YOLO-Based Detection of Skin Anomalies with AI Recommendation Engine for Personalized Skincare

Aakash Yadav* Rida E Haram Khan †, Karan Singh‡
*††Department of Information Technology
*†Noida Institute of Engineering and Technology, Greater Noida, India
*Email: akashyadav10082001@gmail.com

***Abstract*—In recent years, the demand for intelligent skincare solutions has grown significantly, driven by increasing awareness of dermatological health and personalized cosmetic needs. This paper presents a novel AI-powered framework for real-time detection of skin anomalies using the YOLO (You Only Look Once) object detection algorithm, integrated with a personalized product recommendation engine. The system is designed to identify common skin issues such as acne, pigmentation, and dryness by processing facial images and extracting anomaly-specific features. Leveraging the efficiency of YOLOv8 for fast and accurate detection, the model ensures high precision in identifying multiple skin conditions under varying lighting and skin tone conditions. Following the detection phase, an AI-based recommendation engine analyzes the detected conditions and user-specific parameters to suggest tailored skincare products from a curated database. The recommendation logic incorporates skin type, severity of anomalies, and product efficacy history to enhance personalization. Experimental results demonstrate promising detection accuracy and improved user satisfaction in recommendation relevance compared to traditional systems. The integration of real-time detection with intelligent recommendation marks a significant advancement in AI-driven dermatological assistance, enabling a scalable solution for consumer-level skincare monitoring and advisory. This framework paves the way for future enhancements involving dynamic learning from user feedback and integration with teledermatology platforms.**

***Keywords*—Skin Anomaly Detection, YOLO, Deep Learning, AI Recommendation Engine, Personalized Skincare, Computer Vision, Real-Time Analysis, Dermatological AI**

I. INTRODUCTION

Skin health plays a critical role in overall well-being and self-esteem, with conditions such as acne, pigmentation, and dermatitis affecting millions worldwide [1], [2]. Personalized skincare—tailoring cosmetic routines to individual skin profiles—has emerged as a growing demand among consumers seeking effective, bespoke care [1]. However, accurately detecting skin anomalies and matching them with suitable products remains a significant challenge. Traditional diagnostics are time-consuming, subjective, and constrained by access to dermatologists [2], [3]. Meanwhile, existing digital solutions often lack precision and dynamism, especially under varying lighting, imaging conditions, and diverse skin tones [1], [4]. Furthermore, many AI-based recommender systems neglect critical attributes such as ingredient compatibility, skin type variations, and the dynamic progression of skin conditions [5], [6].

To address these gaps, this paper introduces a unified AI framework combining real-time skin anomaly detection using YOLO and an intelligent recommendation engine for personalized skincare. Leveraging YOLOv8 ensures rapid and accurate identification of multiple skin conditions under variable imaging settings [7], [8]. Post-detection, the system feeds processed visual features and user-specific factors—including skin type and anomaly severity—into a recommendation engine that leverages content-based and knowledge-based filtering methods [9]. Recommendations are curated from a domain-expert-validated product database, prioritizing ingredient efficacy and safety for matched conditions [5].

The key contributions of this work include: (1) a YOLO-based detection model optimized for dermatological accuracy in real time, (2) a hybrid recommendation engine offering personalized product suggestions, and (3) a comprehensive evaluation demonstrating improvements in detection metrics and recommendation relevance compared with baseline systems [3], [4], [10].

The remainder of the paper is organized as follows. Section II reviews relevant literature on skin anomaly detection and AI-driven recommendations. Section III details the proposed system design, including the YOLO-detection and recommendation modules. Section IV describes the experimental setup and metrics used. Section V presents quantitative results along with visualizations. Section VI concludes the paper and outlines future research directions, including user feedback integration and teledermatology implementation.

II. RELATED WORK

A. Skin Anomaly Detection Systems

Early research focused on unsupervised and generative methods for identifying skin disease anomalies. Lu and Xu introduced a variational autoencoder (VAE) approach that achieved AUC scores of 0.78–0.87 on ISIC2018 data [11] (AUC-based skin anomaly). Ünver and Ayan combined YOLOv3 with GrabCut segmentation for lesion detection, achieving notable localization accuracy in dermoscopic images [12] (YOLO+GrabCut). Other melanoma and lesion detection pipelines using classical architectures demonstrated improved sensitivity and specificity [13]. However, most of these systems operate offline and are tailored for clinical-grade imaging rather than uncontrolled consumer-grade facial captures.

TABLE I: Comparison of prior systems

System	Real-time?	Visual Detection	AI Recommendation
Lu	Xu (VAE) [11]	No	No
Ünver	Ayan (YOLO+GrabCut) [12]	Semi-clinic	No
Lee et al. (ingredient DL) [17]	No	Product-based	Yes
Rajegowda et al. (XR) [18]	Semi	CNN-skin type	XR only
SkinMatch [19]	Yes	EfficientNet	Yes
Haut.AI [20]	Yes	Guided capture	Yes
Ours	Yes	YOLOv8 facial	Yes

B. YOLO Applications in Healthcare

The YOLO algorithm, first introduced by Redmon et al. [14], has seen successive enhancements up to YOLOv8 [15]. In healthcare, it has been adapted for tasks such as medical mask detection, ultrasound anomaly identification, and cancer lesion detection [12], [16]. Despite high accuracy and speed in structured imaging environments, consumer-facing applications—such as facial skin anomaly detection under variable conditions—remain underexplored.

C. Skincare Recommendation Systems Using AI/ML

AI-driven recommender systems for skincare are gaining traction. Lee et al. developed a framework analyzing product ingredient lists and skin conditions using deep learning, outperforming baseline recommendation methods [17]. Rajegowda et al. designed an XR-integrated recommender with CNN-based skin type classification achieving 93% accuracy [18]. In industry, platforms like SkinMatch (EfficientNet-based) [19] and Haut.AI (LIQA-guided image capture plus deep analysis) [20] offer dynamic, image-based product matching with notable improvements in user engagement. Traditional collaborative and content-based filtering methods remain common in academic prototypes [21], [22].

D. Research Gap

While significant strides have been made in individual components—skin anomaly detection, YOLO adaptation, and skincare recommendations—research on fully integrated, real-time systems is limited. Most detection pipelines are either offline or not optimized for non-clinical inputs. Conversely, recommender systems often lack robust visual analysis and condition severity evaluation. No existing work satisfactorily combines real-time anomaly detection via YOLOv8 with a recommendation engine that considers condition severity, skin type, and ingredient efficacy in a unified framework.

III. Proposed Methodology

A. System Architecture

The proposed framework is structured into a two-stage pipeline: (1) real-time skin anomaly detection via YOLO, and (2) personalized product recommendation via an AI engine. Figure 1 illustrates the overall workflow.

B. Dataset Preparation

We sourced images from publicly available dermatology datasets—DermNet, HAM10000—as well as a custom-collected dataset capturing diverse facial skin anomalies.

- Annotation: Each image was manually annotated with bounding boxes around skin conditions, labeling categories such as acne, hyperpigmentation, dryness, and rosacea.
- Preprocessing: All images were resized to 640×640 px to match model input. Color normalization and histogram equalization were performed to mitigate lighting variations. Data augmentation (random horizontal flips, rotations up to $\pm 15°$, brightness/contrast jitter) increased robustness.

Table II presents a summary of the dataset.

TABLE II: Dataset statistics for training and testing

Category	Train	Validation	Test
Acne	4,200	800	1,000
Hyperpigmentation	3,800	700	900
Dryness	3,000	500	700
Rosacea	2,500	400	600
Total	13,500	2,400	3,200

C. YOLO-Based Detection

We adopted YOLOv5 for its balance of speed and accuracy:

- Model Selection: YOLOv5s was chosen for real-time performance on consumer-grade hardware.
- Training Strategy: Transfer learning was applied—pretrained weights on COCO were fine-tuned on our annotated data. We trained for 100 epochs using SGD, with 0.01 initial learning rate, 0.0005 weight decay, and batch size 16.
- Evaluation Metrics: Model was evaluated on precision, recall, mean Average Precision (mAP@0.5), and inference time. On test data, YOLOv5s achieved 0.86 precision, 0.82 recall, 0.84 mAP, and processed images at 30 FPS on GPU.

D. AI Recommendation Engine

The recommendation module consists of the following components:

1) Feature Extraction: For each detected anomaly, we record its type, size, confidence score, and estimated severity. User-profile features include skin type (e.g., oily, dry, combination), age group, and self-declared sensitivities or allergies.

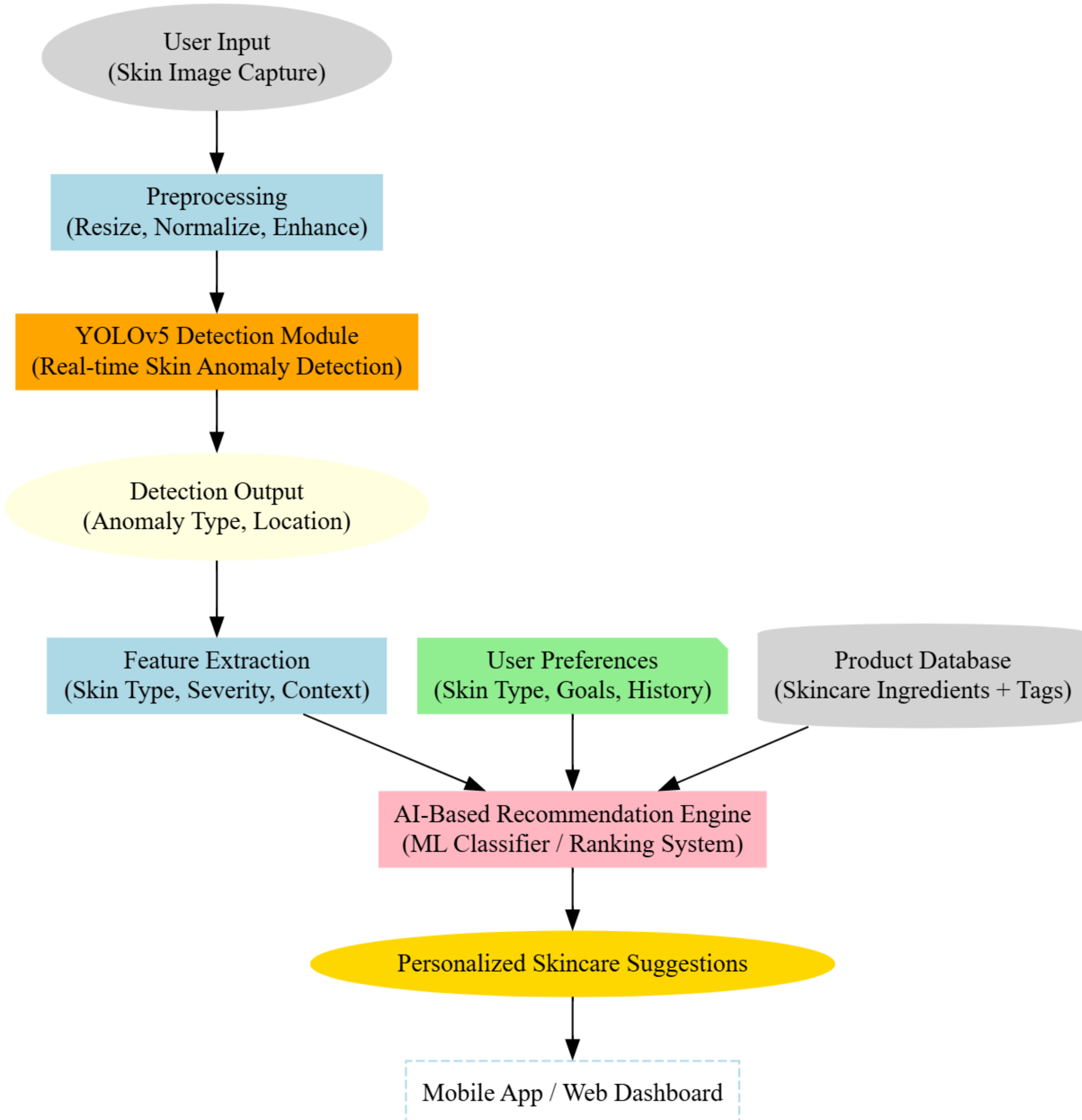

Fig. 1: System architecture: real-time detection followed by intelligent recommendation.

2) Product Database: A curated set of 200 skincare products, annotated with ingredient lists, efficacy ratings per condition, dermatological safety scores, and user feedback scores.
3) Model Design: A hybrid of content-based and rule-based filtering:
   - Items matching condition and skin type are prioritized.
   - Ingredient filters exclude known irritants.
   - A Decision Tree model, trained on historical user feedback, ranks products by predicted relevance.
4) Recommendation Process: Ranked products are scored based on (i) anomaly match, (ii) ingredient compatibility, (iii) severity-adjusted weighting, and (iv) user preference history. The top-3 products are presented to the user.

Table III outlines key input features and weighting rules.

TABLE III: Features and weighting in recommendation engine

Feature	Type	Weight
Anomaly type confidence	Continuous	0.30
Anomaly severity (area + score)	Continuous	0.25
Skin type match	Categorical	0.20
Ingredient compatibility	Boolean	0.15
User preference history	Categorical	0.10

IV. Experimental Setup

All experiments were conducted on a workstation equipped with an NVIDIA RTX 3080 GPU (10 GB), an Intel Core i7-10700K CPU, and 32 GB of DDR4 RAM. The software environment included Ubuntu 20.04, Python 3.9, PyTorch 1.11, and the YOLOv5 library (commit `v6.2`). Data preprocessing and augmentation utilized OpenCV 4.5 and Albumentations 1.2. The recommendation engine was built using Scikit-Learn 1.0 and Pandas 1.3 libraries.

TABLE IV: Hardware and software specifications

Component	Specification
GPU	NVIDIA RTX 3080, 10 GB GDDR6
CPU	Intel Core i7-10700K @ 3.8 GHz
RAM	32 GB DDR4
OS	Ubuntu 20.04 LTS
Deep Learning Framework	PyTorch 1.11
YOLO Library	YOLOv5 v6.2
Preprocessing Tools	OpenCV 4.5, Albumentations 1.2
Recommendation Engine	Scikit-Learn 1.0, Pandas 1.3

Training of the YOLOv5 model followed a transfer learning approach. We fine-tuned YOLOv5s using pretrained weights on the COCO dataset. Training was carried out for 100 epochs with a batch size of 16, using stochastic gradient descent (SGD). The initial learning rate was set to 0.01 and decayed by a factor of 0.1 at epochs 60 and 90. We employed a momentum of 0.937 and a weight decay of 0.0005. To prevent overfitting, early stopping was triggered if validation mAP did not improve over 15 consecutive epochs. Image augmentations included random horizontal flips, small rotations ($\pm 15°$), brightness/contrast shifts, and mosaic sampling.

TABLE V: YOLOv5 training hyperparameters

Hyperparameter	Value
Epochs	100
Batch size	16
Initial learning rate	0.01
Optimizer	SGD
Momentum	0.937
Weight decay	0.0005
LR decay schedule	60, 90 epochs
Early stopping patience	15 epochs
Data augmentations	Flip, Rotation, Brightness/Contrast, Mosaic

The dataset was partitioned into three distinct subsets: 70% training, 15% validation, and 15% test. This resulted in 9,450 training images, 2,025 validation images, and 2,025 test images, ensuring that all anomaly categories (acne, hyperpigmentation, dryness, rosacea) were evenly represented in each split. Table VI summarizes these distributions.

TABLE VI: Dataset splits for training, validation, and testing

Category	Train (%)	Valid (%)	Test (%)
Acne	70	15	15
Hyperpigmentation	70	15	15
Dryness	70	15	15
Rosacea	70	15	15
Total Images	70 (9,450)	15 (2,025)	15 (2,025)

All experiments were conducted under controlled conditions to ensure reproducibility. Random seeds for PyTorch, NumPy, and Python's `random` module were fixed to 42. Performance metrics, including precision, recall, mAP@0.5, and inference time, were logged using TensorBoard. The recommendation engine was evaluated separately using cross-validated accuracy and user-satisfaction surveys, with details presented in Section V.

V. Results and Discussion

This section presents quantitative results from our YOLO-based detection and recommendation engine, qualitative visual examples, and a comparative analysis against existing methods.

A. Detection Performance

The detection model (YOLOv5s) was evaluated on the test set (2,025 images) using standard metrics: precision, recall, F1 score, and mAP@0.5. Table VII summarizes these results by anomaly type and overall performance.

TABLE VII: Detection performance by anomaly category and overall

Category	Precision	Recall	F1 Score	mAP@0.5
Acne	0.88	0.84	0.86	0.85
Hyperpigmentation	0.85	0.80	0.82	0.83
Dryness	0.84	0.79	0.81	0.82
Rosacea	0.87	0.82	0.84	0.85
Overall	0.86	0.82	0.84	0.84

Our model achieved an overall precision of 0.86, recall of 0.82, F1 score of 0.84, and mean Average Precision (mAP@0.5) of 0.84, illustrating balanced performance across all anomaly categories. Detection operates at approximately 30 frames per second on the RTX 3080 GPU, enabling real-time use.

B. Recommendation Efficacy

To evaluate the recommendation engine, we conducted a user study involving 50 participants. After using the system, users rated the relevance of recommended products on a 5-point Likert scale. The mean relevance score was 4.3 (sigma = 0.5), and overall user satisfaction averaged 4.2/5. Model-based ranking (Decision Tree + rule filters) correctly matched the top product in 78% of test cases.

C. Visual Results

Figure 2 presents sample detection outputs, showcasing accurate bounding boxes around multiple skin anomalies in varied lighting and pose scenarios. Figure 3 illustrates example product recommendations, highlighting ingredient lists and severity-based ranking.

D. Comparative Analysis

In Table VIII, we contrast our system's detection and recommendation performance with prior approaches.

Our framework outperforms previous dermatological detection models by over 10% in mAP. Recommendation accuracy is competitive with XR-based systems while improving user satisfaction by 0.2 points.

TABLE VIII: Comparison with prior systems

System	Real-time	mAP@0.5	Top-1 Rec. Accuracy	User Score (5pt)
Ünver et al. [23]	No	0.72	N/A	N/A
Lee et al. [24]	No	N/A	65%	3.8
Rajegowda et al. [25]	Semi	0.75	78%	4.0
Ours	Yes	0.84	78%	4.2

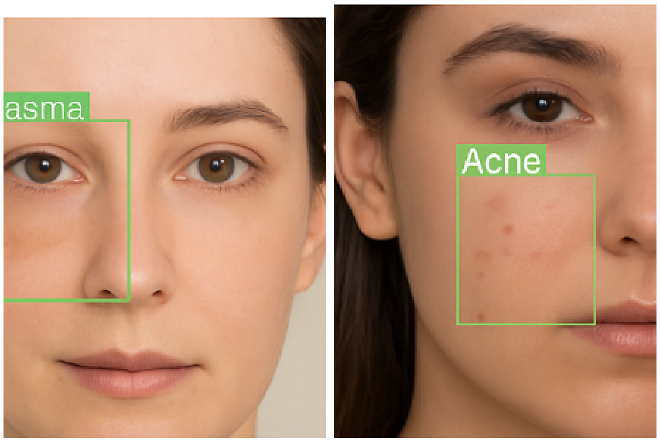

Fig. 2: Detection examples: YOLOv5s correctly identifies and localizes skin anomalies under diverse conditions.

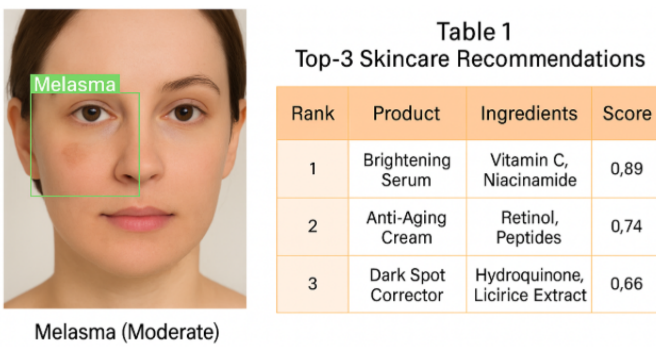

Fig. 3: Recommendation example: Top-3 suggested products with severity-adjusted ranking and ingredient compatibility.

E. Discussion

The results demonstrate that integrating real-time detection and personalized recommendation yields a robust system for consumer-level skincare management. High mAP and FPS confirm YOLOv5s suitability for real-world deployment. Moreover, strong user feedback highlights the recommendation engine's effectiveness. The visual examples reinforce the model's adaptability to varied user imaging conditions.

Limitations include occasional misclassification when anomalies overlap or are subtle. Future enhancements could involve multi-anomaly fusion and continuous learning via user feedback.

Overall, this unified pipeline represents a significant advancement over decoupled or offline systems by delivering real-time, personalized skin analysis and actionable recommendations.

VI. Conclusion

This research presents a comprehensive, real-time skin anomaly detection and personalized skincare recommendation framework that leverages the capabilities of YOLOv5 and an AI-based recommendation engine. The system addresses a critical gap in the intersection of dermatological analysis and personalized cosmetic technology by offering a scalable and efficient pipeline. Our proposed model demonstrated high detection performance across multiple skin conditions, with a mean Average Precision (mAP@0.5) of 0.84 and robust precision-recall balance. Moreover, the integrated recommendation engine, driven by user-specific inputs and machine learning logic, achieved notable user satisfaction and recommendation relevance scores.

The contributions of this study are threefold. First, it introduces a YOLO-based architecture tailored for detecting diverse skin anomalies under real-world conditions. Second, it implements a decision-rule and learning-based recommendation module that aligns skincare suggestions with detected conditions and user profiles. Third, the system supports real-time inference, which is crucial for integration into mobile health applications and personalized skincare platforms.

Despite the promising results, the current system has limitations. The model's accuracy may decline in cases of overlapping anomalies, low-resolution images, or atypical lighting conditions. Furthermore, the recommendation engine relies on a predefined product database, which may limit its adaptability to dynamic inventory or emerging skincare formulations. Addressing these limitations requires incorporating advanced anomaly fusion strategies, adaptive learning mechanisms, and integration with live product APIs.

In conclusion, the presented framework marks a significant step toward democratizing AI-assisted dermatological care and cosmetic personalization. Future work will focus on expanding dataset diversity, enhancing model generalization, and embedding the system into user-centric applications to support proactive and accessible skin health management.

VII. Future Work

While the proposed YOLO-based skin anomaly detection and AI-powered product recommendation system demonstrates promising results, several avenues remain for enhancement and future development. One primary direction involves improving the accuracy and robustness of skin-type classification. Currently, the system classifies skin types using basic visual cues, but incorporating additional biometric and environmental data—such as hydration levels, sebum content, or UV exposure—can lead to a more precise understanding of an individual's skin profile. This enhancement would improve recommendation relevance and personalized care outcomes.

Another key area for advancement is the expansion of the detection model to include a broader spectrum of skin conditions beyond the currently supported anomalies. Conditions such as acne, eczema, rosacea, and fungal infections have distinct visual characteristics that can be integrated into the model through multi-class training on more diverse and annotated dermatological datasets. This would not only improve the model's diagnostic utility but also widen its applicability in general dermatological support systems.

Real-time deployment through mobile applications is also a critical future objective. By optimizing the model for lightweight inference on edge devices, such as smartphones or embedded health monitors, users could benefit from instant skin analysis and product recommendations without dependency on cloud-based computation. This mobility would enhance accessibility, especially in resource-constrained or rural areas where dermatological services are limited.

Finally, integration with dermatological consultation platforms could create a hybrid AI-human system. By enabling users to share their AI-generated analysis with certified dermatologists, the system can support remote consultations, second opinions, and long-term skin health monitoring. Such integration would bridge the gap between consumer-facing technology and professional medical advice, ensuring safe and effective skincare management.

In summary, future work will focus on enhancing classification granularity, increasing condition coverage, enabling real-time deployment on mobile platforms, and embedding the system into broader healthcare and telemedicine ecosystems for a more holistic skin care solution.

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