DERMASCAN+: A Mobile Skin Condition Detection and Personalized Skincare Recommender System for Young Adults

Glaisa Mae C. Andales,
Jan Michael J. Cabahug, Roswell Rey Ceniza,
Jhun Kenneth M. Curacha, James David A. Guba
College of Computer Studies
University of Cebu Lapu-Lapu and Mandaue
Cebu, Lapu-Lapu, Mandaue, Philippines
glaisamaeandales25@gmail.com

Engr. Virginia B. Verdun
College of Computer Studies
University of Cebu Lapu-Lapu and Mandaue
Cebu, Lapu-Lapu, Mandaue, Philippines
Bgie8311@gmail.com

***Abstract*—DermaScan+ is a mobile skin condition detection and personalized skincare recommender system designed specifically for adolescents and young adults in Mandaue City and Lapu-Lapu City. The research focuses on bridging three main gaps: limited access to dermatologists, high reliance on unverified online skincare advice, and the lack of structured, youth-friendly decision-support tools for mild skin concerns. The artificial intelligence (AI) component uses a dermatology-specific foundation model with a Convolutional Neural Network (CNN)/ResNet backbone as a frozen feature extractor. This generates embeddings that a logistic regression head classifies into mild skin conditions. Concurrently, a dermatologist-aligned rule-based algorithm combines these AI outputs with questionnaire-derived skin type indicators to generate safe skincare recommendations. Implemented in a modular Android architecture, the system was evaluated under ISO 9126 and ISO/IEC/IEEE 29119 standards. Out of 420 participants, analysis of 417 youth respondents revealed strong agreement (grand mean of 2.83) that the traditional dermatological consultation pathway is time-consuming, logistically difficult, and financially challenging. Dermatologist feedback confirmed the application's viability as a non-diagnostic, consumer-level decision-support tool confined to mild concerns. Results indicate that DermaScan+ is technically feasible, systematically engineered, and well-matched to the safety expectations and needs of its intended demographic.**

***Keywords*—Mobile Health (mHealth), Skin Condition Detection, Artificial Intelligence, Recommender System, Deep Learning, Transfer Learning.**

I. INTRODUCTION

The human skin is a complex organ that protects the body from toxins, pathogens, ultraviolet (UV) exposure, and dehydration while supporting essential sensory and immunological functions. According to Harris-Tryon et al. [1], the skin acts as a physical barrier and works in partnership with the skin microbiota to maintain hydration and regulate the immune system, preventing adverse reactions like allergies. However, when the skin barrier is compromised by unsafe products, pollution, or sun damage, it becomes susceptible to infections, dryness, and inflammation.

During adolescence, hormonal changes often trigger widespread skin concerns. Young adults frequently struggle to manage these conditions, leading to significant social, psychological, and physical impacts. Such challenges can adversely affect self-image, interpersonal relationships, and mental health [2], [3]. In an attempt to address these issues, many adolescents resort to unverified recommendations from social media. The adoption of do-it-yourself (DIY) remedies—such as citrus-induced masks and detox drinks promoted by uncredentialed influencers—has been shown to exacerbate skin conditions and cause adverse effects [4]–[6].

In response to these challenges, mobile health (mHealth) applications and teledermatology have emerged as viable solutions. Digital health interventions can overcome geographical and financial obstacles by facilitating continuous monitoring and early detection [7]. The integration of Artificial Intelligence (AI) into mHealth systems further enhances analytical accuracy while reducing assessment costs and wait times [8]. While the traditional approach to skincare often relies on trial and error [9], AI-driven platforms provide personalized, objective, and data-driven suggestions, promoting better self-management of skin welfare [10].

In the Philippines, skin diseases represent a major health issue. However, dermatological care is hindered by a maldistribution of specialists, who are predominantly located in highly urbanized centers [11]. The lack of PhilHealth-accredited dermatologists forces patients to pay out-of-pocket, creating severe logistical and financial barriers, particularly for low-income demographics. Research indicates that low-income individuals are nearly four times more likely to self-medicate rather than seek professional help [12], [13].

In Cebu, residents outside central commercial hubs—such as Barangay Pamutan—frequently face high consultation costs and travel distances. Consequently, there is a strong preference for Complementary and Alternative Medicine (CAM) and informal advice [14], [15]. This reliance on unverified treatments poses significant risks for persistent or worsening skin conditions.

Despite these barriers, the integration of AI in Philippine dermatology is gaining momentum. Recent local studies have demonstrated the efficacy of transfer learning, CNNs, and mobile applications in providing timely and reliable skin assessments [16]–[18]. However, the deployment of such systems requires strict adherence to ethical considerations, transparency, and human accountability [19].

To address the gaps in dermatological accessibility and the dangers of unverified online advice among young populations, this study proposes *DermaScan+*, a mobile application that detects non-clinical skin conditions and provides personalized, dermatologist-validated product recommendations.

This research analyzes, designs, and develops an advanced mobile app, DermaScan+, for detecting skin conditions and providing personalized skincare recommendations to adolescents and young adults in Mandaue and Lapu-Lapu Cities. Using pre-trained CNNs and transfer learning, it creates an accessible, AI-driven tool. The study first assesses traditional skin management methods and user challenges to identify core features. It then implements optimal algorithms for skin assessment, AI image classification, rule-based recommendations, routine calendars, journals, and prompts, while curating a dataset of real-world mild skin concerns for accuracy. Finally, usability testing ensures an intuitive, user-friendly interface.

This study focuses on the development of DermaScan+ for adolescents and young adults in Mandaue City and Lapu-Lapu City. The system is deployed in a mobile environment, offering features such as personal profiling, skin observation tracking via journals, routine reminders, and a dermatologist-approved product library.

Ethically, the application serves as a non-diagnostic, consumer-level tool and does not replace professional dermatological evaluation. It only addresses mild, manageable skin concerns; complex or severe clinical conditions are explicitly flagged to redirect users to licensed professionals. The app does not facilitate appointment booking or clinic location tracking.

To mitigate the risks of inaccurate or biased outputs, the system does not utilize generative AI for product recommendations. Instead, it employs predefined, dermatologist-approved rule-based algorithms. Recognizing the limitations of image-based AI—such as lighting variations, skin tone differences, and resolution issues—the system does not assign fundamental skin types (e.g., oily, dry, sensitive) solely via image analysis. A prerequisite questionnaire is mandated to collect baseline data, ensuring recommendations are holistic. Furthermore, due to the visual similarities among various skin conditions, the classification model cannot guarantee 100% accuracy. DermaScan+ delivers key value by enabling teenagers and young adults to detect common skin issues early, make informed decisions, and avoid harmful DIY trends for healthier lifestyles. It establishes a foundation for researchers in localized AI and image processing for preventive dermatological care, while offering future researchers a guideline for refining techniques and ethically integrating AI into local healthcare.

II. REVIEW OF RELATED LITERATURE

This section presents and discusses the relevant literature, the conceptual framework, and the comparative matrix, serving as a foundation for understanding the current limitations and gaps in skin-image processing and recommendation systems. This review guides the development of the proposed DermaScan+ system by identifying gaps, similarities, and differences between previous studies and the current research, ultimately laying the foundation for the study's framework and processes.

A. Clinical Foundations and Mobile Modalities

To ensure a strong, well-defined implementation of the proposed system, this section presents processes, concepts, prior research, and critical topics that will advance the understanding of the research's goals and objectives.

1) Step-by-Step Skincare: Effective skincare routines typically follow structured steps: cleansing, treatment, moisturizing, and photoprotection, which have been recognized in dermatology expert consensus [20]. These steps provide a foundation for guiding recommendations and structuring comparative analyses in subsequent evaluations.

2) Mobile Platforms for Skin Condition Detection: Mobile technology has become an essential medium for dermatological assessment due to the widespread availability of smartphones, advances in high-resolution mobile cameras, and improvements in mobile machine learning. Recent literature demonstrates that mobile platforms can reliably capture, process, and evaluate dermatological images. Ali et al. [21] provided foundational evidence that smartphone photography can serve as a valid source for clinical skin assessment, demonstrating excellent interrater reliability (ICC = 0.93) in atopic dermatitis evaluations. Their findings indicate that mobile devices are sufficiently accurate for remote dermatologic evaluation.

Similarly, Hadeler et al. [22] emphasized the suitability of mobile applications for dermatology research and patient monitoring. They noted that smartphones unify multiple functions critical for dermatology within a single device. The capability of smartphones to support advanced AI-driven classification was further demonstrated by Sangers et al. [23], who validated a CE-marked mobile health application for skin cancer triage, achieving 86.9% sensitivity and 70.4% specificity. Collectively, these studies justify implementing DermaScan+ as a mobile application capable of analyzing mild skin conditions.

3) Camera-Based User Input: Recent research highlights the essential role of mobile device cameras as a primary input modality in mHealth systems. According to Sharma et al. [24], mobile cameras allow users to capture real-time, high-quality images that support remote diagnosis, monitoring, and self-assessment. Preclaro et al. [25] demonstrated that smartphone camera inputs significantly improved the accuracy and feasibility of teledermatology in a Philippine clinical setting, underscoring that camera quality and user compliance are essential for reliable AI-assisted interpretation.

B. AI-Driven Skin Type Detection and Classification

Velasco et al. [26] highlighted the vital role of artificial intelligence in supporting dermatological decision-making through image-based analysis, showing that AI-driven image recognition enhances assessment consistency for Filipino dermatologists. Oda et al. [27] emphasized the importance of testing under physical, real-world conditions and taking into account camera clarity, lighting, and focus. Their research reinforces the necessity of an in-app camera for capturing high-quality images.

Consistent with best practices, DermaScan+ applies explicit criteria before generating a final classification, utilizing a minimum confidence threshold of 70%. To maintain accuracy, the system implements an image-quality gate requiring adequate lighting, sufficient facial visibility, and acceptable sharpness before processing [27]. Furthermore, DermaScan+ focuses strictly on mild, consumer-level skin concerns (e.g., comedonal acne, enlarged pores, mild eczema, and hyperpigmentation) while explicitly excluding medically complex cases that require professional diagnosis.

1) Pre-requisite Question-based Assessment: The implementation of a standardized prerequisite screener is supported by Zhang et al. [28], who introduced a 14-item standardized questionnaire for classifying oily-sensitive skin. Validated against objective biophysical measurements, this questionnaire is utilized in DermaScan+ to classify users into standardized categories (e.g., mildly, moderately, or severely oily-sensitive) prior to AI triage.

2) CNN-Based Foundation Models as Feature Extractors: Building accurate skin condition classifiers requires large image datasets. Foundation models address this by providing large-scale pretrained encoders. Kiraly et al. [29] introduced Google's Derm Foundation, a dermatology-specific pretrained encoder built on a deep ResNet-based CNN architecture. Unlike conventional classifiers, Derm Foundation generates 6144-dimensional embedding vectors that capture clinically relevant visual patterns. This frozen pretrained encoder paradigm, successfully demonstrated in vision tasks by Radford et al. [30], establishes CNN-based architectures as a credible backbone [31].

3) Logistic Regression as a Classifier Head: Panda et al. [32] argue that logistic regression is a reliable and highly interpretable statistical technique in healthcare. Sievering et al. [33] reaffirmed that logistic regression remains competitive alongside complex machine learning algorithms for clinical predictions. Because the Derm Foundation encoder produces semantically structured vectors [29], passing these embeddings to a logistic regression classifier within DermaScan+ reduces computational complexity and enhances the interpretability of recommendations.

4) Transfer Learning in Medical Classification: Transfer learning (TL) addresses data scarcity by utilizing pretrained models that have learned visual features from large-scale datasets [34]. Gulzar et al. [35] implemented a Hybrid Deep Transfer Learning Method (HDTLM) integrating DenseNet121 and EfficientNetB0 to classify non-critical skin conditions, achieving high accuracy. Efat et al. [36] proposed a multi-level ensemble framework utilizing Customized Transfer Learning (CTL) augmented with attention mechanisms, proving effective for multi-class lesion datasets. Furthermore, Jaén et al. [37] and Abbas et al. [38] demonstrated the efficacy of transfer learning in consumer-facing diagnostic web systems and explainable AI (XAI) frameworks, supporting the architecture utilized in the DermaScan+ pipeline.

In DermaScan+, transfer learning is applied by adopting a frozen pretrained encoder as the feature extraction backbone, while a classifier head is trained on top of the extracted embeddings, adapting the pretrained representations to the target classification task.

C. Recommender Systems and User Engagement

1) Rule-based Algorithm for Recommender Systems: Rule-based algorithms convey decision-making logic transparently. Vilone and Longo [39] note that rule-based methods frame decisions as symbolic logic that domain experts can verify. Feremans and Goethals [40] observed that these transparent models work exceptionally well for recommender systems.

2) Product and Guide Recommendations: Lee et al. [41] utilized skin images to provide personalized recommendations; however, their study noted limitations in dataset coverage and ingredient concentration data. To address this, rule-based systems offer explainability grounded in dermatological logic, similarly supported by Jannatin et al. [42], who utilized ontology-based semantic rules to ensure transparent product recommendations.

3) Journaling, Calendars, and Notifications: Ris-

tow et al. [43] demonstrated that regular prompts, automatic notifications, and routine tracking significantly improve self-management for dermatological conditions. Similarly, photo-based skin journaling allows users to reflect on their condition progression [44], [45]. Furthermore, literature on mobile health adoption emphasizes that push notifications must be personalized, context-aware, and thoughtfully timed to avoid alert fatigue [46]–[49].

D. Mild Skin Concerns Datasets from Real-World Samples

Current datasets rarely focus specifically on mild or early-stage acne captured by users in natural lighting [50]–[52]. Pedro et al. [53] advocate for inclusive, population-specific image collections. Validation by Huynh et al. [51], [54] confirms that user-taken smartphone photos are a reliable basis for AI modeling and clinically meaningful automated analysis. Focusing on mild acne lesions addresses an underserved user base that benefits substantially from algorithm-guided preventive care [50], [52].

The conceptual framework of DermaScan+ is structured around three primary interconnected modules: mobile input mechanisms [21]–[23], AI-driven image classification [26], and a personalized recommendation system. User engagement begins with a prerequisite questionnaire [28] and camera-based input [24], [25], alongside skin journaling [45]. Image data is fed into a CNN-based feature extractor [29], [31] and processed via transfer learning [34], [35] and a logistic regression classifier [32], [33]. Outputs converge into a rule-based product recommender [40]–[42] that populates a routine calendar [43] managed by adherence notifications [49].

Several studies have explored automated dermatological analysis. Abirami and Karthikeyan [55] developed a mobile-based CNN for skin disease diagnosis, but it lacks skin profiling and personalized routines. Khalid et al. [56] introduced a smart facial acne tracking system, but it does not map to extensive non-clinical cosmetic guidance. Wibowo et al. [57] deployed MobileNet v2 for skin cancer detection, and Sokolov and Shpudeiko [58] evaluated the clinical Skinive algorithm; however, both serve as clinical diagnostic tools for severe pathologies rather than consumer-level mild conditions. Rashid et al. [59] developed SkinCareAI, which offers general suggestions but lacks rule-based routine customization.

Table I highlights how DermaScan+ improves upon these current platforms by synthesizing AI detection, journaling, routine calendars, and rule-based personalization.

III. METHODOLOGY

This section outlines the research and development strategies utilized to create DermaScan+, a mobile skin condition detection and personalized skincare recommender system designed for young adults in Mandaue City and Lapu-Lapu City. It details the research design framework, target demographic, data collection instruments, statistical treatments, and the software engineering methodology guiding the system's development from conception to deployment.

This study employed a quantitative descriptive research design to evaluate the proposed DermaScan+ system, aligning with recent literature utilizing mobile and AI-based tools for dermatologic assessment and cosmetic decision-making. The design focuses on collecting numerical data from target users to describe their perceived usability, acceptability, and effectiveness of the system, a method consistent with prior digital dermatology and mobile health (mHealth) studies that quantify user experiences using structured metrics.

Quantitative data were gathered through structured survey questionnaires utilizing closed-ended items and Likert-scale responses. The surveys were administered to a defined sample of young adults (aged 13 to 25) who actively use mobile devices and skincare products, reflecting earlier methodologies examining self-management behaviors. The process was carefully structured to ensure the consistency and reliability of responses within the Philippine context. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were computed to summarize user ratings.

Simultaneously, a qualitative descriptive approach was integrated by engaging licensed dermatologists to validate the system's recognized skin conditions, ingredient database, and product recommendation logic. This dual approach ensures that AI-driven diagnostic processes are complemented by human expertise and ethical oversight, rather than attempting to replace professional medical judgment.

The development of DermaScan+ began with a foundational assessment of existing dermatological practices, focusing on parameters such as process efficiency, accessibility, and cost limitations. Input at this stage relied heavily on qualitative data from dermatologist interviews.

The process then transitioned to identifying appropriate algorithms and system architectures for the mobile AI-assisted platform. As the project progressed, formal surveys were conducted alongside the refinement of research aims, operational definitions, and technical requirements. The study's workflow follows Agile principles, focusing on the iterative design of features, preliminary model selection, data preprocessing, and planned usability testing. This flow emphasizes objective-setting and the continuous integration of qualitative insights to pave the way for data-driven validation.

The research was conducted within selected highly urbanized communities and institutions across Mandaue City and Lapu-Lapu City, Cebu. These areas host dense populations of students and working young adults, making them highly suitable for collecting relevant user-level data regarding skincare practices, accessibility barriers, and perceptions of AI-assisted skin analysis.

The primary respondents were young adults aged 13 to 25. Their active participation was vital, as their perspectives

directly shaped the conceptualization and design of the DermaScan+ system. To ensure data reliability, "sincerity questions" were incorporated into the survey to flag and filter out inauthentic or careless responses. Individuals falling outside the target demographic or those possessing clinically complex or severe skin conditions requiring specialized medical treatment were explicitly excluded to maintain the system's focus on non-critical skin issues.

In parallel, licensed dermatologists from clinics within Cebu were consulted purely as expert reviewers for technical and ethical oversight.

TABLE 1. DISTRIBUTION OF VALID AND INVALID ENTRIES

Validation Status	**No. of Survey Entries**
Valid	420
Invalid	280
Total	**670**

TABLE 2. DISTRIBUTION OF RESPONDENTS

Respondents	**No. of Respondents**	**%**
Teenagers	241	57.38%
Young Adults	176	41.90%
Dermatologists	3	0.71%
Total	**420**	**100.00%**

Data collection utilized printed and online survey questionnaires (via Google Forms) carefully formulated to align with the objectives of the DermaScan+ system. The instrument is divided into four sections:

Section A: Demographic information and baseline skincare routines. Describe your age, gender, occupation, location, skin type, common concerns, and daily/weekly skincare routine including products and frequency.

Section B: Evaluation of existing skin health check-ups (procedures, accessibility, and cost limitations). Describe your experiences with skin check-ups, including procedures used, how accessible they are (e.g., time, location), and any cost barriers.

Section C: Perceptions of the proposed DermaScan+ features (AI analysis, product recommendations, journaling, and progress tracking). Describe your views on usefulness, appeal, and potential improvements for AI skin analysis, product recommendations, journaling, and progress tracking features.

Section D: Technical evaluation of the proposed system to help identify suitable algorithms and design elements. Describe preferences for algorithms (e.g., rule-based, ML), UI design elements, performance needs (speed, accuracy, privacy), and other technical features.

Responses for Sections B and C were measured using a four-point Likert scale (Strongly Agree to Strongly Disagree). Official transmittal letters were secured prior to data collection to authorize the gathering of data from dermatology clinics and local young adults.

Data gathered from the Likert-scale items were subjected to quantitative statistical analysis. Open-ended items were thematically summarized to provide supplementary qualitative insights.

1) Weighted Mean: The weighted mean was utilized to analyze the respondents' experiences with manual dermatologist consultations for minor skin conditions. Indicators such as cost, appointment availability, convenience, and perceived accessibility were evaluated to quantify the burdens of traditional skin health check-ups.

2) Scoring Procedure: A structured scoring procedure was employed to evaluate users' acceptance, perception, and readiness to adopt DermaScan+. Utilizing a standard Likert scale (4 – Strongly Agree, 3 – Agree, 2 – Disagree, 1 – Strongly Disagree), the aggregated scores provided a clear metric of system usability and user satisfaction.

TABLE 3. SCORING RANGE AND QUALITATIVE DESCRIPTION

Range	**Description**	**Interpretation**
3.26 – 4.00	Strongly Agree (SA)	Users are highly satisfied; AI analysis and features are perceived as very reliable.
2.51 – 3.25	Agree (A)	Users are generally satisfied; features are effective and easy to use.
1.76 – 2.50	Disagree (D)	Users find aspects lacking or inconsistent; not fully satisfied with performance.
1.00 – 1.75	Strongly Disagree (SD)	Users are highly dissatisfied; features are perceived as ineffective/unreliable.

IV. RESULTS AND DISCUSSION

This section presents the analysis and interpretation of the empirical data collected for the DermaScan+ study. It highlights key findings regarding respondents' skincare practices, the limitations of traditional dermatological consultations, user perceptions of the proposed system, expert clinical validation, and the technical evaluation of the developed AI model.

The study achieved its target sample size of 420 respondents from Mandaue City and Lapu-Lapu City. The sample is composed primarily of teenagers (57.38%, $n = 241$) and young adults (41.90%, $n = 176$), representing the core

demographic experiencing mild skin concerns and high mobile technology engagement. Additionally, three licensed dermatologists (0.71%) participated as expert validators to provide clinical oversight.

Demographically, the 16–18 age group accounts for the largest share (34.05%), followed by the 19–21 age group (30.94%). Female respondents comprise the majority at 47.72%, followed by males at 37.88%, and other gender identities at 14.39%. Educationally, the respondents are predominantly senior high school students (35.73%) and college students (31.89%), with working young adults making up a smaller segment (10.31%). This distribution confirms that the system targets a digitally engaged, diverse adolescent and young adult demographic navigating academic demands and appearance-related concerns.

Survey results indicate high active engagement in skincare routines, with the vast majority of females (90.95%) and a significant portion of males (75.32%) applying products daily or several times a week. Furthermore, 85.13% of the total respondents expressed being "very concerned" or "somewhat concerned" about the risks associated with unverified skincare products popularized by social media trends, highlighting a critical need for evidence-based digital guidance.

Respondents exhibited a generally negative perception of traditional skin health check-ups (Grand Mean = 2.83, "Agree" on a 4-point Likert scale regarding negative statements).

TABLE 4. EVALUATION OF MANUAL SKIN CONDITION ASSESSMENT

Current Process of Existing Skin Health Check-Up	**Mean**	**Std. Dev.**	**Qualitative Description**
1. The traditional consultation process with dermatologists is time-consuming.	3.63	0.66	Strongly Agree
2. The steps required before getting treatment (appointment, check-up, prescription) are complicated.	3.62	0.66	Strongly Agree
3. It is difficult to schedule an appointment with a dermatologist.	3.56	0.72	Strongly Agree
4. There are enough dermatologists in my area to meet demand.	2.22	0.66	Disagree
5. There are NOT enough dermatologists in my area to meet demand.	2.90	0.72	Agree
6. The waiting time before consultation is tolerable.	2.02	0.66	Disagree
7. The waiting time before consultation is NOT tolerable.	3.33	0.84	Strongly Agree
8. Skincare clinics are accessible and easy to reach from my area.	2.31	0.61	Disagree
9. Most clinics are only located in cities.	3.14	0.65	Agree
10. Some recommended products are difficult to find.	2.48	0.68	Disagree
11. Some recommended products are out of stock.	2.82	0.59	Agree
12. The traditional approach provides a wide variety of skincare products to choose from.	2.43	0.62	Disagree
13. Dermatologists recommend products that are affordable and accessible.	2.12	0.70	Disagree
14. Dermatologists recommend products that are NOT affordable and accessible.	3.06	0.80	Agree
Grand Mean	**2.83**	**0.68**	**Agree**

As shown in Table 4, users strongly agree that traditional dermatological consultations are time-consuming, difficult to schedule, and often lead to product recommendations that are financially or practically inaccessible. These pain points validate the demand for a convenient, cost-effective alternative like DermaScan+.

Respondents showed high acceptance of the proposed DermaScan+ features. The inclusion of AI-based skin condition detection (Mean = 3.10) and personalized recommendations (Mean = 3.13) were met with solid agreement. However, features related to user support and behavioral adherence received the highest ratings: the product recommendation engine (Mean = 3.48), routine calendar (Mean = 3.46), skincare journal (Mean = 3.46), and notification system (Mean = 3.40) all garnered "Strongly Agree" responses.

When evaluating preferred system techniques, respondents ranked Skin Characterization (pre-requisite questionnaire) highest at 17.88%, followed by the Product Recommender (17.51%) and Skin Analysis (17.37%). This indicates that users prioritize explicit profiling and actionable product mapping alongside AI imaging.

To ensure ethical boundaries and user safety, three licensed dermatologists validated the system's scope.

1) Severity and Recommendation Scope: Dermatologists consistently classified comedonal conditions (blackheads, whiteheads) and mild inflammatory lesions (papules, pustules) as appropriate for over-the-counter (OTC) recommendations. Conversely, deep or chronic conditions like nodules, cysts, melasma, and psoriasis were unanimously flagged as "Not Recommendable," establishing a strict safety boundary where the system halts recommendations and advises clinical referral.

2) Ingredient and Routine Mapping: Expert feedback established a structured OTC framework. Salicylic acid and benzoyl peroxide were heavily endorsed for acne-related issues, while emollients were preferred for eczema. For routine construction, dermatologists validated a sequential application format: Cleanser, Toner, Serum, Eye Cream, Moisturizer, and Sunscreen. Formulation mapping matched skin types directly to product textures; for example, gel cleansers and moisturizers were unanimously recommended for oily/combination skin, whereas cream-based formulations were reserved for dry and sensitive profiles. Sunscreen recommendations overwhelmingly favored mineral and hybrid filters for daytime use across all profiles.

The DermaScan+ AI model was built using a two-stage classification pipeline designed to identify the condition and its severity.

1) Data Collection and Preprocessing: A dataset spanning 14 skin conditions was curated from public repositories. To overcome data scarcity and computational overhead, the Google Derm Foundation pretrained model was utilized as a frozen feature extractor. Raw images (resized to 448×448) were passed through the ResNet-based encoder to generate 6144-dimensional embedding vectors.

2) Stage 1: Condition Classification: A Logistic Regression classifier head was trained on the embedding matrix utilizing an 80/20 stratified split and balanced class weights. As shown in Table 5, the Stage 1 condition classifier achieved an overall test accuracy of 96.17%.

TABLE 5. STAGE 1 CONDITION CLASSIFICATION REPORT

Skin Condition	Precision	Recall	F1-Score
Acne – Blackheads	0.97	0.93	0.95
Acne – Cyst	0.92	0.90	0.91
Acne – Fungal	0.98	0.99	0.99
Acne – Nodules	0.97	0.95	0.96
Acne – Papules	0.95	0.92	0.94
Acne – Pustules	0.94	0.96	0.95
Acne – Whiteheads	0.99	1.00	0.99
Eczema	0.96	0.96	0.96
Enlarged Pores	0.99	0.98	0.99
Melasma	0.99	0.96	0.97
Milia	0.96	0.98	0.97
Post-Inflammatory Erythema	0.92	0.95	0.93
Post-Inflammatory Hyperpigmentation	0.95	0.98	0.96
Out-of-Scope	0.95	0.96	0.95

Confusion matrix analysis revealed that misclassifications predominantly occurred among visually similar conditions (e.g., acne papules confused with pustules, or post-inflammatory erythema misclassified as eczema due to shared surface redness).

TABLE 6. STAGE 2 SEVERITY CLASSIFICATION REPORT

Condition	Severity	Precision	Recall	F1-Score	Overall Accuracy
Acne Blackheads	Mild	0.95	0.95	0.95	89.34%
	Moderate	0.81	0.86	0.83	
	Severe	0.90	0.86	0.88	
Acne Fungal	Mild	0.99	0.99	0.99	98.36%
	Severe	0.98	0.98	0.98	
Acne Papules	Mild	0.94	0.92	0.93	86.52%
	Moderate	0.74	0.85	0.79	
	Severe	0.88	0.77	0.82	
Acne Pustules	Mild	0.96	0.94	0.95	94.70%
	Moderate	0.88	0.91	0.90	
	Severe	0.98	0.98	0.98	
Acne Whiteheads	Mild	0.88	0.84	0.86	86.45%
	Moderate	0.78	0.86	0.82	
	Severe	0.95	0.91	0.93	
Eczema	Mild	0.81	0.84	0.82	79.41%
	Severe	0.76	0.74	0.75	
Enlarged Pores	Mild	0.78	0.78	0.78	82.61%
	Moderate	0.80	0.77	0.79	
	Severe	0.88	0.91	0.90	
Melasma	Mild	0.75	0.74	0.74	84.68%
	Moderate	0.81	0.83	0.82	
	Severe	0.97	0.96	0.96	
Milia	Mild	0.84	0.77	0.80	65.73%
	Moderate	0.57	0.58	0.58	
	Severe	0.34	0.43	0.38	
Post-Inflammatory Erythema	Mild	0.90	0.96	0.93	85.65%
	Moderate	0.67	0.48	0.56	
	Severe	0.86	0.89	0.88	
Post-Inflammatory Hyperpigmentation	Mild	0.96	0.94	0.95	93.00%

3) Stage 2: Severity Classification: Independent severity classifiers (mild, moderate, severe) were trained for 11 eligible conditions. Performance varied based on visual distinctiveness. Fungal acne (98.36%), pustules (94.70%), and hyperpigmentation (93.00%) achieved excellent severity grading. However, conditions lacking diverse visual severity data, such as Milia (65.73%) and Eczema (79.41%), demonstrated lower accuracy, marking a known limitation for future dataset expansion.

V. CONCLUSION

This study successfully designed, developed, and evaluated DermaScan+, a mobile skin condition detection and personalized skincare recommender system tailored for adolescents and young adults. Integrating a dermatology-specific foundation model with lightweight logistic regression classifiers, a pre-requisite skin-type questionnaire, and an expert-aligned rule-based engine, the system enables the accurate non-clinical assessment of mild skin concerns.

Empirical findings from 420 target users confirmed the necessity of the system, highlighting the time constraints, high costs, and accessibility barriers of traditional dermatological consultations, juxtaposed with a high demand for safe, AI-guided skincare tracking. Expert dermatologist validation successfully established the ethical and safety boundaries of the application—ensuring the system acts purely as a decision-support tool that curates OTC routines for mild concerns while strictly diverting severe or complex cases to clinical professionals. Technical evaluations verified the AI's robust classification capabilities (96.17% Stage 1 accuracy). Ultimately, DermaScan+ proves to be a technically feasible, systematically engineered, and contextually appropriate mHealth solution capable of complementing traditional dermatological services without replacing formal medical intervention.

VI. FUTURE RESEARCH

Future development of DermaScan+ should expand the dataset with more annotated smartphone images in uncontrolled lighting, particularly minority classes like milia and eczema, to boost severity classification robustness. It should increase expert dermatologist involvement for annotations, reviews, and rule-logic validation to enhance clinical validity. The recommendation database requires ongoing updates with locally available, evidence-based OTC products aligned to current guidelines. Architectures should integrate teledermatology for interoperability with health systems and referrals, while formalizing privacy-by-design, data minimization, and compliance audits for ethical AI deployment.

REFERENCES

1. T. Harris-Tryon et al., "The role of skin microbiota in barrier function and immunity," *Journal of Dermatological Science*, 2022. https://doi.org/10.1126/science.abo0693
2. A. Flinn et al., "Impact of skin concerns on adolescents: Social, psychological, and physical factors," *Adolescent Health Review*, 2024. https://www.tandfonline.com/doi/abs/10.1080/08870446.2024.2434483
3. M. Kelly et al., "Adverse reactions to skin conditions among youth: Self-image and mental health implications," *Pediatric Dermatology*, 2021. https://www.mdpi.com/2227-9067/8/11/1057

4. S. Gupta et al., "Social media influence on adolescent skincare: The rise of unverified recommendations," *Journal of Digital Health*, 2025. https://doi.org/10.32996/jbms.2022.4.1.16
5. L. Murray et al., "Adverse effects of DIY skincare remedies on adolescent skin," *Clinical Dermatology*, 2021. https://doi.org/10.1111/ced.14422
6. J. Fryt et al., "The impact of uncredentialed influencers on cosmetic choices," *Cosmetics & Health*, 2022. https://doi.org/10.1016/j.alcr.2022.100515
7. R. Kizy et al., "Expanding care access through mobile health applications and teledermatology," *Telemedicine Journal*, 2025. https://www.researchgate.net/publication/394239479
8. D. Giansanti, "Integrating artificial intelligence into mHealth systems for diagnostic accuracy," *Healthcare Technology Letters*, 2023. https://doi.org/10.3390/ijerph20105810
9. A. Lima, "Consumer behavior in cosmetic product selection: The role of trial and experience," *Journal of Consumer Health*, 2024. https://www.researchgate.net/publication/387820908
10. C. Charman et al., "Mobile platforms for personalized skincare suggestions and self-management," *Journal of Dermatological Treatment*, 2023. https://doi.org/10.1093/ced/llad139
11. M. Genuino et al., "Maldistribution of dermatological care and health access barriers in the Philippines," *Philippine Journal of Health Research*, 2024. https://pubmed.ncbi.nlm.nih.gov/38883103/
12. R. Cruz and S. Tapales, "Self-medication vs. professional care: A socio-economic analysis of healthcare accessibility," *Southeast Asian Medical Journal*, 2022. https://journals.lww.com/jpds/toc/2022/31020
13. M. López-Liria et al., "Cost-effectiveness of online tools for skin concern classification," *Health Economics Review*, 2022. https://pmc.ncbi.nlm.nih.gov/articles/PMC8909884/
14. A. Gonzales et al., "Healthcare access and preference for Complementary and Alternative Medicine in mountainous barangays of Cebu," *Philippine Journal of Public Health*, 2024. https://doi.org/10.37899/journallamedihealtico.v5i3.1216
15. K. Barnowska et al., "The risks of informal advice for persistent skin conditions," *International Journal of Dermatology*, 2024. https://journals.plos.org/digitalhealth/article?id=10.1371%2Fjournal.pdig.0000629
16. J. Velasco et al., "Transfer learning and CNNs for local skin disease classification in the Philippines," *IEEE Access*, 2023. https://doi.org/10.48550/arXiv.2304.02852
17. A. Preclaro et al., "Teledermatology and AI-assisted systems bridging healthcare gaps in the Philippines," *Journal of Medical Internet Research*, 2022. https://pubmed.ncbi.nlm.nih.gov/37632883/
18. C. Nisperos et al., "Development of an AI-driven virtual cosmetics consultant mobile application," *Asian Conference on Intelligent Information and Database Systems*, 2021. https://ieomsociety.org/proceedings/2021monterrey/275.pdf
19. T. Aquino, "Ethical considerations and human accountability in AI healthcare tools," *Bioethics & Health Policy*, 2025. http://doi.org/10.4103/JPDS.JPDS_21_25
20. C. Goh et al., "Expert consensus on structured step-by-step skincare routines," *Journal of Dermatological Practice*, 2023. https://pubmed.ncbi.nlm.nih.gov/36409588/
21. F. Ali et al., "Validity of smartphone photography for clinical skin assessment in atopic dermatitis," *Dermatology and Therapy*, 2021. https://formative.jmir.org/2021/5/e24766
22. E. Hadeler et al., "Suitability of mobile applications for dermatology research and patient monitoring," *Mobile Health in Dermatology*, 2021. https://link.springer.com/article/10.1007/s13555-021-00604-x
23. P. Sangers et al., "Validation of a CE-marked mobile health application for skin cancer triage," *Clinical Dermatology*, 2022. https://karger.com/drm/article/238/4/649/828305/
24. S. Sharma et al., "The role of mobile device cameras as input modalities in modern mHealth applications," *Journal of Health Informatics*, 2022. https://pubmed.ncbi.nlm.nih.gov/35309626/
25. M. Preclaro, A. Gulmatico-Flores, and C. Tianco, "Accuracy and feasibility of teledermatology smartphone camera inputs in a Philippine clinical setting," *Philippine Journal of Dermatology*, 2023. https://pubmed.ncbi.nlm.nih.gov/37632883/
26. J. Velasco et al., "AI-driven image recognition as a diagnostic aid for Filipino dermatologists," *Asian Journal of Medical AI*, 2023. https://doi.org/10.48550/arXiv.2304.02852
27. K. Oda et al., "Testing AI-based dermatology evaluation applications under real-world physical conditions," *Journal of Dermatological Science*, 2025. https://www.nature.com/articles/s41598-025-03546-y
28. Y. Zhang et al., "Development and validation of a prospective questionnaire for assessing oily sensitive skin," *Skin Research and Technology*, 2024. https://doi.org/10.1111/ics.12946
29. M. Kiraly et al., "Health AI Developer Foundations (HAI-DEF) and Derm Foundation pre-trained models," *Google Research Publications*, 2024. https://arxiv.org/abs/2411.15128
30. A. Radford et al., "Learning transferable visual models from natural language supervision (CLIP)," *Proceedings of the 38th International Conference on Machine Learning*, 2021. https://proceedings.mlr.press/v139/radford21a.html
31. H. Choy et al., "Convolutional Neural Networks as the dominant approach for visual data analysis in dermatology," *Medical Image Analysis*, 2023. https://doi.org/10.1038/s41746-023-00914-8
32. S. Panda et al., "Logistic regression as a reliable statistical technique in healthcare categorical predictions," *Journal of Clinical Statistics*, 2022. https://njcmindia.com/index.php/file/article/view/22/1700

33. M. Sievering et al., "Comparing logistic regression with modern machine learning models for clinical predictions," *Health Data Science*, 2022. https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-022-02057-4
34. J. Kim et al., "Transfer learning approaches in medical image classification: A systematic review," *IEEE Transactions on Medical Imaging*, 2022. https://doi.org/10.1186/s12880-022-00793-7
35. Y. Gulzar et al., "Next-generation approach to skin disorder prediction employing hybrid deep transfer learning," *Computers in Biology and Medicine*, 2025. https://doi.org/10.3389/fdata.2025.1503883
36. M. Efat et al., "Multi-level ensemble framework for skin lesion classification based on Customized Transfer Learning," *Medical AI Journal*, 2024. https://doi.org/10.1371/journal.pone.0309430
37. A. Jaén et al., "Web-based system for skin lesion diagnosis using deep learning and transfer learning," *Proceedings of the IEEE International Conference on E-Health*, 2024. https://laccei.org/LACCEI2024-CostaRica/papers/Contribution_940_final_a.pdf
38. Q. Abbas et al., "SkinMarkNet: Intelligent skin disease prediction using transfer learning and explainable AI," *Scientific Reports*, 2025. https://doi.org/10.1038/s41598-024-83966-4
39. G. Vilone and L. Longo, "Rule-based algorithms in the realm of model explanation and interpretability," *Information Fusion*, 2021. https://pmc.ncbi.nlm.nih.gov/articles/PMC8596373
40. L. Feremans and B. Goethals, "Efficiency, interpretability, and accuracy of rule-based algorithms for recommender systems," *Expert Systems with Applications*, 2025. https://www.researchgate.net/publication/392870644
41. S. Lee et al., "Image-based cosmetic and skincare ingredient recommender systems," *Journal of Cosmetic Science*, 2024. https://doi.org/10.1111/jocd.16218
42. M. Jannatin et al., "Ontology-based skincare recommendation system utilizing semantic rules," *Journal of Intelligent Information Systems*, 2025. https://doi.org/10.32877/bt.v8i1.2857
43. L. Ristow et al., "Mein Hautschutz im Alltag (MiA): Feasibility of a smartphone application for work-related skin diseases," *Digital Health*, 2025. https://doi.org/10.2196/66791
44. E. Karaturhan et al., "Integrating photos and journal entries for skin-concern tracking," *Interactive Computing in Healthcare*, 2022. https://doi.org/10.1145/3546155.3546676
45. A. MacIsaac et al., "Smartphone-based journaling interventions for daily skin concern reflection," *Journal of Patient Experience*, 2022. https://doi.org/10.1017/bec.2022.24
46. R. Jakob et al., "Design factors of mobile health apps associated with better adherence," *Journal of Medical Internet Research*, 2022. https://doi.org/10.2196/35371
47. S. Johari et al., "Drivers and barriers to mHealth adoption: The role of reminders," *Health Informatics Journal*, 2025. https://doi.org/10.21037/mhealth-24-44
48. L. van Genugten et al., "Tailored scheduling of push notifications in health applications," *Behavioral Medicine*, 2025. https://doi.org/10.3389/fdgth.2025.1460167
49. X. Gao et al., "Impact of context-aware health notifications on user engagement," *IEEE Access*, 2023. https://doi.org/10.2196/45430
50. A. Ghazanfar et al., "Underrepresentation of mild skin concerns in public clinical datasets," *Dermatology Data Science*, 2025. https://doi.org/10.2196/60883
51. T. Huynh et al., "Validation of smartphone photos for automated acne assessment," *Journal of Investigative Dermatology*, 2022. https://doi.org/10.3390/diagnostics12081879
52. M. Zein et al., "Addressing the data gap in mild-to-moderate acne AI modeling," *Artificial Intelligence in Medicine*, 2024. https://doi.org/10.1371/journal.pone.0297958
53. R. Pedro et al., "Methodological considerations for building population-specific dermatology datasets," *Dermatology Informatics*, 2025. https://doi.org/10.1186/s12874-025-02706-y
54. T. Huynh et al., "Machine-learning-guided recommendations based on mobile facial images," *Clinical Trial Data Reports*, 2025. https://doi.org/10.3390/diagnostics12081879
55. A. Abirami and V. Karthikeyan, "Mobile-based skin disease diagnosis system using convolutional neural networks," *International Journal of Computer Applications*, 2022.
56. M. Khalid et al., "A smart facial acne disease monitoring system using AI and IoT," *IEEE Internet of Things Journal*, 2025. https://link.springer.com/article/10.1007/s10791-025-09503-7
57. A. Wibowo et al., "Smartphone-based skin cancer detection and classification on Android devices," *Procedia Computer Science*, 2020. https://ijain.org/index.php/IJAIN/article/view/492
58. A. Sokolov and V. Shpudeiko, "Performance evaluation of the Skinive neural network for skin pathology risk assessment," *Dermatologic Therapy*, 2022. https://doi.org/10.4103/ijd.ijd_1070_21
59. M. Rashid et al., "SkinCareAI: Automated skin-disease classification mobile app," *Journal of Mobile Computing*, 2023. https://publisher.uthm.edu.my/periodicals/index.php/eeee/article/view/6776