

TalaSkin: An AI-Powered Dermatological Support System for Skin Disease Detection and Consultation in the Philippines

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Abstract— Access to dermatological care in the Philippines and Southeast Asia remains limited due to high costs, few specialists, and geographic barriers. While AI-driven diagnostic tools can achieve dermatologist-level accuracy, most underperform on darker skin tones because existing datasets primarily feature individuals with lighter skin tones. This study presents Tala Skin, an AI-powered dermatology support system designed for Filipino and Southeast Asian users with Fitzpatrick skin tones III–V. Using a YOLOv12-seg model with transfer learning, the system will be trained on a diverse dataset sourced in collaboration with the Mapúa School of Medicine and supplemented by public dermatology datasets. The model will be rigorously preprocessed, augmented, and validated using precision, recall, F1-score, and mean Average Precision (mAP). Grounded in the Technology Acceptance Model (TAM) and Health Belief Model (HBM), Tala Skin integrates a responsive web interface for accessible, device-independent use, offering image-based analysis, educational insights, and referral guidance. This research advances equitable dermatological AI and promotes fair, accessible healthcare for Southeast Asian populations.

Keywords— *AI dermatology, deep learning, healthcare accessibility, algorithmic fairness, computer vision, skin tone bias, YOLOv12*

I. INTRODUCTION

Stage I: The Setting

Access to specialized healthcare, such as dermatology, remains a significant challenge in the Philippines and the broader Southeast Asia region due to high costs, long wait times, and an uneven distribution of

specialists. Skin conditions are among the most common health concerns in this region. In response, many have turned to technology, with Artificial Intelligence (AI) in healthcare emerging as a promising field to expand access. AI-powered diagnostic tools, particularly those utilizing computer vision, have demonstrated potential in identifying dermatological issues.

Stage II: Review of Literature (Brief)

Landmark studies have demonstrated that deep learning models can achieve dermatologist-level accuracy in classifying skin conditions. This has led to the development of several skin health applications. However, a critical problem has been identified: the performance of these AI models often drops significantly when applied to darker skin tones. This disparity is primarily due to biased training datasets that lack diversity, leading to unreliable and potentially harmful results for populations not well-represented in the data, such as Filipinos and Southeast Asians.

Stage III: Missing Information (The Gap)

The existing literature and commercially available tools demonstrate a clear gap: a lack of AI dermatology applications specifically trained, validated, and optimized for Filipino and Southeast Asian complexions. While some local research has begun to address this, there is still a need for a validated system that not only accounts for skin tone diversity but is also designed for accessible triage and referral.

Stage IV: The Statement of Purpose

The purpose of this study is to develop and evaluate "Tala Skin," an AI-powered dermatology support system

designed for Filipino and Southeast Asian users. This research aims to answer the following question: How accurately can an AI model trained on Filipino and Southeast Asian clinical images identify common skin conditions on local skin tones, and how can its performance be improved and validated for safe triage and referral use?

This study will focus on AI skin condition recognition to develop a system that can accurately identify common dermatological issues and provide practical triage and referral recommendations.

Stage V: The Statement of Value

This research addresses a critical gap in healthcare accessibility for Filipinos and other Southeast Asians. By developing a tool validated for local skin tones, this study may provide a reliable and accessible first step in dermatological care. The "Tala Skin" system has the potential to alleviate the physical, financial, and emotional burden of misdiagnosis or delayed treatment. The results of this study could help demonstrate how to mitigate algorithmic bias in AI-driven healthcare and provide a practical framework for connecting users in underserved areas to professional dermatologists via telehealth.

II. RELATED LITERATURE

Introduction

This chapter presents a comprehensive review of published research relevant to the development of Tala Skin, an AI-powered dermatology support system designed for Filipino and Southeast Asian users. The review is organized thematically to address four critical areas: (1) the feasibility and accuracy of AI in dermatology, (2) the critical issue of skin tone bias and dataset disparity, (3) related studies in the Asian and Philippine context, and (4) theoretical frameworks for adoption and triage. By synthesizing existing literature, this review identifies gaps in current research and establishes the conceptual foundation for developing a validated, accessible dermatological AI tool optimized for Southeast Asian complexions.

Body: Thematic Review of Literature

Feasibility and Accuracy of AI in Dermatology

The application of convolutional neural networks (CNNs) for dermatological diagnosis has been well-established through landmark studies, which have demonstrated clinical-level accuracy. Esteva et al. (2017) provided groundbreaking evidence that deep neural networks could achieve dermatologist-level classification of skin cancer using over 100,000 clinical images, proving that

CNNs can learn complex visual patterns necessary for accurate skin condition identification. This foundational work established the technical feasibility of AI-powered dermatology and demonstrated that machine learning models could match the diagnostic performance of board-certified specialists.

Building upon this foundation, Han et al. (2018) further validated the approach by using a large dataset of Asian patients, specifically from Korea, to classify benign and malignant cutaneous tumors. Their work is particularly relevant as it demonstrated how training on regional skin tones significantly improves performance, supporting the rationale for developing population-specific models. The study achieved high accuracy rates and highlighted the importance of dataset composition in determining model effectiveness across different demographic groups.

More recent work by Liu et al. (2020) expanded the scope of AI dermatology by developing a deep learning system capable of differential diagnosis across 26 common skin conditions, utilizing over 16,000 images that span diverse skin tones. Their system achieved diagnostic accuracy comparable to board-certified dermatologists, even when tested on smartphone images, demonstrating the practical viability of accessible, mobile-based dermatology AI. This research validates the potential for AI systems to expand access to dermatology in resource-limited settings, directly supporting the concept behind Tala Skin.

The evidence from primary care settings further reinforces the clinical utility of AI. Escalé-Besa et al. (2024) conducted a systematic review showing that CNN-based AI can outperform non-expert clinicians in primary care dermatology, suggesting that such tools could serve as effective triage systems to connect patients with appropriate specialist care. However, their review also highlighted significant variability in study quality and limited evidence across diverse skin tones, underscoring the need for rigorous validation on underrepresented populations.

Tschandl et al. (2020) demonstrated that human-computer collaboration produces superior diagnostic outcomes compared to either humans or AI working alone. This finding directly aligns with Tala Skin's approach of providing AI-assisted triage before connecting users to dermatologists via telehealth, rather than attempting to replace professional diagnosis entirely. The collaborative model represents a practical pathway for integrating AI into healthcare workflows while maintaining appropriate clinical oversight.

Collectively, this body of work confirms that CNNs possess the technical capability to perform dermatological image analysis at clinically relevant accuracy levels. The feasibility of AI dermatology has been established across multiple contexts, from specialized dermoscopic imaging to

consumer-grade smartphone photos, providing strong evidence that the technical foundation for Tala Skin is sound.

The "Gap": Skin Tone Bias and Dataset Disparity

Despite the demonstrated feasibility of AI dermatology, a critical challenge has emerged: AI models exhibit significant performance degradation when applied to darker skin tones. Daneshjou et al. (2022) conducted a seminal study that quantified these disparities using the Diverse Dermatology Images (DDI) dataset of 656 clinically curated images. Their research revealed that commercially available AI models showed markedly reduced accuracy on darker skin tones and uncommon diseases, with performance drops of up to 30% compared to lighter skin tones. This disparity stems primarily from biased training datasets that predominantly feature lighter-skinned patients, leading to models that fail to learn the visual features characteristic of conditions as they manifest on darker skin.

Benčević et al. (2024) investigated the mechanisms underlying skin color bias in deep learning-based skin lesion segmentation, demonstrating that the problem extends beyond simple classification to include fundamental image processing tasks. Their analysis revealed that models trained on imbalanced datasets systematically fail to accurately delineate lesion boundaries on darker skin, potentially leading to both false negatives and false positives with profound clinical implications. This research emphasizes that addressing bias requires attention to all stages of the AI pipeline, from segmentation through classification.

The consequences of dataset disparity are particularly severe for populations underrepresented in training data. Daneshjou et al. (2022) specifically highlighted that Asian, Black, and Hispanic populations face higher risks of misdiagnosis due to algorithmic bias, creating a form of digital health disparity that could exacerbate existing inequities in healthcare access. This finding is especially relevant for Southeast Asian populations, including Filipinos, who remain significantly underrepresented in major dermatology datasets.

To address these disparities, Hasan et al. (2024) proposed fairness-aware methods that move beyond simple accuracy metrics to consider cost-weighted performance across different skin tone groups. Their cost-aware approach recognizes that false negatives may have more severe consequences for specific conditions or populations, necessitating models to be optimized for equitable outcomes rather than solely for aggregate performance. This methodology provides a framework for evaluating Tala Skin's performance across the diverse skin tones present in Southeast Asian populations.

Aquil et al. (2025) demonstrated that hybrid approaches combining machine learning techniques

(Random Forest, SVM, Decision Trees) with deep learning models (EfficientNet, MobileNetV2, DenseNet121) can improve performance across diverse skin tones. Their work emphasizes the value of ensemble methods and the importance of carefully selecting models based on the specific characteristics of the target population. The explicit focus on skin tone diversity in their methodology offers practical guidance for developing Tala Skin's classification system.

Jaiyeoba et al. (2024) provided comprehensive methodological guidance for addressing bias through dataset inclusivity, subgroup reporting by skin tone, and bias reduction via augmentation and reweighting techniques. Their framework emphasizes the importance of transparent reporting of model performance across demographic subgroups, ensuring that disparities are visible and can be addressed systematically. These methodological practices will be essential for Tala Skin's development and validation process.

This body of literature establishes a clear gap: while AI dermatology is technically feasible, existing commercial systems fail to serve darker-skinned populations equitably. The call for fairness-aware methods, diverse training datasets, and rigorous subgroup validation directly motivates the development of Tala Skin as a system specifically designed and validated for Filipino and Southeast Asian skin tones.

Related Studies in the Asian and Philippine Context

Recognizing the need for population-specific dermatology AI, researchers have begun developing datasets and models tailored to Asian populations. Huang et al. (2021) developed Xiangya-Derm, a comprehensive Chinese database encompassing six common skin diseases. They demonstrated that models trained on Asian patients achieve superior performance compared to models trained primarily on Western populations. Their work provided comparative benchmarks showing that AI performance on Asian patients could match or exceed dermatologist accuracy when appropriate training data is available.

The development of region-specific datasets has continued to expand. Li et al. (2023) introduced DIET-AI, a large dataset comprising over 200,000 images and 220,000 medical records from Asian demographics, encompassing 31 common skin diseases. The scale and scope of this dataset, if publicly accessible, could provide valuable benchmarking opportunities. Their innovative dual-mode input system, which combines image analysis with extracted text from medical records, suggests promising directions for enhancing diagnostic accuracy through multimodal learning.

In India, Madarkar et al. (2025) developed DermaCon-IN, a multi-concept annotated dataset featuring

approximately 5,450 clinical images from roughly 3,000 patients, covering more than 240 distinct diagnoses. While pictures from India may have limited direct applicability to Filipino populations due to differences in skin tone distribution and disease prevalence, the rigorous annotation methodology by board-certified dermatologists provides a model for dataset development that prioritizes clinical validity and comprehensive coverage of diverse conditions.

Specifically, research addressing tropical and regional diseases has emerged in Southeast Asian contexts. Yotsu et al. (2023) applied deep learning to skin-related neglected tropical diseases, demonstrating the potential of AI in low-resource regions where such conditions are prevalent. Their pilot study highlighted challenges common to Southeast Asian contexts, including limited datasets, underrepresented conditions, and the need for models that can function effectively with varying image quality from consumer devices.

Most critically for this study, local Philippine research has begun addressing the specific needs of Filipino patients. Velasco et al. (2023) developed a CNN-based classification system utilizing transfer learning on a dataset comprising approximately 3,400 images representing seven common skin diseases: chickenpox, acne, eczema, Pityriasis rosea, psoriasis, Tinea corporis, and vitiligo. Their work represents one of the first attempts to create a dermatology AI system specifically trained on Filipino patients, providing important baseline data on condition prevalence and model performance in the local context.

Similarly, Tomas et al. (2024) applied YOLOv5 deep learning to recognize common skin diseases in the Philippines, with a focus on real-time detection capabilities. Notably, one of the authors, Mary Christine A. Tomas, is affiliated with Mapúa University, suggesting potential opportunities for collaboration or data sharing. Their research demonstrated the viability of object detection architectures for dermatological applications in the Philippine setting.

These local studies are seminal contributions to Philippine AI research in healthcare. However, gaps remain that Tala Skin aims to address. Both Velasco et al. (2023) and Tomas et al. (2024) focused on a limited number of conditions and did not extensively address user adoption factors, telehealth integration, or comprehensive validation across the full range of Filipino skin tones (Fitzpatrick types III-V). Furthermore, neither study appears to have progressed to a publicly accessible, deployed system that could serve as an actual healthcare access point for underserved populations.

The present study builds upon these foundational works by expanding the scope to include a broader range of non-life-threatening conditions, integrating the AI model into a complete triage and referral system, emphasizing validation

across diverse Southeast Asian skin tones, and implementing theoretical frameworks (TAM and HBM) to ensure user adoption and appropriate use. By incorporating lessons learned from Asian datasets while focusing specifically on Filipino and broader Southeast Asian populations, Tala Skin represents an evolution from proof-of-concept research toward a validated, accessible clinical support tool.

Theoretical Frameworks for Adoption and Triage

The technical success of an AI dermatology system depends not only on diagnostic accuracy but also on user acceptance and appropriate clinical use. Two established theoretical models provide the conceptual foundation for Tala Skin's design: the Technology Acceptance Model (TAM) and the Health Belief Model (HBM).

The Technology Acceptance Model (TAM), initially proposed by Davis (1989), posits that user adoption of technology is primarily determined by two factors: perceived usefulness and perceived ease of use. In the context of Tala Skin, perceived usefulness relates to whether users believe the system will help them make informed decisions about their skin health and connect them with appropriate care. Perceived ease of use addresses whether the web-based interface is intuitive, accessible across devices, and requires minimal technical expertise to operate effectively.

Applying TAM principles, Tala Skin's design prioritizes accessibility through a responsive web-based interface that functions seamlessly across smartphones, tablets, and desktop computers, eliminating the need for application installation—a critical consideration for users in rural or low-resource areas who may face bandwidth or storage limitations. The interface design emphasizes clarity in presenting AI-generated information, accompanied by appropriate disclaimers that frame the system as supportive rather than diagnostic, thereby managing user expectations while building trust through transparency.

The Health Belief Model (HBM), developed by Rosenstock (1966) and subsequently expanded by other researchers, explains health-related behaviors through several key constructs: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy. For dermatological conditions, many individuals may underestimate their susceptibility to severe skin diseases or the severity of what they perceive as minor cosmetic issues. Conversely, they may face significant barriers to seeking professional care, including high costs, long distances to specialists, lengthy wait times, and stigma.

Tala Skin addresses HBM constructs by serving as a "cue to action" prompting users who might otherwise delay seeking care to take an initial step toward diagnosis. By providing educational information about skin conditions, the system increases awareness of perceived susceptibility and

severity when appropriate. The accessibility and low barrier to entry (web-based, free at point of use) directly reduce perceived barriers to engaging with dermatological health. Most importantly, the clear pathway to telehealth referral bridges the gap between self-assessment and professional care, thereby enhancing self-efficacy by providing users with a concrete next step.

The integration of TAM and HBM creates a comprehensive framework for Tala Skin's design. The system must not only be technically accurate (a necessary condition) but also perceived as helpful, easy to use, appropriately serious without being alarming, accessible to those facing barriers to traditional care, and effective at guiding users toward professional consultation when needed. This dual-framework approach ensures that Tala Skin addresses both the human factors and health behavior dimensions necessary for successful deployment in real-world Filipino and Southeast Asian contexts.

The theoretical grounding also informs evaluation metrics beyond technical performance. Success will be measured not only by classification accuracy but also by user satisfaction, adoption rates, appropriateness of triage recommendations, and ultimately, whether the system succeeds in connecting underserved populations with dermatological care they might not otherwise access. This holistic approach distinguishes Tala Skin from purely technical AI research, positioning it as a health intervention designed with a clear understanding of the psychosocial factors influencing its effectiveness.

Conclusion

This comprehensive review of related literature confirms several key findings that establish the foundation for Tala Skin's development. First, AI-powered dermatology has been demonstrated to be technically feasible, with deep learning models achieving clinical-level accuracy across multiple studies and contexts. CNNs can successfully classify skin conditions from various image sources, including consumer smartphone cameras, making accessible dermatology AI a realistic goal.

Second, a critical gap exists in the form of algorithmic bias and performance disparities across skin tones. Existing AI models, predominantly trained on lighter-skinned populations, show significant accuracy degradation on darker skin tones, creating a form of digital health disparity that could worsen existing inequities in healthcare access. This bias particularly affects Asian, Black, and Hispanic populations, who remain underrepresented in major dermatology datasets.

Third, while research in Asian contexts has begun addressing this gap through population-specific datasets and

models, Southeast Asian populations—including Filipinos—remain significantly underserved. Local Philippine research by Velasco et al. (2023) and Tomas et al. (2024) has made critical initial contributions, demonstrating the feasibility of dermatology AI for Filipino patients. However, these studies have not yet progressed to validated, deployed systems that incorporate comprehensive triage, telehealth referral, and user adoption frameworks.

Fourth, successful health technology implementation requires attention to both technical performance and human factors. The Technology Acceptance Model and Health Belief Model provide complementary frameworks for ensuring that Tala Skin is not only accurate but also perceived as helpful, accessible, and effective at motivating appropriate health-seeking behaviors.

The gap that Tala Skin addresses is thus multifaceted: it is simultaneously a technical gap (lack of models validated on Filipino/Southeast Asian skin tones), a health equity gap (algorithmic bias creating disparate outcomes), an access gap (limited availability of dermatological expertise in underserved areas), and an implementation gap (lack of deployed systems incorporating sound adoption principles). This study aims to bridge these gaps by developing a rigorously validated AI model trained on diverse Filipino and Southeast Asian skin tones, integrated into a user-centered triage system grounded in established behavioral theory, and explicitly designed to connect underserved populations with professional dermatological care through accessible telehealth pathways.

By building upon the technical foundations established by landmark dermatology AI research, incorporating the fairness-aware methodologies proposed to address bias, learning from Asian and Philippine dataset development efforts, and applying established frameworks for technology adoption and health behavior, Tala Skin represents a comprehensive response to the identified literature gaps. The system's development will contribute to both the technical literature on population-specific dermatology AI and the practical goal of expanding equitable access to dermatological care for Filipino and Southeast Asian communities, which traditional healthcare systems and emerging AI technologies have historically underserved.

III. METHODOLOGY

A. Research Design

This study employs an experimental and developmental research design, aimed at creating, training, and evaluating an artificial intelligence (AI) model for dermatological image analysis. The primary objective is the development of Tala Skin, a deep learning-based dermatology support system that assists users in identifying skin conditions, providing educational information, and referring them to professional care when necessary. The

study integrates both quantitative evaluations, as measured by model performance metrics, and qualitative considerations regarding accessibility, ethical deployment, and user experience.

The various phases of the research process are as follows: dataset collection in collaboration with medical experts, preprocessing and augmentation of dermatological images, training and optimization of model hyperparameters, and evaluation and validation of standard metrics. Through iterative refinement of the dataset and model architecture, this work seeks to identify the optimal configuration for detecting various dermatological conditions across the diverse skin tones of Southeast Asia.

B. System Overview

Tala Skin will integrate a convolutional neural network (CNN) for image-based skin analysis, paired with a responsive web-based interface, ensuring accessibility across devices with internet connectivity and compatible browsers. The system's primary function is to enable users to upload images of skin conditions, which the AI model will analyze to provide informative feedback, self-care suggestions, and referral recommendations. This design ensures universal access without the need for mobile application installation, lowering barriers for rural or low-resource users.

The AI model will be trained using PyTorch due to its flexibility for research and optimization. Training will be conducted locally on a GPU-equipped PC, specifically an RTX 3060, for greater control over experiments, and optionally on Google Colab, allowing for a comparison of speed, memory usage, and cost efficiency. Deployment will be on a web-based platform; for this, Flask or any similar web framework can be used to host the model and manage user interactions. The web-based system also allows for the integration of disclaimers and guidance, ensuring users understand that the tool is supportive and non-diagnostic in nature.

C. Dataset Collection and Preparation

The dermatological dataset will be developed through collaboration with Dr. Malaya P. Santos, the Dean of the Mapúa School of Medicine, and affiliated medical staff. The research team hopes to collaborate with the medical department to obtain a sufficiently large and representative dataset. However, the exact scale and method of acquisition have yet to be finalized. If access to institutional data is limited, publicly available datasets such as DermNet, HAM10000, or PAD-UFES-20 may be used as supplementary sources to ensure initial model training and benchmarking (Tschandl et al., 2018; Souza et al., 2020; Maron et al., 2021).

All collected images will be anonymized and annotated to reflect relevant dermatological features. To ensure diverse representation, the dataset will include

Fitzpatrick skin tones III–V, reflecting the predominant Southeast Asian complexions (Fitzpatrick, 1988). While the specific target skin conditions have yet to be finalized, the dataset is expected to cover non-life-threatening conditions, including acne, dermatitis, eczema, fungal infections, and pigmentation disorders. This approach enables the model to learn generalized dermatological features before potentially narrowing its focus in future iterations.

This will split the dataset into three partitions: training (70%), validation (15%), and testing (15%), with strict separation to avoid data leakage and ensure non-duplication in evaluation.

D. Preprocessing Overview

Preprocessing is necessary to standardize the quality of input for deep learning models, particularly when images originate from different devices and under varying lighting conditions. All photos will be resized to 1024×1024 pixels; this resolution strikes a good balance between computational feasibility and the need to maintain fine dermatological details. Color normalization and contrast enhancement will also be performed to improve the visibility of skin lesions. Background noise and irrelevant skin regions will be cropped or masked to focus the model's attention on diagnostically relevant areas.

E. Preprocessing Approaches

Preprocessing will entail the following steps:

- **Color Normalization:** It normalizes the color features between images to reduce color variation induced by camera sensors and lighting. It ensures that a model, instead of artifacts, learns color-related lesion features.
- **Contrast-Limited Adaptive Histogram Equalization (CLAHE):** Improves local contrast without affecting overall color distribution, thereby increasing the visibility of subtle lesions.
- **Cropping and Background Removal:** The model focuses on the relevant skin areas by removing extraneous elements, such as clothing or hair.
- **Noise Reduction and Smoothing:** This performs Gaussian or bilateral filtering on the compression artifacts, allowing the model to extract more accurate features.
- **Aspect Ratio Standardization:** This helps to provide a constant input for the model, thereby reducing the geometric distortion of the lesions.

These steps collectively contribute to enhancing the consistency and quality of the dataset, enabling the model to learn more robust and medically relevant features.

F. Data Augmentation

Data augmentation increases dataset diversity, improving model generalization and performance in real-world scenarios.

The following techniques will be applied:

- **Brightness and Contrast Adjustment $\pm 20\%$:** This simulates variations in lighting conditions.
- **Saturation and Hue Variation $\pm 15\%$:** Takes into consideration skin tone variation as well as device capture.
- **Zoom and Crop ($0.9 \times - 1.1 \times$):** Simulates changes in distance or framing.
- **Horizontal Flip (50%):** Reflects symmetry in certain skin areas without distorting lesion structure.
- **Slight Gaussian Blur $\sigma = 0.5 - 1.0$:** Compensates for minor focus anomalies existing in user photographs.
- **Cutout/Random Erasing:** Simulates occlusions like hair, shadows, or small objects.

These enhancements maintain lesion integrity, whereas geometric rotations could distort irregular dermatological patterns.

G. Model Architecture and Training

The solution will leverage YOLOv12-seg, which was chosen due to its real-time object detection and segmentation capabilities, striking a balance between accuracy and computational efficiency. The model will utilize transfer learning with pre-trained weights to use previously learned low-level visual features from the COCO dataset. Fine-tuning will be done on the curated dermatology dataset.

Training Configuration and Rationale:

- **Framework:** PyTorch, selected for flexibility, debugging capability, and its friendliness to research.
- **Hardware Environment:** Local GPU - RTX 3060 for control and efficiency; optionally Google Colab for comparison.
- **Epochs:** 400–600 with early stopping if the validation metrics reach a plateau.
- **Batch Size:** 8–16, balancing memory consumption and gradient stability.

- **Imaging resolution:** 1024×1024 , retaining fine skin lesion details while remaining computationally feasible.
- **Optimizer:** SGD (learning rate = 0.01, momentum = 0.937), selected for stable convergence.
- **Loss Functions:** Bounding box regression, segmentation mask loss, and classification loss are used to handle multi-class lesion detection.
- **Validation Split:** The remaining 15% for monitoring model generalization.

Each setting is carefully chosen to optimize model performance, while also considering computational efficiency and ensuring compatibility with a web-based deployment environment.

H. Evaluation Metrics and Validation

Model performance will be measured using the following standard metrics:

- **Precision:** Proportion of correct predictions among predicted positives.
- **Recall:** Fraction of true positives correctly identified.
- **F1 Score:** Harmonic means of the precision and recall.
- **mAP@50 and mAP@50–95:** refer to Mean Average Precision calculated over different IoU thresholds for both bounding boxes and masks.
- **Confusion Matrix:** It helps in spotting class-specific misclassifications.

If the dataset size allows, 10-fold cross-validation will be performed to ensure robustness in the evaluation. Moreover, explainability techniques such as Grad-CAM will visualize attention regions to confirm medically relevant features used in model predictions.

I. Ethical Considerations

Medical AI essentially involves ethical compliance. All images will be anonymized, and the handling will be compliant according to the Data Privacy Act of 2012 (RA 10173) (Republic of the Philippines, 2012). Consultation and collaboration will proceed with active involvement in ethical sourcing and aspects of dataset quality and representativeness, led by Dr. Malaya P. Santos.

Tala Skin is a strictly supportive tool and in no way a replacement for professional diagnosis. Its intended use will be clearly disclosed to users, and data storage will be secure

and access restricted. The research team will follow institutional review board guidelines and all applicable laws regarding the collection, use, and protection of patient data.

IV. References

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