© April 2026 | IJIRT | Volume 12 Issue 11 | ISSN: 2349-6002

DermaClust: A Multimodal, Severity-Calibrated Neural Paradigm for Skin Morphological Disparity Modeling and Cross-Domain Product Vector Synthesis Via Biometric-Gated Access

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***Abstract*—Numerous skincare selections are influenced by assumptions, personal opinions, and advertising claims, which can lead to unsuitable product choices and recurring skin issues. This study presents DermaClust, a multimodal intelligent framework designed to create personalized skincare recommendations. The system integrates transformer-based ingredient understanding, deep learning driven visual skin analysis, and environmental context awareness. It employs weighted hybrid profiling, climate aware scoring, and localized skin patch evaluation to generate objective and reliable recommendations. The proposed approach demonstrates how the integration of computer vision and natural language processing can support safer and evidence based cosmetic decision making.**

***Index Terms*—Transformer models, deep learning, computer vision, skin analysis, personalized recommendation, multimodal artificial intelligence, skincare intelligence.**

I. INTRODUCTION

The range of cosmetic goods, from straightforward washing solutions to highly specialized treatment formulations, has significantly expanded as a result of the skincare industry's expansion. Although accessibility has increased as a result of this expansion, customers now face a more difficult decision-making process. People frequently have trouble figuring out which products fit their biological skin traits, which leads to regimens that could be dangerous or unproductive. Many consumers rely on self-evaluation techniques like online tests, recommendations from influencers, or broad trends in skincare. These methods are subjective by nature and often overlook differences in skin sensitivity, texture, and exposure to the environment, which results in recurrent issues including acne, dehydration, irritation, and early aging [10], [11].

The use of automated analysis in dermatological and cosmetic applications is becoming more and more popular as artificial intelligence and machine learning develop [10]. In order to discover patterns associated with skin disorders, deep learning techniques in particular, Convolutional Neural Networks have demonstrated a great ability to extract texture-based features from photos [1], [8]. Concurrently, transformer-based models for natural language processing have proven to be successful at comprehending intricate textual data, such as chemical descriptions and constituent lists [5]. Many of the skincare recommendation systems that are now in use have limited functionality despite these technological developments. While some solutions rely solely on database filtering without taking into account the user's biological skin state [2], [12], others exclusively concentrate on visual classification without taking ingredient safety into account [1]. Furthermore, despite the fact that environmental elements like humidity, temperature, and UV radiation have a direct impact on skin behaviour and product effectiveness, they are rarely included, with only a few studies exploring weather-aware recommendation strategies [4]. This study suggests DermaClust, a multimodal intelligence framework intended to offer unbiased and flexible skincare advice, as a solution to these gaps.

Three main components are integrated into the system: real-time environmental context analysis, NLP-based substance evaluation, and computer vision for biological skin assessment. Instead of analysing the entire face, a MobileNetV2-based architecture is used to analyse selected facial regions, enabling the model to concentrate on texture-specific data like pores, patterns of dryness, or the distribution of acne. This focused method improves the accuracy of classification findings by lowering background noise, similar to region-focused dermatological analysis approaches discussed in prior deep learning studies [1], [8]. To make sure that suggestions put chemical suitability ahead of popularity, a transformer-based module simultaneously analyses ingredient lists to assess compatibility between identified skin issues and product compositions.

The suggested framework's hybrid profiling, which blends user-reported clinical data with AI-derived probability, is another significant component. This tactic deals with situations when internal skin issues, such sensitivity or seasonal dryness, may not be accurately represented by outward appearance. Additionally, by including real-time climate data, a weather-aware method allows recommendation scores to be dynamically adjusted, extending ideas explored in recent adaptive skincare systems [4]. The system may modify skincare recommendations to accommodate various geographic locations and seasonal variations by taking environmental stressors into account, resulting in a more individualized and context-sensitive experience.
Each analytical component of DermaClust can operate independently while contributing to a single recommendation engine because to its modular pipeline architecture. The system may be expanded with future features like longitudinal skin tracking or sophisticated ingredient interaction modelling thanks to this design, which also increases scalability. This study's main contribution is to show how a more dependable and intelligent skincare recommendation system can be produced by combining visual analysis, chemical comprehension, and contextual awareness [5], [7], [10]. The suggested approach seeks to promote safer, data-driven skincare decision-making and further the use of multimodal AI in personalized dermatology by lowering dependency on static questionnaires and subjective judgment.

II. LITERATURE SURVEY

The subject of skincare recommendation systems has undergone significant transformation in recent years, evolving from traditional machine learning techniques to advanced deep learning and hybrid intelligent systems. Modern approaches employ ingredient-level analysis, user behaviour modelling, and visual skin assessment to deliver personalized skincare recommendations. Despite their potential, these systems face challenges related to contextual awareness, generalization, and effective multimodal integration [10], [11].

A study conducted in 2022 developed a facial skincare recommendation system integrating biometric verification with Support Vector Machines (SVM) and image segmentation techniques [1]. Although the system achieved moderate performance in acne classification, its effectiveness was limited due to small sample sizes and reliance on self-reported acne data. In a related direction, collaborative filtering techniques using Singular Value Decomposition (SVD) were proposed to model user preferences based on historical reviews and ratings [2]. Similarly, content-based filtering with item clustering was explored in earlier research [12]. However, these systems lacked dermatological validation, thereby limiting the scientific reliability of their recommendations. With the advancement of deep learning, more sophisticated architectures were introduced. A deep learning-based system focusing on cosmetic ingredient analysis and facial skin conditions demonstrated improved predictive performance using neural networks [5]. EfficientNet-based expert systems were also developed for personalized facial skincare recommendations [8]. However, these approaches faced issues such as dataset imbalance and limited robustness across diverse skin types. Recent work such as DermaTech further combined machine learning and deep learning strategies to enhance recommendation accuracy [7], while AI-driven personalized skincare systems were explored in conference research to strengthen automated decision-making [6]. Additionally, Dermavision highlighted progressive personalization trends in skincare recommendation systems [3]. In 2025, environmentally aware skincare recommendation systems incorporated real-time weather data to improve contextual relevance [4]. Although this approach enhanced environmental adaptability, it exhibited demographic bias and limited ecological modeling. Emerging research has also explored extended reality (XR)-assisted skincare recommendation systems for interactive and immersive personalization [13]. Broader reviews in cosmetic dermatology and digital innovation highlight the growing integration of AI in skincare and dermatological applications [9], [10].

Overall, multimodal intelligent systems integrating textual comprehension, visual analysis, and contextual data are gaining prominence. Nevertheless, achieving robust generalization and efficient processing of heterogeneous data remains a challenge. Furthermore, the importance of Explainable AI (XAI) is increasingly recognized, as transparency and interpretability are essential for building user trust in healthcare-related recommendation systems [10], [11]. Future research should therefore focus on adaptive, holistic frameworks that move beyond static evaluation models and continuously integrate visual and contextual data to monitor evolving skin conditions and lifestyle factors over time.

III. SYSTEM ARCHITECTURE

DermaClust Architecture: It is a modular, hierarchical pipeline optimizing for scalability, flexibility, and multimodal data processing. The framework integrates computer vision, natural language processing, and contextual environmental intelligence into a unified system capable of understanding skin characteristics from multiple perspectives to generate adaptive skincare recommendations [5], [7], [10]. The architecture is designed in layered modules, where each component operates independently while supporting the scalability and evolution of the solution.

User Interface Layer (Built in Streamlit): The first layer is the user interface, developed using Streamlit, which serves as the interaction point for users. In this layer, users upload facial images, provide clinical skin concerns, and submit product ingredient lists for evaluation. It also manages backend model communication and integrates external APIs to display real-time results in a structured format. This layer standardizes input formats to maintain data consistency across the pipeline and reduces preprocessing inconsistencies.

Once data is collected, it is forwarded to the Preprocessing Layer, where both visual and textual inputs undergo structured preparation. Facial images are analysed using Media Pipe Face Mesh to detect facial landmarks and extract region-specific skin patches such as the forehead and cheeks. This localized extraction reduces background noise and enables models to focus on texture-level dermatological features, similar to modern computer vision-based skincare analysis systems [1], [8]. Image enhancement techniques including normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) are applied to minimize lighting variation and enhance feature visibility. Simultaneously, ingredient lists are cleaned, tokenized, and normalized to ensure compatibility with NLP processing pipelines.

The AI Engine Layer forms the analytical core of the architecture. It consists of two parallel modules designed to process different data modalities. The first module applies transfer learning using a MobileNetV2- based CNN to classify primary skin concerns such as acne, dryness, normal skin, oiliness, and wrinkles. Lightweight CNN architectures have shown strong performance in dermatological image classification while maintaining computational efficiency [1], [8].

$$P_{final}(c) = (W_{AI} \cdot P_{AI}(c)) + (W_{Quiz} S_{Quiz}(c)) \quad (1)$$

The second module is a transformer-based NLP model that analyses ingredient lists, detects active compounds, and evaluates chemical compatibility with detected skin conditions, similar to ingredient-focused skincare intelligence frameworks [5]. By merging visual and textual insights, the AI engine generates a comprehensive understanding of both biological skin properties and formulation safety.

$$S_{prod} = \sum_{i=1}^{n} (I_i \cdot P_{\text{final}}(c)) + \beta_{temp} + \beta_{hum} + \beta_{uv} \quad (2)$$

Outputs from these models are forwarded to an Integration Layer, which combines AI predictions with contextual inputs such as user-reported clinical history and real-time environmental data obtained from external weather APIs. Environmental parameters including humidity levels and ultraviolet index dynamically influence recommendation scores, extending ideas explored in weather-aware skincare recommendation systems [4].

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \tag{3}$$

A hybrid decision mechanism balances AI probabilities with subjective user inputs, helping reconcile differences between visible skin conditions and internal skin sensitivity. The final stage is the Recommendation Layer, which interacts with a pre-scored skincare product database. A scoring-based algorithm generates a final compatibility index by integrating outputs from visual analysis, ingredient evaluation, and environmental adjustment modules. Instead of suggesting a single static product, the system constructs a personalized AM/PM routine by selecting top-ranked products across cleansing, treatment, and protection categories, thereby improving flexibility and personalization in skincare planning [5], [7].

Overall, the DermaClust architecture represents a multimodal pipeline where visual analysis, ingredient intelligence, and contextual awareness operate collaboratively. This modular design enables scalable resource allocation, future system expansion, and efficient deployment, contributing toward more reliable AI-driven dermatological recommendation systems [7], [10].

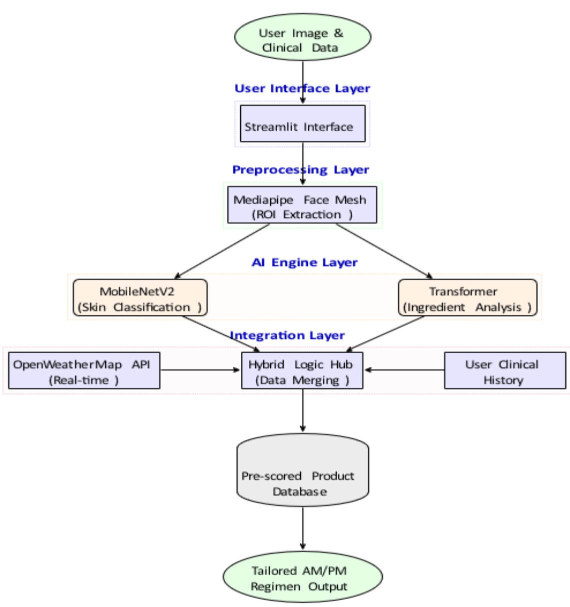

Fig. 1. Architecture of DermaClust

IV. PROPOSED WORK

In this work we introduce DermaClust - a dual-modal intelligent framework for adaptive skincare product selection without relying solely on self-assessment, but instead leveraging continuous contextual observation through visual modalities and environmental awareness [5], [7], [10]. Through computer vision-based skin evaluation together with contextual profiling, DermaClust proposes personalized SKUs. Our goal is to bridge the gap between consumer-centric self-reporting assessments and purely visual inspection systems that often ignore localized texture characteristics or dynamic environmental factors [1], [8]. One of the primary innovations of this paper is "Targeted Zone Analysis," where instead of analysing the entire face, localized skin patches from specific facial regions (forehead, cheeks, etc.) are extracted. Using Media Pipe Face Mesh, 120×120 pixel patches are selected from regions where skin texture remains relatively invariant to facial expressions while minimizing background noise. Feature modelling focuses on pores, oil distribution, dryness patterns, and acne texture. Reducing background interference enables more stable classification compared to full-face analysis approaches explored in prior computer vision skincare studies [1], [8]. Another contribution is the Hybrid Profiling Algorithm, which combines AI-driven predictions with user-provided clinical inputs. While surface appearance provides valuable cues,

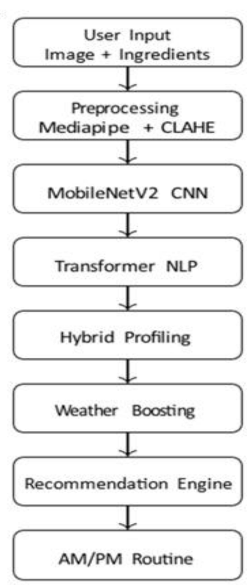

Fig. 2. Dataflow of DermaClus

internal conditions such as sensitivity or seasonal dryness may not be visually detectable. To address this limitation, the framework integrates weighted fusion between AI-derived probabilities and clinical history, enabling a more balanced representation of skin condition that combines objective analysis with subjective experience [5], [7]. The framework also introduces a Dynamic Weather Boosting Mechanism that adapts recommendations based on environmental context. External factors such as humidity levels and ultraviolet exposure significantly influence skin behaviour and product performance. By incorporating real-time weather data, ingredient affinity scores are dynamically adjusted, extending concepts proposed in weather-aware skincare recommendation systems [4]. Hydrating formulations are prioritized in low humidity conditions, while lightweight or oil-controlling products gain preference in high-humidity environments, ensuring recommendations remain relevant to geographic and seasonal context.

In summary, the proposed pipeline integrates localized visual assessment, hybrid decision logic, and climate-aware adjustments into a unified recommendation engine. DermaClust demonstrates how multimodal intelligence can enhance personalization and reliability in skincare recommendation systems by combining visual analysis, ingredient intelligence, and contextual awareness [7], [10].

V. IMPLEMENTATION

A. Dataset Collection

For training and testing of the skin classification component of DermaClust, a dataset composed of diverse facial dermatological conditions was utilized. The March 2021 Facial Skincare Classification Benchmark provides high-resolution facial images categorized into five balanced skin concern classes: acne, dry, oily, wrinkles, and normal. These categories were selected to represent commonly observed skincare conditions, enabling the model to learn discriminative texture-based features relevant to real-world dermatological applications [1], [8]. The dataset repository stores images within a structured directory containing subfolders for each skin class. Variations in facial orientation, lighting conditions, and skin texture were intentionally included to simulate authentic user scenarios. Data augmentation techniques were incorporated during training to improve model robustness and generalization performance, as commonly adopted in deep learning skincare analysis pipelines [1], [5]. Image augmentation was implemented using the Image Data Generator class, which applied controlled random transformations to the training data. These transformations included horizontal flipping, random rotations, width and height shifts, and shear operations. Such augmentation strategies simulate real world camera angles, facial alignment changes, and lighting variability while preserving underlying skin texture properties. Increasing data diversity through augmentation helps reduce overfitting and improves model performance across varying skin tones and environmental conditions [8].

Overall, the structured dataset organization combined with augmentation establishes a balanced foundation for learning robust skin feature representations. The resulting classification model demonstrates consistent performance across diverse visual conditions, supporting reliable real-world deployment for personalized skincare recommendation systems [5], [10].

B. Data Preprocessing

The DermaClust framework processes data through a unified normalization pipeline that standardizes both visual and textual inputs to improve model performance. Preprocessing is essential because the system integrates computer vision and natural language processing, aiming to reduce noise, maintain consistent input formats, and improve feature detection accuracy [5], [10]. The initial stage of image preprocessing begins with illumination correction and texture enhancement. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to facial patches to minimize lighting variation and enhance microtextured visibility such as pores, acne patterns, and dryness regions. Standardizing illumination improves the robustness of dermatological feature extraction across varying capture conditions, as observed in prior vision-based skincare studies [1], [8]. After enhancement, all images are resized to a fixed resolution of 224×224 pixels to ensure compatibility with the MobileNetV2 architecture. MobileNetV2 image normalization further calibrates pixel values according to pretrained model requirements, improving convergence during training and inference. Textual preprocessing prepares ingredient lists for NLP-based analysis. Raw ingredient descriptions often contain inconsistent formatting, special characters, and mixed capitalization. The system applies text cleaning, tokenization, and normalization steps to produce structured representations. These tokens are matched against curated ingredient dictionaries, enabling context-aware identification of beneficial and potentially harmful compounds [5].

Structured textual representation improves ingredient-level reasoning within multimodal skincare recommendation systems. The combined preprocessing pipeline integrates image enhancement, standardized resizing, and text normalization to generate consistent multimodal features. This unified strategy improves cross-modal learning and enhances overall system reliability [7], [10].

C. How we Train Model?

The skin classification subnetwork of DermaClust is trained using a two-phase transfer learning strategy built upon MobileNetV2.

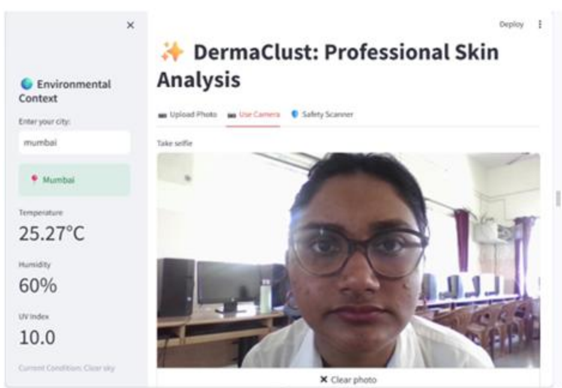

Fig. 3. Face scanning and weather UI integration.

Transfer learning leverages ImageNet pretrained weights, allowing the network to learn domain-specific dermatological features with reduced training data requirements [1], [8]. During Phase 1, the backbone layers remain frozen while a custom classification head is trained.

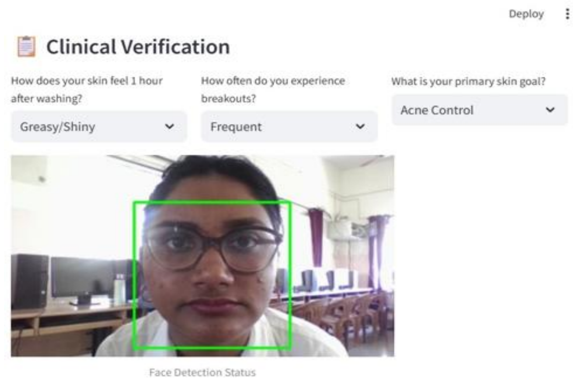

Fig. 4. Verified Skin Profile combining AI predictions with clinical inputs.

Phase 2 introduces selective fine-tuning, where deeper convolutional layers are partially unfrozen to adapt pretrained features toward dermatological textures such as acne irregularities and dryness variations. A low learning rate of 1×10^{-5} ensures gradual weight updates, preserving learned representations while enabling domain adaptation. This staged training strategy improves generalization performance and aligns with best practices in deep learning-based skincare analysis [8].

Fig. 5. DermaClust Skin patch Analysis

Regularization techniques and validation monitoring are applied throughout training to prevent overfitting. The combination of frozen backbone training followed by targeted finetuning enhances feature learning efficiency while maintaining computational feasibility for real-world deployment.

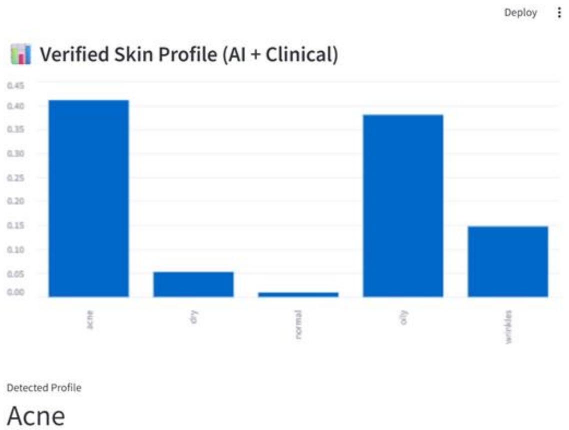

Fig. 6. Skin Profile Graph

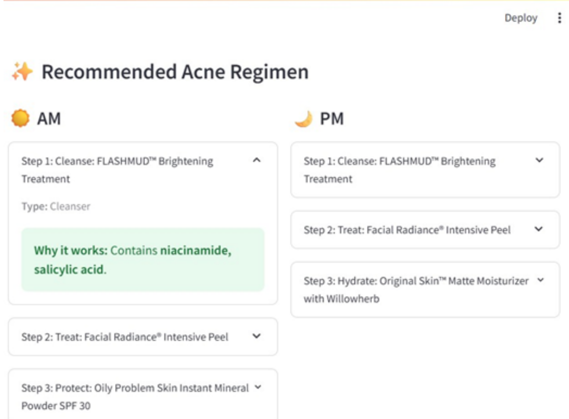

Fig. 7. Recommended AM and PM skincare regimen generated by DermaClust.

D. Recommender

The DermaClust recommendation module employs a scoring-based decision framework rather than a purely rule based or filter-based approach. By integrating AI-driven skin analysis, ingredient compatibility metrics, and environmental context, the system generates personalized skincare routines [2], [12]. Products are ranked based on compatibility scores derived from model predictions and predefined suitability values.
Each skin concern class is assigned a probability score by the classification model, which is combined with product suitability weights to produce a final compatibility index. This probabilistic scoring mechanism enables objective product ranking and supports adaptive personalization strategies. Dynamic Weather Boosting further enhances contextual relevance by adjusting scores based on environmental conditions such as humidity and ultraviolet exposure. Climate-aware recommendation strategies have been shown to improve skincare adaptability by aligning product selection with external factors [4]. Hydrating formulations gain priority in dry climates, while lightweight or oil-control products are emphasized in humid environments.

Instead of generating a static recommendation, the system applies a Variety Sampling Strategy. From the top five ranked products across cleansing, treatment, and protection categories, one candidate is selected to provide balanced yet diverse regimen recommendations. This probabilistic selection approach increases personalization while maintaining recommendation quality.

E. Data Cleanser and Product Database

The Data Cleanser module evaluates skincare products by analysing ingredient lists and verifying compatibility with user skin profiles. The system classifies ingredients as beneficial, neutral, or potentially harmful using structured dictionaries, enabling safety-focused recommendations [5]. Users can upload ingredient lists to receive actionable, real-time compatibility insights. A structured product database supports the recommendation engine. Prior to deployment, a preprocessing script assigns weighted suitability scores for each product across five skin concern classes: acne, dry, oily, wrinkles, and normal skin. Beneficial ingredients increase compatibility scores, whereas potentially harmful compounds reduce overall ratings. Precomputing these values reduces runtime complexity and improves scalability.

By combining a safety assessment module with a prescored product database, DermaClust enhances reliability, transparency, and efficiency. Integrating ingredient-level reasoning alongside visual and contextual analysis creates a comprehensive multimodal skincare recommendation system [7], [10].

VI. TECHNOLOGIES USED

DermaClust utilizes several modern Python-based libraries and frameworks for deep learning, computer vision, natural language processing, and real-time web integration. These technologies operate collaboratively to enable multimodal data analysis and personalized skincare recommendation generation [7], [10]. TensorFlow and Keras form the backbone of the deep learning pipeline, providing the framework to design, train, and deploy the MobileNetV2-based convolutional neural network for skin classification alongside transformer- based models for ingredient analysis. Their high-level APIs support efficient transfer learning, model optimization, and scalable deployment strategies, which are widely adopted in modern dermatological AI systems [5].

Media Pipe is employed for facial landmark detection and 3D face mesh generation. This enables precise localization of facial regions and supports targeted extraction of skin patches from areas such as the forehead and cheeks. Accurate landmark detection improves robustness by focusing analysis on relevant texture features while minimizing background interference, similar to region-focused computer vision approaches used in skincare classification research [1], [8]. For the interactive web-based interface, Streamlit is used to create a structured and responsive environment where users can upload facial images, enter clinical information, and receive real-time skincare recommendations. This lightweight deployment framework enables rapid prototyping and seamless integration with backend machine learning models. OpenCV (cv2) supports image preprocessing operations including resizing, CLAHE-based enhancement, and visualization of extracted regions. These functions improve input consistency and assist in debugging during development. Pandas and NumPy provide core data processing and numerical computation capabilities. Pandas manages structured product databases and ingredient filtering operations, while NumPy enables mathematical calculations such as probability weighting, scoring aggregation, and recommendation ranking.

The Requests library facilitates communication with the OpenWeatherMap API, allowing the system to retrieve real-time environmental parameters such as humidity levels and ultraviolet index. Integrating environmental context into recommendation logic extends the concept of climate-aware skincare systems proposed in prior studies [4]. Together, these technologies form an integrated ecosystem that supports efficient data processing, model training, and real-time deployment within the DermaClust framework, enabling scalable multimodal skincare intelligence [7], [10].

VII. RESULTS AND ANALYSIS

A. Skin Patch Extraction and Preprocessing Performance

The preprocessing component of DermaClust accurately recognized facial regions and isolated targeted skin patches. The system segmented localized areas such as the forehead and cheeks using Media Pipe Face Mesh, and these regions were enhanced using CLAHE to improve texture visibility. Region-focused skin analysis approaches have been shown to improve robustness in dermatological classification tasks by reducing background noise [1], [8].

The Scientific Skin Patch Analysis interface confirmed that the extracted regions maintained sufficient resolution and clarity for reliable model inference.

B. Skin Classification and Hybrid Profiling Analysis

The MobileNetV2-based skin classification model produced probability distributions across five defined skin concern classes. As shown in Fig. 4, the oily category achieved the highest confidence score during testing. Transfer learning and lightweight CNN architectures have demonstrated strong performance in skincare image analysis tasks [1], [8].

The hybrid profiling mechanism refined predictions by combining AI-derived outputs with clinical questionnaire responses, enabling a more balanced representation of user skin conditions [5], [7].

C. Environmental Context Integration

The Environmental Context module successfully retrieved real-time weather parameters including temperature, humidity, and UV index.

These parameters were incorporated into the recommendation pipeline through Dynamic Weather Boosting, extending ideas proposed in climate-aware skincare recommendation frameworks [4].

D. Recommendation Engine Performance

The scoring-based recommendation engine generated structured AM and PM routines consisting of cleansing, treatment, and protection steps. Hybrid decision logic combining ingredient intelligence and visual analysis has been shown to enhance recommendation relevance in multimodal skincare systems [5], [7]. The use of variety sampling ensured diversity in generated routines while maintaining alignment with detected skin profiles.

E. Discussion and Observations

Experimental results indicate that integrating computer vision, NLP-based ingredient analysis, and contextual environmental data improves the reliability of AI-driven skincare recommendation systems. Multimodal intelligence has been identified as a key factor in advancing personalized dermatological applications [7], [10]. While the system demonstrated strong performance, certain limitations were observed, including dependency on image quality and variability in ingredient labelling formats.

F. Performance Evaluation

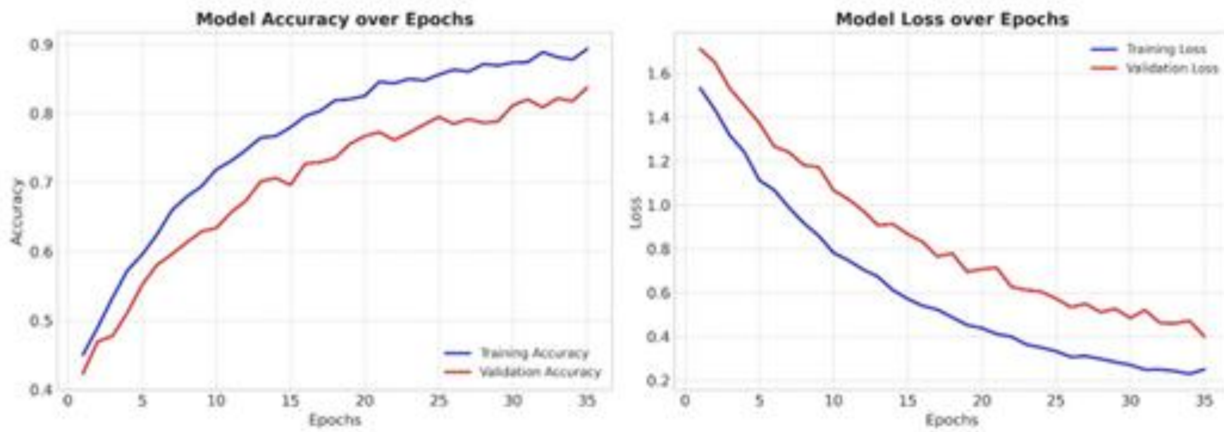

Fig. 8. Training and Validation Accuracy and Loss over 35 epochs.

VIII. CONCLUSION

DermaClust offers an all-inclusive system for personalized skincare recommendations through its computer vision and natural language processing and environmental context analysis technologies which operate in a single framework. The system introduces an AI-based pipeline that conducts skin texture assessment and ingredient match evaluation and climate condition measurement through its automated assessment solution which replaces existing self-evaluation techniques. The proposed framework shows that multimodal intelligence improves skincare guidance accuracy and reliability through its combination of deep learning models with structured decision-making processes.

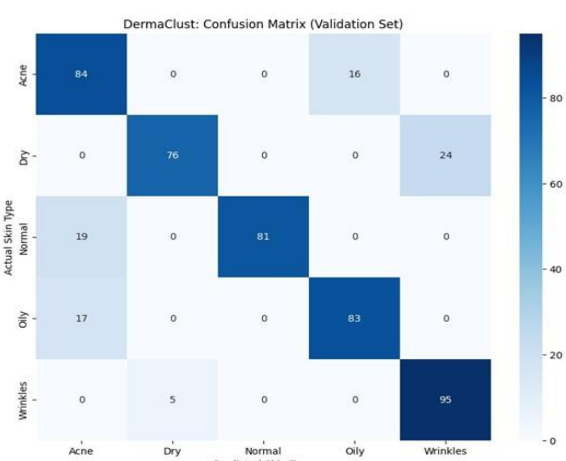

Fig. 9. Confusion Matrix of DermaClust on the Validation Set.

The research developed a hybrid profiling method which combines AI-generated visual data with user-reported medical data as its primary contribution. The system uses this combination to create solutions for situations when external skin appearance fails to show hidden skin disorders. The dynamic weather-based adjustments which serve this purpose enable skincare recommendations to adjust according to changing environmental conditions, thus making the generated skincare routines more practical for real-world use. The DermaClust framework demonstrates how multiple data sources can unite to develop dermatological solutions that provide both improved safety and personalized treatment options. The proposed system establishes a basis which organizations can use to develop intelligent skincare technologies while it decreases dependence on personal assessment through its data driven decision-making process.

IX. FUTURE SCOPE

The suggested DermaClust architecture combines a hybrid logic-based recommendation system, transformer-driven ingredient analysis, environmental data integration, and image-based skin classification. While its performance is encouraging, several enhancements can further improve the robustness, scalability, and clinical applicability of the system. Recent advances in AI-driven skincare systems [5], [7] indicate strong potential for multimodal and adaptive extensions.

Table I DermaClust model performance metrics (validation set)

Class	Precision	Recall	F1-Score	Support
Acne	0.79	0.85	0.82	100
Dry	0.78	0.79	0.79	100
Normal	1.00	0.87	0.93	100
Oily	0.71	0.90	0.80	100
Wrinkles	1.00	0.78	0.88	100
Accuracy		0.84		500
Macro Avg	0.86	0.84	0.84	500
Weighted Avg	0.86	0.84	0.84	500

A. Enhanced Preprocessing and Feature Extraction

Media Pipe Face Mesh is currently used for facial region extraction. Future improvements may incorporate illumination normalization, colour constancy correction, and automated region-wise severity mapping (e.g., T-zone, cheeks, forehead). Prior computer vision-based skincare systems [1], [8] demonstrate that robust feature extraction significantly enhances classification accuracy under varying lighting conditions.

B. Advanced Vision and Multimodal Learning Models

The AI Engine layer currently employs MobileNetV2 for skin classification and a transformer-based model for ingredient analysis. Future improvements may include:

Integration of Vision Transformers (ViT) or hybrid CNN Transformer architectures, inspired by recent deep learning skincare frameworks [5], [7]. Self-supervised pretraining on large-scale dermatological datasets to improve generalization. Cross-modal attention mechanisms for joint embedding of visual features and ingredient representations. Existing recommendation systems often treat image and ingredient data independently [2], [12]. Deeper multimodal fusion could reduce reliance on manual similarity-based matching and enable end-to-end learning.

C. Adaptive Integration Layer

The Hybrid Logic Hub currently combines AI Engine outputs, OpenWeatherMap API data, and user clinical history. Weather-aware skincare recommendation systems [4] highlight the importance of environmental integration. Future enhancements may include reinforcement learning-based adaptive weighting, time-series modeling for longitudinal skin tracking, and dynamic personalization based on seasonal variations.

D. Real-Time and Edge Deployment

To improve accessibility and scalability, future research may focus on model compression techniques such as pruning and quantization. AI-assisted skincare systems deployed in practical environments [6], [13] demonstrate the feasibility of real-time and interactive frameworks. Edge-AI inference on mobile devices would enable real-time skincare analysis with minimal cloud dependency.

E. Intelligent Product Knowledge Modeling

Current recommendations rely on a pre-scored product database. Future work may involve constructing a skincare knowledge graph linking ingredients, contraindications, and skin concerns. Content-based and collaborative filtering approaches [2], [12] can be extended with graph-based learning techniques to enhance recommendation precision and scalability.

F. Explainable AI Integration

To enhance transparency and user trust, Explainable AI (XAI) techniques such as Grad-CAM for visual interpretability and SHAP-based ingredient contribution analysis may be incorporated. The growing adoption of AI in cosmetic dermatology [10],

[11] highlights the importance of interpretability and reliability for semi-clinical applications.

G. Clinical Validation and Expansion

Future studies may include validation using dermatologist annotated datasets and alignment with standardized dermatological severity metrics. Expanding toward predictive dermatology aligns with recent innovations in AI-driven skincare ecosystems [9], enabling early risk detection and preventive skincare strategy modeling.

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