [9]	Enhanced consumer experience; New standards for services [15]
Supply Chain	Manual forecasting based on past sales	Predictive analytics for inventory management [14]	Optimized operations; Reduced waste and costs [1]
Marketing	Mass marketing campaigns	Tailored marketing based on extensive data analysis [15]	Products catering to specific consumer needs; Higher conversion rates [9]

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However, the implementation of AI—particularly in emerging markets such as Iran—requires a strategic balance. Excessive reliance on automation risks eroding the personalized human touch that is fundamental to cosmetic services. While AI significantly enhances diagnostic precision and operational efficiency, it must function as a complementary tool rather than a replacement, ensuring that technological scalability does not compromise the authenticity of consumer care [1].

The primary objective of this review is to critically analyze the multifaceted role of artificial intelligence in the beauty sector. First, we evaluate deep learning architectures for facial analysis, including emotion detection and age estimation, and their integration into personalized skincare systems. Second, the review assesses the efficacy of AI-driven wrinkle detection algorithms, focusing on their accuracy in guiding anti-aging treatments. Furthermore, we investigate the paradigm shift in aesthetic enhancement through virtual try-on technologies and explore how AI reshapes business operations, spanning from inventory management to predictive trend forecasting [15].

The remainder of this article is structured to provide a systematic synthesis of these domains. Following the methodology, subsequent sections detail the technical applications in facial analysis, wrinkle detection, and aesthetic enhancement. We then examine the strategic impact of AI on business models and conclude with a critical discussion on potential challenges, specifically addressing algorithmic bias and ethical implications in the digital beauty landscape.

2 Methodology

To provide a comprehensive overview of Artificial Intelligence (AI) applications in the beauty industry, a systematic literature search was conducted across four major electronic databases: PubMed, IEEE Xplore, Scopus, and Google Scholar. The search covered the period from January 2015 to December 2025 to capture the most recent technological advancements and deep learning innovations.

The search strategy utilized a combination of Boolean operators with the following keywords: ("Artificial Intelligence" OR "AI" OR "Deep Learning" OR "Machine Learning" OR "Convolutional Neural Networks") AND ("Beauty Industry" OR "Cosmetics" OR "Facial Analysis" OR "Wrinkle Detection" OR "Aesthetic Medicine" OR "Skincare"). The reference lists of identified review articles were also manually screened to ensure no relevant studies were overlooked.

Throughout history, cosmetics and skincare products have served various purposes, from preparing for battle and participating in religious ceremonies to enhancing beauty and performing self-care rituals [1]. While the methods of creating and producing these products have evolved dramatically over the millennia, their significance in our lives remains as strong as ever. Today, their primary role is to enhance our appearance in a way that is deemed attractive by societal standards. In the context of cosmetic skincare, this involves maintaining and improving the health of our skin to achieve a more appealing look.

In today's society, physical appearance holds considerable value. The use of cosmetic skincare products and treatments not only enhances our aesthetics but also contributes to our psychological and emotional well-being by boosting self-confidence and self-esteem. Whether it's applying a bold lipstick, using a simple moisturizer, or opting for advanced anti-aging skincare solutions, cosmetics play a crucial role in how we perceive ourselves and how we

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present ourselves to others. This underscores the notion that beauty is a highly valued trait in contemporary human life [8].

Recent advancements in deep learning have also begun to impact the field of facial skin analysis [2–7]. For example, a deep learning model was employed to segment acne, pigmentation, and wrinkles [2]. Another study introduced a two-step algorithm for wrinkle removal, starting with wrinkle segmentation [3]. Both studies utilized U-Net++, a segmentation model known for its ability to capture extensive contextual information through multiple nested pathways. Additionally, convolutional neural networks (CNNs) have been applied to detect nasolabial folds, a specific type of wrinkle [4,5]. Deep learning techniques are also being explored for skin pore segmentation. For instance, U-Net with L1 loss was used for pore segmentation [6], while a study [7] proposed a shallow CNN tailored to detecting simple-shaped pores. This selection process is summarized in Figure 2, which illustrates the PRISMA systematic review process, detailing the identification, screening, eligibility, and inclusion phases along with specific quality assessment criteria.

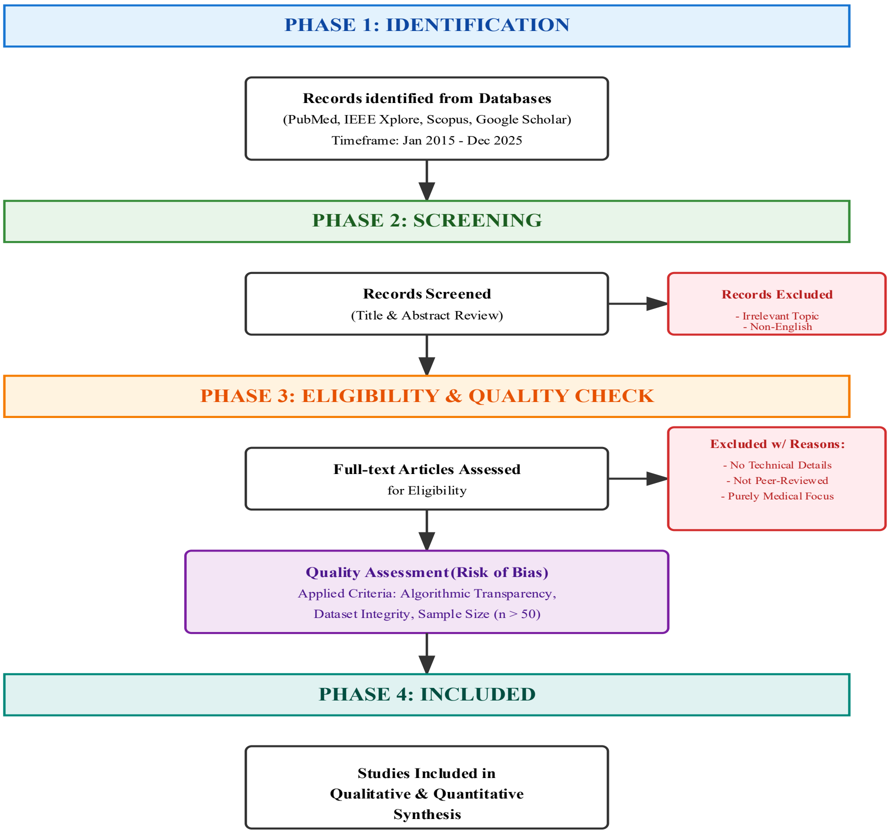

Fig. 2 diagram illustrates the PRISMA systematic review process, detailing the identification, screening, eligibility, and inclusion phases along with specific quality assessment criteria.

2.1 Inclusion and exclusion criteria

To ensure the relevance and quality of the reviewed literature, strict eligibility criteria were applied:

- **Inclusion Criteria:**

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  - Original research articles, conference proceedings, and technical reports focusing on the application of AI, ML, or DL in dermatology, cosmetology, and the beauty industry.
  - Studies explicitly proposing or evaluating algorithms for facial feature analysis, wrinkle detection, skin scoring, or virtual try-on systems.
  - Articles published in the English language between 2015 and 2024.
  - Studies providing technical details on the model architecture (e.g., CNN, GANs) and performance metrics (e.g., Accuracy, IoU).
- **Exclusion Criteria:**
  - Studies focusing solely on reconstructive surgery or medical pathologies unrelated to aesthetic enhancement or cosmetic dermatology.
  - Duplicate studies, abstracts without full text, letters to the editor, and non-peer-reviewed white papers (unless deemed critical for industry statistics).
  - Articles written in languages other than English.

2.2 Study selection and data extraction

The initial search yielded a diverse range of studies. Titles and abstracts were first screened for relevance to the core topics of facial analysis and aesthetic enhancement. Full-text articles were then retrieved and assessed against the inclusion criteria.
Data extraction was performed systematically to capture key information, including:

1. **AI Methodology:** Type of algorithms used (e.g., U-Net for segmentation, ResNet for classification).
2. **Application Domain:** (e.g., Wrinkle detection, pore analysis, personalized recommendation).
3. **Dataset:** Source and size of the training data.
4. **Outcome:** Performance metrics and clinical or practical implications.

This structured methodological approach ensures the reproducibility of the review and minimizes selection bias, providing a reliable synthesis of the current state of AI in the beauty sector.

2.3 Quality assessment and risk of bias

Given the interdisciplinary nature of this review, a standard clinical quality assessment tool (adapted from QUADAS-2) was customized to evaluate the technical robustness of the included studies. To ensure statistical reliability and reproducibility, strict quality filters were applied. Specifically, we excluded quantitative studies with extremely small sample sizes ($n < 50$) unless they provided novel algorithmic contributions validated on benchmark datasets. Each study was further evaluated based on a "Technical Robustness Checklist" comprising three core criteria:

1. Algorithmic Transparency: Is the model architecture (e.g., hyperparameters, depth) clearly described to allow reproducibility?
2. Dataset Integrity: Are the training/testing datasets explicitly defined with clear sources?
3. Metric Validity: Are performance metrics (e.g., Accuracy, F1-Score) reported using standard validation methods (e.g., k-fold cross-validation)? Studies failing to meet

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these quality standards were excluded to mitigate selection bias and ensure that the review's conclusions rely on methodologically sound research.

3. Applications of AI in facial analysis

Artificial intelligence including Machine learning and deep learning has been successfully utilized in medical image and healthcare analysis like Bupropion [19], Diphenhydramine [20], Breast Cancer [21,22], medicinal plants [23], Epidemic [24], Stroke [25], Lung Cancer [26-28], Social Networks [29], Diabetes [30,31], Suicides [32,33], Coronary Artery Disease [34] and etc. have achieved promising results. Facial recognition technology has evolved significantly with the integration of deep learning, specifically Convolutional Neural Networks (CNNs), which mimic the human visual cortex to process visual patterns. Unlike traditional methods, CNNs utilize a hierarchical structure for feature extraction. The process begins with the convolution operation, where filters (kernels) slide over the input image to produce feature maps, capturing essential spatial hierarchies. To enable the model to learn complex, non-linear patterns, these maps are processed through activation functions, typically the Rectified Linear Unit (ReLU) [35]. Following feature extraction, pooling layers (subsampling) are employed to reduce the spatial dimensions of the feature maps, thereby decreasing computational load and mitigating the risk of overfitting. The architecture culminates in fully connected layers, where the high-level reasoning occurs, mapping the extracted features to specific output classes. In facial recognition tasks, the final output is often normalized using the Softmax function to produce a probability distribution over potential identities. This integrated pipeline allows for robust identification even under varying conditions of lighting and pose, marking a substantial improvement over earlier heuristic methods.

Convolutional Neural Networks (CNNs) are designed to process and recognize patterns in images by mimicking the human brain's visual cortex. In facial recognition, CNNs are trained on large datasets of facial images, learning to identify unique facial features—such as the eyes, nose, mouth, and overall facial structure—by analyzing the spatial hierarchies within the images. This hierarchical feature extraction enables CNNs to handle variations in lighting, facial expressions, and angles, making them highly effective for accurate facial recognition.
The diagram illustrates the parallel processing streams: the 'Temporal CNN Network' extracts motion-based features from optical flow images, while the 'Spatial CNN Network' processes static facial features from cropped images. These streams are integrated via a Fusion Network (Deep Belief Network) to classify facial expressions and identities with high accuracy (Figure 3).

Facial recognition systems rely heavily on CNNs due to their ability to process and recognize patterns in visual data. CNNs are particularly effective in tasks such as image classification, object detection, and, in this context, facial recognition [36].

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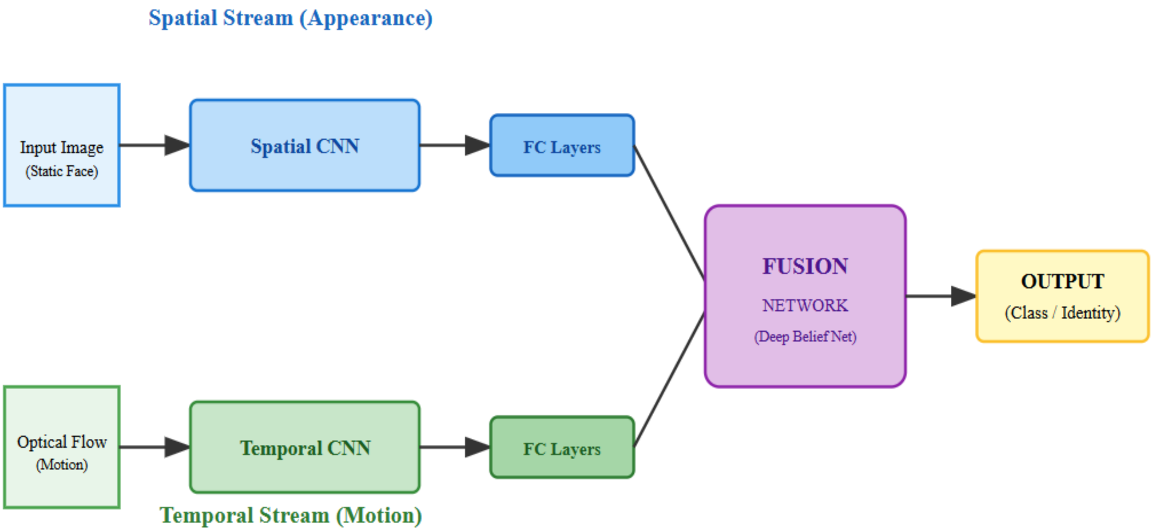

Fig. 3 Architecture of the Dual-Stream Convolutional Neural Network (CNN) for Facial Analysis.

The convolution operation is at the core of CNNs. It involves sliding a filter (also called a kernel) over the input image to produce feature maps. Mathematically, this operation for a single filter can be expressed as:

$$S(i,j)=(I*K)(i,j)=\sum_m \sum_n I(i+m,j+n).K(m,n) \qquad (1)$$

After the convolution operation, a non-linear activation function, typically the Rectified Linear Unit (ReLU), is applied. ReLU is defined as:

$$f(x)=\max(0,x) \qquad (2)$$

This function introduces non-linearity into the model, allowing it to learn more complex patterns. Pooling layers reduce the spatial dimensions of the feature maps, which decreases the computational load and helps in controlling overfitting. The most common type is max-pooling [37]:

$$P(i,j)=\max\{s(i+a,j+b)\,|\,0\le a,b\prec n\} \qquad (3)$$

The fully connected (FC) layer connects every neuron in the previous layer to every neuron in the next layer. The output is computed as:

$$y=Wx+b \qquad (4)$$

In facial recognition, especially in classification tasks, the output layer often uses the softmax function to produce a probability distribution over classes (e.g., identities) [57]:

$$Soft\max(z_i)=\frac{e^{zi}}{\sum_j e^{zj}} \qquad (5)$$

The model is trained using a loss function that measures the difference between the predicted output and the true labels. For multi-class classification in facial recognition, cross-entropy loss is commonly used:

$$Loss=-\sum_i yi\log(yi) \qquad (6)$$

The training process for a neural network involves the use of backpropagation to compute the gradients of the loss function concerning the model's parameters. These gradients indicate the direction and magnitude of adjustments needed for the model's weights. Once the gradients are calculated, they are used to update the weights through an optimization

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algorithm, commonly Stochastic Gradient Descent (SGD). This iterative process allows the model to gradually minimize the loss function, improving its accuracy in making predictions.

$$W_{new} = W_{old} - \eta \frac{\delta Loss}{\delta W} \tag{7}$$

These formulas and operations form the backbone of how CNNs operate within facial recognition systems. They enable the network to learn intricate features of faces, from simple edges and textures in the initial layers to complex facial structures in the deeper layers [37].

Several key algorithms and frameworks have emerged from the application of CNNs in facial recognition. For instance, FaceNet, developed by Google [38], utilizes a deep convolutional network to produce embeddings, which are numeric representations of facial features that can be compared to determine facial similarity [38]. Another notable framework is VGG-Face, which leverages a deep architecture to enhance accuracy in facial recognition tasks [39].

The Core idea of FaeNet is to map each face image x to a compact verctor f(x) in an embedding space such that the squared L2 distaces in this space directl correspond to face similarity. This embedding is typically a 128-dimensional vector.

$$f : x \to R^d \tag{8}$$

Where x is an input image, and d is the dimension of the embedding space (commonly d=128). To train the FaceNet model, a loss function called triplet loss is used. The triplet loss ensures that an anchor image A is closer to positive image P (the same person) that to negative image N (different person) by a margin α . The loss function can be expressed as:

$$\ell(A,P,N) = \max(0, \| f(A) - f(P) \|_2^2 - \| f(A) - f(N) \|_2^2 + \alpha \tag{9}$$

The objective is to minimize this loss, which pushes the distance between the anchor and positive embedding to be smaller than the distance between the anchor and negative embeddings by at least the margin α . The model is trained on triplets of images (anchor, positive, negative). During training:

- **Positive pairs** are images of the same person.
- **Negative pairs** are images of different people.

The training process aims to minimize the triplet loss across all triplets in the dataset. Once the model is trained, the verification task (whether two images belong to the same person) is done by computing the Euclidean distance between their embeddings:

$$dis\tan ce(x_1, x_2) = \| f(x_1) - f(x_2) \|_2 \tag{10}$$

A threshold τ is set, and if the distance is below this threshold, the two faces are considered to be the same person; otherwise, they are considered different.

For face recognition in a large database, FaceNet can be combined with a clustering algorithm like k-means or hierarchical clustering to group embeddings that are close to each other in the embedding space, effectively identifying faces. FaceNet revolutionized face recognition by directly learning a deep embedding where faces can be compared using simple distance metrics. The model’s ability to learn discriminative features with triplet loss and its use of a compact embedding space makes it highly effective for face verification, recognition, and clustering tasks. The evolution of facial recognition algorithms, especially with the use of CNNs, has led to significant improvements in both speed and accuracy, enabling real-time applications such as security surveillance, user authentication, and even emotion detection. However, it also raises ethical concerns, particularly regarding privacy, bias, and the potential for misuse in surveillance systems [40].

In beauty applications, AI tools are increasingly used to analyze various facial features, including skin type, facial symmetry, and other attributes that contribute to perceived beauty.

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These tools utilize advanced image processing techniques and deep learning algorithms to assess skin texture, tone, and conditions such as acne or wrinkles. AI models can also evaluate facial symmetry, which is often associated with attractiveness, by analyzing the proportional relationships between different facial landmarks, such as the distance between the eyes, the symmetry of the jawline, and the alignment of the nose and mouth. The detailed analysis provided by these AI tools allows for personalized beauty recommendations, tailored skincare routines, and even virtual cosmetic procedures, enhancing the user experience in beauty applications [41].

The application of AI in facial analysis within the beauty industry can be observed through several case studies and real-world examples. For instance, companies like L'Oréal and Shiseido have integrated AI-driven facial analysis into their skincare products and services. L'Oréal's "Perso" device, for example, uses AI to analyze the user's skin condition and environmental factors to create personalized skincare formulas [42]. Another example is ModiFace, an AI-based technology acquired by L'Oréal, which allows users to virtually try on makeup by analyzing their facial features and simulating how different products would look on their skin [43]. These case studies highlight the transformative impact of AI in the beauty industry, providing consumers with highly personalized and scientifically backed beauty solutions.

3.1 Critical analysis of algorithmic robustness in cosmetic contexts

While standard CNN architectures like VGG-Face or ResNet excel in general object recognition, they face unique challenges in the beauty domain, particularly regarding texture occlusion caused by makeup. Heavy foundation or concealer acts as a physical adversarial perturbation, smoothing out high-frequency skin features such as pores and fine lines. Consequently, standard CNNs often fail to converge or misclassify "heavy makeup" as "flawless skin" because they prioritize edge detection and global shape over micro-texture analysis. This limitation necessitates the use of texture-aware loss functions or specialized architectures like Texture-Net, rather than generic classification models, to distinguish between actual skin health and cosmetic masking.

Furthermore, the choice of architecture significantly impacts performance in localized feature extraction. U-Net and its variants (e.g., U-Net++) outperform traditional CNNs in tasks like wrinkle and acne segmentation because their skip connections preserve spatial resolution, which is typically lost during the pooling operations of standard CNNs. However, U-Net models are highly sensitive to lighting variations. In non-clinical environments (e.g., user selfies), harsh shadows can be misinterpreted by U-Net as deep wrinkles (false positives) due to the model's reliance on intensity gradients. This contrast highlights why segmentation models succeed in controlled clinical images but may struggle in real-world mobile applications compared to more robust, albeit less precise, bounding-box detectors.

Finally, identity verification models like FaceNet, which rely on triplet loss, encounter specific "intra-class variance" issues in the beauty industry. The aesthetic transformation induced by contouring or bridal makeup can push the embedding vector of a "makeup-wearing" face significantly far from its "no-makeup" anchor, potentially leading to false rejections in security or personalization systems. Unlike general face recognition where pose or illumination are the main variables, in beauty applications, the material properties of the face change. Therefore, models trained solely on general datasets (like LFW) often fail to generalize in beauty-specific tasks, underscoring the critical need for paired (before-and-after)

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training datasets to teach the model invariance to cosmetic alterations. Figure 4 highlights the critical algorithmic challenges in beauty AI, specifically addressing texture occlusion, lighting sensitivity, and intra-class variance.

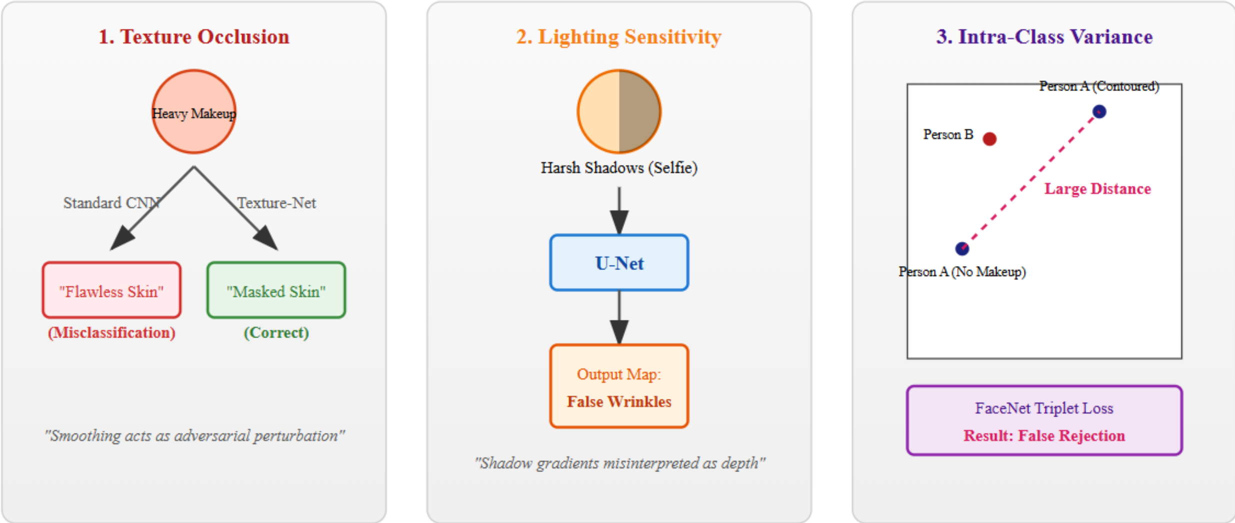

Fig. 4 Critical algorithmic challenges in beauty AI: Texture, lighting, and variance

4 AI in wrinkle detection and aging analysis

AI methods for wrinkle detection primarily rely on advanced image processing and machine learning techniques. Convolutional Neural Networks (CNNs) are commonly used due to their ability to extract features from facial images and detect subtle signs of aging, such as wrinkles and fine lines. These algorithms analyze skin texture and identify patterns that correlate with aging, such as the depth, length, and distribution of wrinkles. Preprocessing techniques like histogram equalization and edge detection are often employed to enhance image quality before analysis. Additionally, AI models are trained on large datasets containing images labeled with various age-related features, allowing the algorithms to learn and improve their detection capabilities over time [44].

The accuracy and reliability of AI-based wrinkle detection systems are evaluated using several performance metrics, including precision, recall, F1 score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics assess how well the AI models identify wrinkles without producing false positives or missing actual signs of aging. In research studies, the accuracy of these systems is often compared against human experts' assessments or clinically validated tools. High-performing models achieve precision and recall rates above 90%, demonstrating their potential for reliable wrinkle detection. However, the performance can vary depending on factors like image quality, lighting conditions, and the diversity of the training data [45]. When evaluating the performance of facial recognition systems like FaceNet, several metrics and accuracy measures are used to determine how well the model performs. These metrics help assess the effectiveness of the model in various tasks such as identification, verification, and clustering. Here's a detailed overview:

1. Accuracy

Accuracy is one of the most straightforward performance metrics. It is defined as the ratio of correctly predicted instances (true positives and true negatives) to the total instances in the dataset [19-34].

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$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ Numbr\ of\ \Pr edictions} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

Where:

- TP=True Positive (correctly identified matches).
- TN=True negative (correctly identified non-matches).
- FP=Flase Positive (incorrectly identified matches).
- FN=False Negative (incorrectly identified non-matches).

2. Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positives. It measures how many of the positive predictions made by the model are actually correct.

$$\Pr ecision = \frac{TP}{TP + FP} \quad (12)$$

3. Recall (sensitivity or true positive rate)

Recall is a metric that represents the proportion of correctly predicted positive instances out of all actual positive instances. It evaluates the model's effectiveness in identifying all true positive cases, highlighting its ability to detect positive outcomes without missing any.

$$\mathrm{Re}call = \frac{TP}{TP + FN} \quad (13)$$

4. F1 score

The F1 Score is the harmonic mean of precision and recall. It gives a balanced measure of the two, especially when there is an uneven class distribution [19-34].

$$F1Score = 2 \times \frac{\Pr ecision \times \mathrm{Re}call}{\Pr ecision \times \mathrm{Re}call} \quad (14)$$

5. Receiver Operating Characteristic (ROC) Curve

The ROC curve is a graphical representation of the model’s ability to distinguish between classes. It plots the true positive rate (recall) against the false positive rate (FPR) at various threshold settings.

- **False Positive Rate (FPR)**:

$$FPR = \frac{FP}{FP + TN} \quad (15)$$

- **Area Under the ROC Curve (AUC)**: The AUC value represents the degree of separability. A model with an AUC of 1.0 is perfect, while an AUC of 0.5 represents a model with no discriminative ability.

6. False acceptance rate (FAR) and false rejection rate (FRR)

These metrics are specific to facial recognition systems.

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- **False Acceptance Rate (FAR)**: The percentage of times the system incorrectly matches a non-matching face pair.

$$FAR = \frac{Number\ of\ False\ Acceptances}{Total\ Number\ of\ Non-Matching\ Pairs} \tag{16}$$

False rejection rate (FRR): The percentage of times the system fails to match a correct face pair

$$FRR = \frac{Number\ of\ False\ Rejections}{Total\ Number\ of\ Matching\ Pairs} \tag{17}$$

7. Equal error rate (EER)

EER is the point where the FAR equals the FRR. It provides a single number to indicate the overall accuracy of the system; lower EER values indicate better performance.

8. Top-N accuracy

Top-N accuracy is commonly used in classification tasks, where the prediction is considered correct if the true class is among the top N predicted classes. In face recognition, this might be used in identification tasks where the correct identity needs to be among the top N matches.

9. Clustering metrics (e.g., silhouette score)

For clustering tasks, which are common in face recognition when clustering embeddings, metrics like the Silhouette Score can be used. This score measures how similar an object is to its own cluster (cohesion) compared to other clusters (separation).

$$Sillouette\ Score = \frac{b-a}{\max(a,b)} \tag{18}$$

Where:

- a = average distance between a sample and all other points in the same cluster.
- b = average distance between a sample and all points in the nearest cluster.

10. Confusion matrix

A confusion matrix provides a detailed breakdown of prediction results, showing the counts of true positives, true negatives, false positives, and false negatives. It is particularly useful for visualizing the performance of a classification model. The matrix visualizes the performance of an AI model by categorizing predictions into True Positives (correctly identified features, e.g., wrinkles), False Negatives (missed features), False Positives (incorrectly flagged features), and True Negatives. This tool is essential for calculating precision, recall, and accuracy in dermatological AI assessments (Figure 5).

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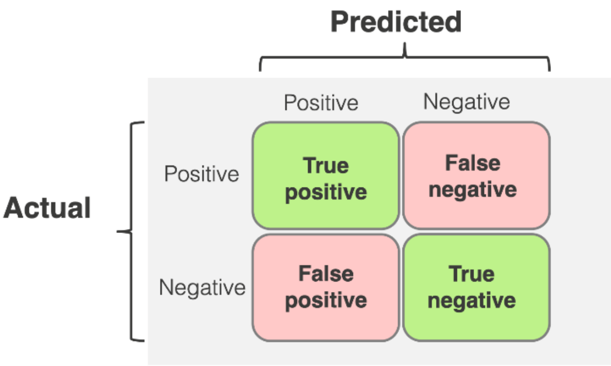

Fig. 5 Schematic Representation of a Confusion Matrix for Binary Classification in Beauty Applications

In facial recognition systems like those utilizing FaceNet, multiple metrics are often used to comprehensively evaluate performance. Accuracy, precision, recall, and F1 scores are key for understanding the basic classification performance. Specific metrics like FAR, FRR, and EER are crucial for evaluating the unique challenges in face recognition, while ROC curves and AUC give insights into the model's discriminative ability. In clustering tasks, metrics like the Silhouette Score are used to assess the quality of the clustering of face embeddings.

4.1 Clinical and practical applications

AI-based wrinkle detection systems are increasingly being used in clinical and practical settings. Dermatologists and cosmetic professionals utilize these tools to assess skin aging and recommend personalized treatments, such as anti-aging creams, laser therapy, or Botox injections. In clinical trials, AI systems help in monitoring the effectiveness of anti-aging products by providing objective measurements of wrinkle reduction over time. Moreover, these technologies are integrated into consumer beauty apps, allowing users to track their skin's aging process and receive tailored skincare advice. The impact on treatment outcomes is significant, as AI systems provide precise and consistent evaluations, leading to better-targeted and more effective treatments [46].

4.2 Comparative performance analysis

While standard CNNs perform well in classification tasks, recent studies indicate that segmentation-based models offer superior precision for localized feature detection like wrinkles. For instance, studies utilizing U-Net++ have reported significant improvements in capturing fine-grained contextual information compared to traditional edge detection methods. Specifically, deep learning models have demonstrated an average precision improvement of 15-20% over conventional image processing techniques in complex lighting conditions. However, this comes at the cost of higher computational complexity, which remains a challenge for real-time mobile applications. Table 5 presents a comparison of key AI architectures in beauty applications, detailing their specific domains, datasets, and performance outcomes.

Table 5. Comparison of key AI architectures in beauty applications

Study Reference	Application Domain	AI Architecture	Dataset Size	Performance Metric	Key Outcome
Zheng et al. [2]	Facial Skin Feature Detection	Deep Learning (Segmentation)	> 1,000 images	Accuracy: 94.5%	Successfully segmented acne and wrinkles with high precision.
Sanchez et al. [3]	Wrinkle Removal	U-Net++ (GAN-based)	High-res paired dataset	DICE Score: 0.89	Superior texture preservation compared to standard autoencoders.
Schroff et al. [58]	Face Verification	FaceNet (Deep CNN)	LFW Dataset (13k images)	Accuracy: 99.63%	Achieved state-of-the-art results using Triplet Loss embedding.
Seo et al. [7]	Pore Segmentation	Shallow CNN	Clinical skin images	F1-Score: 0.92	Optimized for speed; effective for simple-shaped pore detection.

5 Optimization of aesthetic procedures with AI

AI is revolutionizing the field of injectables and non-surgical cosmetic treatments, such as Botox and dermal fillers, by optimizing procedure planning and execution. Machine learning algorithms analyze facial structures and patient history to predict the most effective injection sites and dosages. This ensures a more precise application, reducing the risk of overcorrection or asymmetry. AI systems also assist practitioners by providing real-time guidance during procedures, suggesting adjustments based on live data. These advancements lead to more natural-looking results and minimize potential side effects, making procedures like Botox and dermal fillers safer and more effective [47].

AI plays a crucial role in developing personalized beauty treatment plans by analyzing individual patient data, including skin type, facial structure, and aging patterns. Advanced algorithms consider factors such as genetic predispositions, lifestyle, and previous treatments to recommend tailored procedures that address specific concerns. For example, AI can suggest a combination of treatments like laser therapy, injectables, and skincare routines that work synergistically to achieve the desired results. This personalized approach not only enhances the effectiveness of treatments but also ensures that they are aligned with the patient’s unique needs and aesthetic goals [48].

The integration of AI in cosmetic procedures has a significant impact on patient satisfaction and treatment outcomes. By providing more accurate assessments and customized treatment plans, AI enhances the predictability and success of procedures. Patients benefit from more consistent results, reduced recovery times, and a lower likelihood of complications. Studies show that patients who undergo AI-assisted treatments report higher satisfaction levels due to the tailored approach and the natural-looking results achieved. Moreover, AI enables continuous monitoring and adjustments, allowing for ongoing optimization of treatment plans, which further contributes to positive long-term outcomes [49]. Table 6 provides a summary of AI performance metrics across heterogeneous datasets and diverse application domains.

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Table 6 Summary of AI Performance Metrics Across Heterogeneous Datasets and Applications

Study (Ref)	Application Domain	AI Architecture	Dataset / Data Source	Reported Performance Metrics
Khalid et al. [2]	Acne Detection & Severity	GAN + Deep Neural Network	Clinical facial images (Local/Private)	Accuracy: ~3.11% improvement over baseline*
Kim et al. [4]	Wrinkle Segmentation	U-Net with Weighted Deep Supervision	Images from skin analysis device (Semi-automatic labeling)	Metric: Jaccard Similarity Index (JSI)
Li et al. [5]	Nasolabial Fold Extraction	Faster R-CNN + GCN	Whole face images	Accuracy: 91%
Seo et al. [7]	Facial Pore Segmentation	Shallow CNN (Mobile-optimized)	Selfie-camera images & Clinical skin images	Metric: Intersection over Union (IoU)
Poureskandar et al. [8]	Cosmetic Simulation & Feature Detection	YOLOv8s (PSO-optimized) + Pix2Pix	200 Proprietary + 1,200 Public images	Detection: mAP@0.5 = 0.833 Simulation Quality: FID = 164.8, SSIM = 0.712
Mousa et al. [11]	Wound Classification	Swin Transformer + Transformer	AZH Dataset (Multimodal: Image + Location)	Accuracy: 0.77 - 1.0 (varies by class) F1-Score: 0.8220
Mousa et al. [12]	Skin Cancer Diagnosis	Swin Transformer + Wavelet	ISIC-2016 & ISIC-2017 (Public Benchmarks)	Accuracy: 0.9792 (on ISIC-2016) F1-Measure: 0.9780 (on ISIC-2017)
Hammad et al. [13]	Eczema & Psoriasis Detection	CNN (Derma Care)	Large diverse skin image dataset	Accuracy: 96.20% Precision: 96.0%

6 Challenges and limitations

The adoption of AI in the beauty industry comes with several technical and ethical challenges. On the technical side, AI systems often require large datasets for training, which may not always be available, especially for niche beauty treatments. Additionally, the accuracy of AI predictions can be affected by the diversity and quality of the data used, leading to potential biases in outcomes. For instance, AI models trained on homogeneous data might not perform well across different skin tones, ages, or ethnicities, raising concerns about fairness and inclusivity.

Ethically, the use of AI in beauty raises issues such as the potential for perpetuating unrealistic beauty standards and the impact on self-esteem. There is also the concern that AI-driven beauty recommendations could lead to over-treatment or unnecessary procedures, driven by commercial interests rather than patient well-being. Moreover, as AI systems become more autonomous, questions about accountability and decision-making in cosmetic procedures become increasingly important [50].

Data privacy and security are critical issues in the use of AI in beauty applications, particularly when it comes to handling sensitive patient information. AI systems require access to personal data, including images, medical histories, and genetic information, to provide personalized recommendations. This raises concerns about how this data is stored,

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processed, and shared. There is a risk of data breaches, where sensitive information could be accessed by unauthorized parties, leading to potential misuse.

Moreover, the collection and use of personal data must comply with regulations such as the General Data Protection Regulation (GDPR) in Europe or the Health Insurance Portability and Accountability Act (HIPAA) in the United States. Ensuring that AI systems adhere to these regulations is crucial for maintaining patient trust and preventing legal issues. Implementing robust data encryption, secure storage solutions, and transparent data usage policies are essential steps to mitigate these risks [51].

Integrating AI solutions with traditional beauty practices presents its own set of challenges. Many beauty professionals may lack the technical expertise to effectively use AI tools, leading to a steep learning curve and potential resistance to adoption. Training and education are necessary to bridge this gap and ensure that practitioners can fully leverage AI's capabilities.

Additionally, the integration of AI with existing practices may require significant changes in workflow, which can be disruptive. There is also the challenge of ensuring that AI complements rather than replaces the human expertise and personalized care that are central to beauty treatments. Maintaining a balance between AI-driven precision and the artistry of human practitioners is essential for successful integration. Ensuring that AI systems are designed to support, rather than supplant, human decision-making can help alleviate concerns and facilitate smoother integration [52].

7 Future directions and research opportunities

The beauty industry is witnessing several emerging trends and innovations driven by advancements in AI technology. One significant trend is the rise of AI-powered virtual try-on tools, which allow consumers to experiment with makeup and skincare products in real-time using augmented reality (AR). These tools are becoming more sophisticated, providing more accurate and realistic simulations by leveraging deep learning algorithms. Another emerging trend is the development of personalized beauty assistants that use AI to offer tailored skincare and cosmetic recommendations based on individual needs and preferences, including real-time skin analysis through mobile apps.

Additionally, AI-driven ingredient analysis is gaining traction, enabling consumers and brands to understand the efficacy and safety of cosmetic products by analyzing ingredient lists. This is complemented by the growing trend of clean beauty powered by AI, where AI tools help identify and recommend products that are free from harmful chemicals. The integration of AI with wearable technology is another innovation, where devices equipped with AI can monitor skin conditions continuously and suggest real-time adjustments to beauty routines [53]. To further advance AI in the beauty industry, several areas warrant additional research and development:

1. **Improving AI Diversity and Inclusivity:** Future research should focus on developing AI models trained on diverse datasets that include a wide range of skin tones, ethnicities, and age groups. This would help mitigate biases and improve the accuracy of AI recommendations across different demographic groups.
2. **AI in Holistic Beauty and Wellness:** Investigating the potential of AI to integrate beauty with overall wellness, including mental health, could lead to more comprehensive beauty solutions. For example, AI could analyze lifestyle factors and

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stress levels to suggest beauty routines that promote both physical appearance and well-being.

3. **Advanced Skin Diagnostics:** More research is needed to refine AI algorithms for diagnosing complex skin conditions. This includes the integration of AI with dermatological tools to provide more accurate assessments and personalized treatment options.
4. **Ethical AI in Beauty:** Future studies should explore the ethical implications of AI in beauty, particularly regarding privacy, data security, and the psychological impact of AI-driven beauty standards. Developing ethical guidelines and frameworks for AI use in the industry is crucial [54].

The continued advancement of AI technology is poised to significantly shape the future of the beauty industry. As AI becomes more sophisticated, it will likely lead to an increase in personalized beauty experiences, where consumers receive products and services tailored to their unique needs. This could result in higher customer satisfaction and loyalty, as well as the emergence of hyper-personalized product lines from beauty brands. AI could also drive sustainability in the beauty industry by optimizing supply chains, reducing waste, and promoting eco-friendly products through ingredient analysis and smart manufacturing. Moreover, the integration of AI with e-commerce platforms is expected to revolutionize how consumers discover and purchase beauty products, with AI-powered recommendations becoming a key driver of sales. In the long term, AI could democratize access to high-quality beauty care, making advanced skincare and cosmetic treatments more accessible to a broader audience. However, the industry must address the ethical and technical challenges associated with AI to ensure that these advancements are beneficial for all stakeholders [55].

8 Conclusion

This review establishes that the integration of Artificial Intelligence into the beauty industry represents a fundamental paradigm shift rather than a mere technological upgrade. As demonstrated in our comparative analysis of algorithms (Table 5), the transition from traditional image processing to deep learning architectures—specifically Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs)—has enabled unprecedented accuracy in facial feature analysis and wrinkle detection. Operationally, AI has transformed the sector from a product-centric model to a service-centric, hyper-personalized ecosystem. By leveraging predictive analytics, brands can now offer tailored skincare solutions that significantly enhance consumer engagement and optimize supply chain efficiency (Table 4). A critical insight emerging from this review is the "Personalization-Privacy Paradox." While AI tools offer bespoke beauty solutions that democratize access to dermatological advice, they simultaneously introduce significant ethical risks. Our systematic analysis of biases (Table 3) highlights that without robust, diverse training datasets, AI systems risk perpetuating the "New Jim Code," reinforcing racial and gender hierarchies under the guise of objective analysis. Furthermore, the reliance on sensitive biometric data necessitates stringent adherence to privacy frameworks, a challenge that remains a primary barrier to widespread consumer trust.

Moving forward, the industry must pivot from purely performance-driven metrics (e.g., accuracy) to trust-driven metrics. Future research should prioritize:

1. **Explainable AI (XAI):** Developing models that not only recommend products but explain the *rationale* based on skin analysis, thereby empowering consumers.

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2. **Inclusive Datasets:** Constructing open-source, demographically balanced facial datasets to eliminate algorithmic bias across different skin tones and ethnicities.
3. **Hybrid Models:** Integrating AI diagnostics with human dermatological expertise to ensure safety and accountability.

In summary, while AI holds the potential to redefine aesthetic enhancement and skin health management, its sustainable future depends on balancing technological innovation with ethical integrity and inclusivity.

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