ISSN:1738-6764, eISSN:2093-7504

# Bridging Deep Learning in Skincare and Dermatology: Opportunities for Hybrid Models and Early Skin Cancer Prediction

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https://doi.org/10.5392/IJoC.2025.21.2.024

Manuscript Received 29 May 2025; Received 27 June 2025; Accepted 28 June 2025

***Abstract:*** *In recent years, deep learning has gained significant traction in the fields of skincare and dermatology, with research primarily focused on two areas: cosmetic skin assessments and clinical diagnoses of skin diseases. Approximately two-thirds of the literature is dedicated to medical conditions such as melanoma and seborrheic keratosis, while the remaining third addresses cosmetic issues like UV damage, oiliness, pore size, and wrinkles. Although both domains utilize a similar methodological framework—training deep learning models on skin images for classification—they remain largely separate. Recent publications from 2024 and 2025 indicate a growing interest in integrating deep learning across these two fields. AI-driven skincare applications have shown promise in delivering rapid, personalized assessments, although challenges like biases in skin tone analysis continue to exist. In contrast, medical applications have made strides with deep learning models for skin cancer detection, achieving high accuracy and proving their potential as decision-support tools for dermatologists. The convergence of these domains presents a significant opportunity for hybrid models that could link cosmetic and medical applications, particularly for early skin cancer detection. By utilizing the extensive data and feature extraction techniques prevalent in skincare analysis, deep learning models could improve predictive accuracy and aid in the early identification of malignant conditions. This integration could facilitate proactive skin health monitoring by incorporating dermatological risk assessments into routine skincare evaluations. However, realizing this potential necessitates addressing challenges related to data diversity, model generalizability, and ethical considerations in AI-driven diagnostics. Bridging deep learning applications in skincare and dermatology not only offers the promise of improved early detection of serious skin conditions but also paves the way for more accessible, AI-powered dermatological care. Continued interdisciplinary collaboration is essential to develop these hybrid models and fully harness their potential in enhancing skin health diagnostics.*

**Keywords:** Deep Learning, Skincare, Dermatology, Hybrid Models, Skin Cancer Detection, Early Diagnosis

## 1. Introduction

Early detection of skin cancer remains one of the most crucial challenges in dermatology, as timely intervention significantly improves prognosis and survival rates [1, 2]. While traditional diagnostic methods rely on clinical examinations and histopathological analysis, recent advances in artificial intelligence (AI) and deep learning have introduced powerful tools for automated skin condition assessment [3]. For example which is shown in Figure 1, by training on millions of skin disease images, AI can recognize different types of skin diseases and achieve diagnostic accuracy close to or even surpassing that of dermatologists. However, a fundamental question arises: can these technologies be leveraged not only for clinical diagnosis but also for proactive, early-stage detection before visible symptoms emerge?

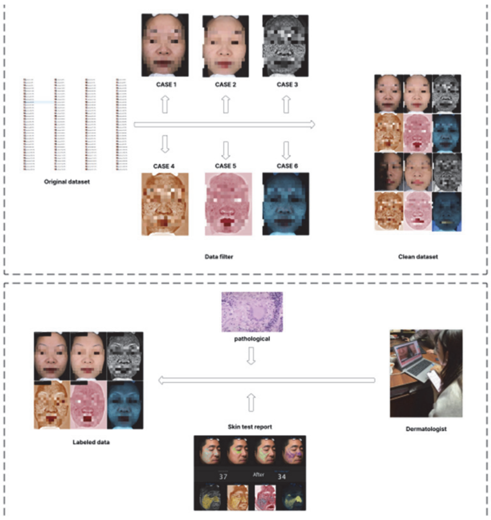


**Figure 1.** Deep learning model is induced by training it with annotated datasets that predict skin types.

Deep learning has been extensively applied in both medical dermatology and cosmetic skincare, with a significant body of research focused on classification models trained on skin images [4]. A review of recent studies published in 2024 and 2025 reveals that approximately two-thirds of the literature addresses medical concerns such as melanoma and seborrheic keratosis, while the remaining third focuses on cosmetic skin conditions like UV damage, oiliness, pore size, and wrinkles [5, 6]. Despite their shared methodological foundations, these two domains remain largely separate, limiting the potential for cross-disciplinary advancements.

The intersection of skincare and dermatological deep learning presents an untapped opportunity for hybrid models capable of bridging cosmetic and medical applications. By integrating AI-driven skincare assessment techniques with medical diagnostics, deep learning models could facilitate continuous skin health monitoring and early identification of malignant conditions [7]. This convergence may enhance predictive accuracy by leveraging vast datasets from the skincare industry while improving accessibility to dermatological risk assessment in non-clinical settings [8]. Figure 2 shows the possibilities that beautician in a skin-care shop was annotating problematic skin regions which may include those that are related to early skin cancer such as melanoma and irregular-shaped moles.

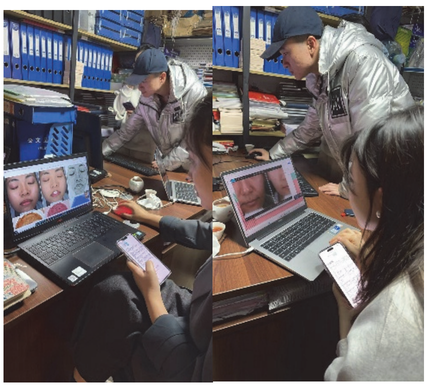

**Figure 2.** An annotation task was being performed with the cooperation of a beautician and dermatological clinician that shows the importance of interdisciplinary knowledge required for skincare AI.

This review explores the current state of deep learning applications in skincare and dermatology, examining the potential for hybrid models that enable early cancer detection. By identifying gaps and opportunities in existing research, we highlight the need for interdisciplinary collaboration to develop AI-driven solutions that improve both cosmetic skin analysis and clinical dermatology, ultimately advancing proactive skin health management. In this paper, we provide Appendix A which reviews the most recent contributions towards the direction of applying deep learning on skincare. In particular, in Appendix B, we attempt to find answers from the reviewed paper on the question of 'How closely the study of applying deep learning contribute to early detection of potential skin problems as reported in the most recent literature?'.

## 2. Hybrid Models in Dermatology: Enhancing Diagnostic Performance

Deep learning has introduced a new era of hybrid models that combine various deep learning architectures, leading to improvements in diagnostic performance across both skincare and dermatology. Hybrid models are built on the premise that combining the strengths of different architectures can overcome the limitations of individual models and improve overall accuracy and generalization.

For instance, hybrid models combining InceptionV3 with DenseNet121 have been shown to improve skin cancer detection accuracy by enhancing feature extraction and classification capabilities [9]. In particular, DenseNet121's ability to reuse features from previous layers aids in learning more complex representations, which is vital for detecting subtle skin lesions. By merging these models, accuracy improves, and overfitting is reduced, particularly in the complex and variable task of skin cancer classification.

Similarly, the RvXmBlendNet model, which incorporates ResNet50, VGG19, Xception, and MobileNet, has demonstrated superior performance when applied to skin cancer datasets, achieving significant improvements over individual models [10]. The rationale behind combining these diverse models is to capture different aspects of skin pathology, from the textures and patterns visible in the lesion's surface to its underlying biological features. Figure 3 shows the possibility of visualizing the skin condition from the textures and patterns visible in the lesion's surface to its underlying biological features.

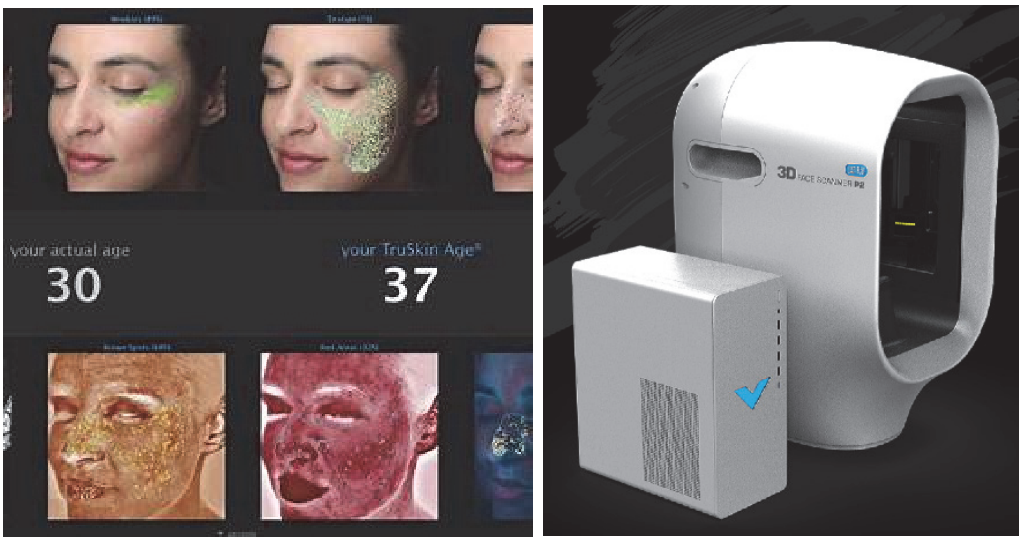


**Figure 3.** Visualizing skin surface details by high-precision 3D modeling in ~30 seconds for accurate skin diagnostics.

While these hybrid models excel in medical dermatology applications, they are also gaining traction in the skincare industry. Personalized skincare solutions are being developed through deep learning models that analyze individual skin types, assess the effects of various skincare products, and adjust recommendations based on real-time feedback from IoT-enabled devices. Obayya et al. (2024) [11] demonstrated how IoT systems can complement deep learning models to track real-time skin changes, optimizing skincare routines by analyzing users' responses to products and external factors, such as UV exposure and environmental pollution.

The challenge with these hybrid models, however, is the need for diverse, high-quality training data. Many deep learning models in dermatology have been trained on limited datasets, which may not fully capture the wide variation in skin types, ages, and ethnicities. This limitation can result in reduced generalizability of the models and can bias predictions, particularly when models are tested on populations that differ significantly from the training data [12]. Addressing these challenges requires collaboration across geographical regions to create more inclusive datasets, which is critical for improving the robustness of hybrid models.

## 3. Advancements in Early Skin Cancer Detection: Deep Learning's Role

One of the most significant contributions of deep learning in dermatology is its ability to detect skin cancer at an early stage. Early detection is crucial for improving survival rates, as melanoma and other skin cancers can become fatal if left undiagnosed in their early stages [13]. Several deep learning models have demonstrated high accuracy in skin cancer detection, leading to a shift toward real-time, AI-driven diagnostic tools.

The SkinEHDLF model, which combines an enhanced VGG19 architecture with transformer layers, offers a notable example of such a system. With an impressive real-time accuracy rate of 96.2%, this model is a testament to the efficacy of deep learning in skin cancer detection [14]. The inclusion of transformer layers enables the model to capture long-range dependencies in skin images, which is essential for distinguishing between benign and malignant lesions that may appear similar in superficial examinations.

Furthermore, IoT devices that monitor skin health in real-time can complement AI models, providing continuous data for analysis. These devices, equipped with sensors to measure skin temperature, moisture levels, and even UV radiation exposure, enable the continuous monitoring of skin conditions [11]. The integration of these IoT systems with deep learning models allows for ongoing tracking of skin changes and early detection of potential skin cancers. By offering personalized recommendations based on real-time data, such systems enhance preventative skincare measures, offering proactive, customized solutions.

However, as the literature points out, there are significant challenges related to dataset biases. A major concern is the representation of diverse skin tones, as current deep learning models tend to be trained on datasets with limited diversity. Daneshjou et al. (2022) [15] found that many dermatological models perform poorly on images of individuals with darker skin tones, which could lead to suboptimal performance in real-world settings. This issue is particularly critical in the cosmetic skincare domain, where accurate pigmentation analysis is necessary. For instance, distinguishing between hyperpigmentation caused by sun exposure and lesions that may indicate early-stage melanoma requires precision, which can be hindered by dataset biases.

## 4. Ethical Considerations and Model Interpretability

As deep learning models become more integrated into clinical dermatology and skincare, ethical considerations surrounding transparency and interpretability must be addressed. One of the core challenges of AI in healthcare is the “black-box” nature of many deep learning models, where the decision-making process remains opaque. This lack of interpretability poses a significant challenge for clinicians who need to trust AI systems in order to make informed decisions.

The SkinEHDLF model, despite its high accuracy, remains a black-box model, meaning that while it can identify malignant lesions with great precision, it does not provide a clear explanation of why a particular lesion is classified as cancerous [14]. This lack of transparency can create reluctance among dermatologists and skincare professionals, as they cannot fully understand or explain the rationale behind AI-driven decisions. This issue is exacerbated in clinical settings where human oversight is essential, and AI recommendations must be explained to patients.

In response, there is increasing interest in explainable AI (XAI) frameworks that provide insights into how deep learning models make their predictions. XAI aims to improve trust in AI systems by offering human-understandable explanations for model decisions. For instance, the use of heatmaps and saliency maps can help visualize which areas of a skin image contributed to the model’s decision, thus offering dermatologists a better understanding of the AI’s reasoning. Furthermore, integrating XAI into hybrid models can make them more suitable for clinical adoption, as dermatologists will be able to assess the reliability of AI-driven recommendations [16].

## 5. Conclusion: Future Prospects and Challenges

The application of deep learning in both skincare and dermatology has the potential to transform both industries, offering enhanced diagnostic capabilities and personalized skincare solutions. Hybrid models that combine multiple deep learning architectures have demonstrated improvements in skin cancer detection, particularly when applied to complex and varied datasets. However, challenges related to dataset diversity, model generalizability, and interpretability remain significant hurdles that must be addressed.

Future research should focus on collecting diverse datasets that represent a wide range of skin types, ages, and ethnicities to reduce biases in deep learning models. Furthermore, incorporating explainable AI into dermatological and skincare models will be crucial to gaining the trust of clinicians and patients alike. By addressing these challenges, the full potential of deep learning in skin health can be realized, leading to more accurate, personalized, and equitable skincare and dermatology solutions. As the convergence of cosmetic skincare and clinical dermatology through deep learning continues to gain momentum, several critical directions merit the attention of the broader research community. One pressing need is the systematic evaluation of hybrid AI models in real-world contexts. Beyond algorithmic performance, future studies should focus on deployment scenarios in teledermatology, consumer skincare platforms, and clinical support systems. Longitudinal case studies and implementation trials can offer valuable insights into user engagement, model reliability in diverse settings, and pathways toward regulatory approval.

Equally important is addressing persistent challenges related to dataset bias and demographic imbalance. While awareness around fairness in AI has increased, the development of shared protocols for constructing balanced dermatological datasets remains limited. Future work should encourage the creation and open sharing of demographically diverse image repositories, including underrepresented skin tones, age ranges, and geographical populations. Approaches such as federated learning, skin-tone-aware augmentation, and equity-centered benchmarking could play a central role in minimizing unintended biases.

Explainable AI (XAI) is another area ripe for advancement. Current visualization methods, while informative, may not always align with dermatological reasoning or clinical workflows. Researchers are encouraged to explore task-specific explanation paradigms that incorporate domain-relevant features, such as lesion shape, symmetry, and texture. In parallel, the development of standardized quantitative metrics—for example, explanation faithfulness, localization accuracy, and alignment with expert judgment—would help validate the utility of XAI in practice.

Finally, the potential for early detection and preclinical diagnosis of skin-related conditions presents an exciting frontier. Multimodal AI systems that integrate static imagery with temporal skin changes, patient metadata, and contextual information (such as environment, climate, air/water pollution, mental stress or lifestyle) could enable proactive dermatological care. Investigating these predictive pipelines not only extends the clinical relevance of hybrid models but also aligns with the broader goal of preventative, personalized skincare.

Together, these research directions point toward a more inclusive, explainable, and clinically meaningful future for AI at the intersection of beauty technology and dermatological science. It is hoped that this review paper paves potential research arena for peer researchers and practitioners crossing AI and skincare domains.

**Acknowledgments:** This research was funded by Guangzhou Development Zone Science and Technology 2023GH02, the University of Macau (MYRG2022-00271-FST), and The Science and Technology Development Fund (FDCT) of Macau (0032/2022/A).

**Conflicts of Interest:** The authors declare no conflicts of interest to report regarding the present study.

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## Appendix A: Review Comparison Table of Deep Learning in Skincare and Dermatology Studies:

This appendix presents a detailed comparison of several studies that apply deep learning (DL) in the domains of dermatology and skincare. The table below outlines various attributes, including the target skin condition, AI methodologies, dataset information, and the specific applications in skincare.

| Authors | Target | Type | Personalized skincare? | Datasets | AI techniques | Pre-processing | Hardware | Novelties |
|---|---|---|---|---|---|---|---|---|
| Obayya et al [11] | Skin condition assessment and dynamic skin cancer diagnosis | Medical skincare, general skincare, skin condition diagnosis, adaptive skincare regimens. | Yes | Skin types, skin conditions. | Deep learning, RNNs | No | IoT sensors | IoT sensing and deep learning (RNNs) for continuous skin condition assessment, personalized skincare, and early skin concern identification |
| Haykal et al [14] | Skin condition diagnosis, treatment optimization, predictive care. | Medical skincare, general skincare, skin treatment, anti-aging, aesthetics. | Yes | Real-time data, sensors, wearable devices, high-resolution imaging, electronic health records. | Deep learning, and digital phenotyping. | No | Sensors and wearable devices | Digital twins in dermatology for predictive care, personalized treatment, and real-time skin condition simulation. |
| Kuang et al [17] | Horse oil, adulteration detection, authenticity verification. | General skincare, adulteration detection, skincare products, healthcare | No | Infrared spectral data, horse oil, butter, sheep oil, lard, mixed proportions | Deep learning, ResNet model, combined with infrared spectroscopy. | Standard normal variable transformation and detrending (SNV-DT) | PerkinElmer Fourier infrared spectrometer | Combination of infrared spectroscopy and deep learning (ResNet) for rapid horse oil adulteration detection |
| Herimanto et al [18] | Skin condition classification. | General skincare, skin type classification, skincare treatments, product recommendation | Yes | Facial images, augmented dataset, from Bing and Kaggle | Deep learning CNN and MobileNet V3 | Rescale preprocessing | No | MobileNetV3 for improved facial skin type classification accuracy, integrated into an Android-based application |
| Senevirathne et al [19] | Skin condition identification, skin color analysis, and makeup recommendation | General skincare, beauty solutions. | Yes | Facial images, augmented dataset, from Bing and Kaggle | Deep learning and machine learning, CNN, XGBoost, and SVM | No | No | Use of a Custom CNN for improved skin condition identification accuracy and a hybrid recommendation system for personalized makeup suggestions |
| Saiwaeo et al [20] | Skin type detection | Medical skincare, general skincare, skin | No | Facial images, processed , | Deep learning, EfficientV2 | Contrast Limited Adaptive Histogra | No | EfficientV2 for real-time skin type detection |

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| | | type recognition, skin disease diagnosis, skincare applications | | augmented, diversity, model generalization | | m Equalization (CLAHE) | | with 98.04% accuracy and 22.59 MB compact model size |
| Pakkala et al [21] | Skin type classification and product recommendation. | General skincare, skin type classification, tailored product recommendations | Yes | Facial photos | Gray-Level Co-occurrence Matrix (GLCM), Graph Neural Networks (GNNs) | GLCM for image preprocessing | No | GLCM for texture extraction and GNNs for accurate skin type classification and personalized skincare recommendations |
| Vats et al [22] | Product recommendation. | General skincare, tailored product suggestions | Yes | Product information, brand, user ratings, skin type, skin tone, product category, price, ingredients from Sephora.com | Demographic Filtering, Content-Based Filtering, Collaborative Filtering, and Deep Learning methods | No | No | Comparative assessment of skincare recommendation methods and a Hybrid approac |
| Sahu et al [23] | Skin condition detection, specifically skin cancer. | Medical skincare, skin cancer detection, skin cancer classification. | No | Melanoma images from Kaggle | Deep learning, CNN | Resizing and rescaling | No | Early skin cancer detection and comparison of CNN optimizers (RMSprop, Adam, Nadam) for optimal accuracy |
| Tonello et al [24] | Product recommendation. | General skincare, cosmetic product recommendations, facial image analysis. | Yes | Facial images from Color FERET and internet searches | Deep learning, CNN, VGG16 and DeepFace for age prediction. | Cropping ROIs, gray balance, normalization, and rotation | No | VGG16 for wrinkle classification and DeepFace's age prediction for personalized product recommendations |
| Pereira et al [25] | Product recommendation. | General skincare, cosmetic products, facial image analysis, product recommendations | Yes | Facial images from Color FERET and internet searches | Deep learning, CNN, VGG16 and DeepFace for age prediction. | Cropping ROIs, gray balance, normalization, and rotation | No | VGG16 for wrinkle classification and DeepFace's age prediction for personalized product recommendations. |
| Rasal et al [26] | Product recommendation. | General skincare, cosmetic products, skin type, product recommendations | Yes | Skin types images | Deep learning, CNN | Resizing, patching, and data augmentation | No | CNN for personalized cosmetic recommendations and feature extraction |

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| | | | | | | | | for improvement |
| Rismayani et al [27] | Predicting facial skin disorders. | Medical skincare, facial skin disorders, diagnosis. | Yes, the study includes personalized skincare by predicting facial skin disorders based on individual non-visual information. | Non-visual data from respondents aged 20-50, covering patient ID, age, gender, skin type, family history, symptoms, and diagnosis | Artificial Neural Networks (ANN) | No | No | ANN for predicting facial skin disorders from non-visual data with 100% accuracy |
| Yutika et al [28] | Sentiment analysis of beauty product reviews. | General skincare | No | IndoBERT and mBERT were used for aspect extraction and sentiment analysis. | Consumer sentiment prediction algorithm | No | No | Pre-trained models applied to Indonesian beauty reviews, with error analysis on English word impact |
| Firdaus et al [29] | Product recommendations | General skincare | Yes | Ingredient lists of various skincare products | Cosine similarity, for evaluating ingredient lists | No | No | Cosine similarity for ingredient analysis and personalized skincare recommendations, validated by user feedback |
| Manurung et al [30] | Product recommendations. | General skincare | Yes | Historical user preferences and skin condition data | Neural Collaborative Filtering (NCF), combining deep neural network architecture with collaborative filtering | No | No | Incorporating temporal skin changes and user data for a dynamic skincare recommender system |
| Vinutha et al [31] | Product recommendations. | General skincare | Yes | Ingredient lists of 1472 skincare products from Sephora.com | Content-based filtering, tokenization, one-hot encoding, and T-distributed Stochastic Neighbor Embedding (t-SNE). | No | No | Content-based filtering for ingredient analysis and t-SNE visualization to enhance user experience |
| Khalid et al [32] | Skin condition detection | General skincare | No | Large data collection from various Internet sources, including real-time multimedia data via IoT | Deep Learning, CNNs with IoT | No | IoT devices and ESP 32 connect cameras. | IoT and CNN integration for AC-Skin, enabling continuous facial acne monitoring and diagnosis |

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| Choi et al [33] | Skin condition analysis. | General skincare | Yes | Skin measurements and characteristics of aged 20's | Deep learning and skin analysis algorithms. | No | No | AI-based skin analysis for personalized self-care and skin characteristic analysis |
| Yu et al [34] | Skin condition assessment | General skincare | No | N/A | Deep learning, DeepLab v3 with enhanced attention mechanisms | No | No | DeepLab v3 with attention mechanisms for skin quality assessment and device applications |
| Lee et al [35] | Skin condition analysis. | General skincare | Yes | Skin measurements and characteristics of 30's | Deep learning with skin analysis algorithms. | No | Yes | AI-based skin analysis for personalized beauty care targeting aging skin |
| Li et al [36] | Analyzing skin condition, acne severity. | General skincare | Yes | Frontal selfie photos of Chinese adult women and questionnaire data | Deep learning, CNN | No | Yes | AI analysis of selfies for acne severity trends and correlations with skin, diet, and environmental factors. |
| Yadav et al [37] | Skin condition detection and personalized care. | General skincare | Yes | Selfie images and user information such as age, gender, and skin sensitivity. | Deep learning with regression classification | No | No | Ensemble model for acne severity prediction and personalized care, improving diagnosis |
| Ray et al [38] | Product recommendations | General skincare | Yes | Various skin types and their corresponding suitable cosmetic products. | Deep learning | No | No | Deep learning algorithms for personalized skincare product recommendations |
| Sun et al [39] | Skin condition analysis, identification and severity assessment of nasal blackheads. | General skincare | No | Facial photos with blackhead symptoms in the nasal region | Deep learning, YOLO-v5 | Scaling, translation, cropping, rotation, and color transformation | No | Deep learning for accurate nasal blackhead identification, enhancing cosmetic clinical trials |
| Hanchinal et al [40] | Product recommendations | General skincare. | Yes | Images and information about different skin types and conditions | Deep learning, CNN | No | No | AI-driven web app for personalized skincare recommendations and cross-platform price comparisons |
| Lee et al [41] | Product recommendation | General skincare | Yes | Cosmetic ingredients and | Transformer encoder and U-Net- | Segmentation and features | LUMINI Kiosk V2 | AI-driven skin and ingredient |

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| | | | | facial skin images collected from various sources | based segmentation networks | enhancement | | analysis for personalized cosmetic recommendations based on actual content. |
| Sudharson et al [42] | Skin condition analysis and monitoring, refining treatment recommendations | Medical skincare | Yes | Extensive patient data, including images of skin conditions. | Siamese neural network | Standard data preprocessing | No | Siamese neural network for precise skin condition analysis and monitoring |
| Rezaei et al [43] | Skin condition analysis, detection of facial wrinkles | General skincare | Yes | Facial images of original and augmented | Fast R-CNN with ResNet-50v2 and YOLOv8 | Scaling, translation, cropping, rotation, and color transformation | No | New wrinkle detection and real-time analysis using YOLOv8 and Fast R-CNN |
| Simanihuruk et al [44] | Sentiment analysis of product reviews | General skincare | No | Product reviews from Shopee | Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) models. | No | No | Bi-LSTM for accurate sentiment analysis of skincare product reviews |
| Bhaska et al [45] | Skin condition analysis, personalized skincare recommendations. | Medical skincare | Yes | Skin lesions images of eczema and melanoma | Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) | Resizing to 224x224, normalization, and augmentations like flips, rotations, cropping, zooming, and brightness adjustment | No | Hybrid CNN-SVM model for skin condition analysis with 95.09% accuracy and data privacy integration |
| Qi et al [46] | Skin condition analysis, whitening level estimation. | General skincare | No | Facial skin images of five whitening levels | Scale-Invariant Feature Transform (SIFT) and Reduced Support Vector Ordinal Regression (Reduced SVOR) | Resizing images to 60x80 pixels | High resolution cameras and wearable devices | Non-contact whitening level estimation with edge computing, SIFT, and Reduced SVOR for mobile devices. |

## Appendix B Summary of Reviewed Papers

This appendix provides a concise summary of the main contributions and distinctive findings of the studies reviewed in this work.

| Authors | How closely this study of applying deep learning contribute to early detection of potential skin problems? |
|---|---|
| Obayya et al [11] | The application of deep learning, particularly RNNs combined with IoT sensors, significantly contributes to early detection by continuously monitoring skin health and identifying early signs of skin concerns. This allows for timely and personalized skincare interventions, potentially preventing further skin issues. |
| Haykal et al [14] | The application of deep learning contributes significantly to early detection by continuously analyzing real-time data to predict future skin issues, allowing for proactive and tailored care. This predictive capability minimizes trial-and-error treatment and enhances preventive strategies, making early detection and intervention more effective. |
| Kuang et al [17] | While the study is not directly focused on skincare, the application of deep learning and infrared spectroscopy in detecting adulteration can indirectly contribute to early detection of potential skin problems by ensuring the authenticity and quality of skincare products, thus preventing health risks associated with adulterated products. |
| Herimanto et al [18] | The application of deep learning, particularly MobileNetV3, significantly contributes to early detection by accurately classifying facial skin types. This allows for precise recommendations of treatments and products, potentially preventing skin issues caused by incorrect skincare practices. |
| Senevirathne et al [19] | The application of deep learning significantly contributes to early detection by accurately identifying skin conditions such as acne, pimples, and dark spots. This allows for timely and personalized skincare interventions, potentially preventing further skin issues. |
| Saiwaeo et al [20] | The application of deep learning, particularly EfficientV2, significantly contributes to early detection by accurately classifying skin types in real-time. This allows for timely and personalized skincare interventions, potentially preventing further skin issues. |
| Pakkala et al [21] | The application of deep learning, particularly GNNs combined with GLCM, significantly contributes to early detection by accurately classifying skin types. This allows for personalized skincare routines that can prevent skin issues and encourage optimal skin health. |
| Vats et al [22] | While the study primarily focuses on product recommendations, the application of deep learning and recommendation systems can indirectly contribute to early detection of potential skin problems by suggesting appropriate skincare products based on individual skin attributes and concerns. |
| Sahu et al [23] | The application of deep learning, particularly CNN, significantly contributes to early detection by accurately identifying and classifying skin cancer at an early stage. This allows for timely medical intervention, potentially improving patient outcomes and minimizing the progression of the disease. |
| Tonello et al [24] | he application of deep learning, particularly the VGG16 architecture in a CNN and the DeepFace algorithm, indirectly contributes to early detection by accurately identifying wrinkles and age-related skin concerns. This allows for tailored product recommendations that can address early signs of skin aging and improve overall skin health. |
| Pereira et al [25] | The application of deep learning, particularly the VGG16 architecture in a CNN and the DeepFace algorithm, indirectly contributes to early detection by accurately identifying wrinkles and age-related skin concerns. This allows for tailored product recommendations that can address early signs of skin aging and improve overall skin health. |
| Rasal et al [26] | The application of deep learning, particularly CNN, indirectly contributes to early detection by accurately classifying skin types and recommending suitable cosmetics. This helps in preventing potential skin problems by ensuring that users use products compatible with their skin type. |
| Rismayani et al [27] | The application of deep learning, particularly ANN, significantly contributes to early detection by accurately predicting facial skin disorders using non-visual information. This allows for timely diagnosis and intervention, potentially improving patient outcomes and quality of life. |
| Yutika et al [28] | This study does not directly contribute to the early detection of potential skin problems. It focuses on consumer sentiment analysis rather than medical or skin condition diagnosis. However, it could indirectly inform product development and marketing strategies |
| Firdaus et al [29] | This study does not directly contribute to the early detection of potential skin problems. It focuses on personalized product recommendations rather than medical diagnosis or skin condition detection. However, it could inform better product choices, potentially preventing skin issues due to incompatible ingredients. |
| Manurung et al [30] | This study indirectly contributes to early detection by improving personalized skincare recommendations, potentially preventing skin issues by considering evolving skin conditions and external factors |
| Vinutha et al [31] | This study does not directly contribute to early detection of potential skin problems. It focuses on personalized product recommendations, which can indirectly help consumers make better skincare choices and potentially avoid skin issues. |
| Khalid et al [32] | This study significantly contributes to early detection by providing a fast, efficient, and reliable method for diagnosing facial acne and assessing skin severity, potentially improving timely treatment and preventing further complications. |
| Choi et al [33] | This study closely contributes to early detection by accurately measuring and diagnosing skin conditions, allowing for preventive skincare and timely interventions based on detailed skin analysis. |
| Yu et al [34] | This study contributes to early detection by providing a method for accurate and quantified assessment of skin quality, which can help identify potential skin problems early on. |
| Lee et al [35] | This study closely contributes to early detection by accurately diagnosing and analyzing skin conditions, allowing for timely and personalized skincare interventions based on detailed skin analysis |
| Li et al [36] | This study closely contributes to early detection by identifying acne severity trends and related skin problems, informing personalized skincare and public health strategies for adult women. |
| Yadav et al [37] | This study closely contributes to early detection by providing an accurate method for detecting and assessing the severity of acne, allowing for timely and personalized acne management |
| Ray et al [38] | While the primary focus of the study is on recommending skincare products, the use of deep learning to analyze skin types and conditions can indirectly contribute to the early detection of potential skin problems. By |

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| | understanding individual skin characteristics and recommending suitable products, the system can help prevent and manage skin issues more effectively. |
| Sun et al [39] | The study contributes to early detection by providing accurate and objective evaluation of blackheads, allowing for timely interventions and better management of skin conditions. |
| Hanchinal et al [40] | The study contributes to early detection by recognizing different skin outlines and disorders such as pigmentation, dryness, sensitivity, and acne, allowing users to address skin issues with appropriate skincare products before they become more severe. |
| Lee et al [41] | The study contributes to early detection by analyzing skin conditions such as pores, redness, acne, wrinkles, pigmentation, and dark circles, allowing users to address these issues with appropriate products before they become severe. |
| Sudharson et al [42] | The study contributes significantly to early detection by providing precise skin condition analysis and continuous monitoring, enabling timely interventions and improving patient outcomes. |
| Rezaei et al [43] | The study contributes to early detection by accurately identifying and analyzing facial wrinkles, which can aid in developing personalized skincare treatments and addressing skin aging issues before they become more pronounced |
| Simanihuruk et al [44] | The study does not directly contribute to early detection of skin problems. However, it can provide insights into consumer experiences and concerns, which may inform product development and address common skincare issues. |
| Bhaska et al [45] | The study significantly contributes to early detection by accurately identifying and diagnosing various skin conditions, enabling timely medical interventions and personalized treatment plans. |
| Qi et al [46] | The study does not directly contribute to early detection of skin problems but offers an efficient method for evaluating skin whitening levels, which can be valuable in assessing the effectiveness of skincare products. |