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# A Study on Area Assessment of Psoriasis Lesions Using Image Augmentation and Deep Learning: Addressing the Lack of Thai Skin Disease Data

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## Abstract

Psoriasis is a chronic skin disease with significant global and regional impacts, including in Thailand, where its burden is compounded by diagnostic challenges and limited dermatological resources. Psoriasis was selected for this study because it develops in distinct phases, requiring ongoing monitoring and treatment. The distribution of skin lesions plays a crucial role in disease identification and assessment, making it an essential factor for AI-based analysis. The development of AI-based diagnostic tools offers a potential solution. However, there is no publicly available skin disease dataset in Thailand, and image annotation is a challenging and time-consuming task for dermatologists. This scarcity of annotated datasets remains a critical barrier to AI development. This study utilizes the Dermnet dataset and enhances it through the application of image augmentation and style transfer techniques to generate a more diverse and representative dataset, particularly reflecting Thai skin tones. It also evaluates how augmentation techniques affect AI performance in psoriasis classification. The results showed that augmentation significantly enhanced model performance, with EfficientNetB4 achieving the highest accuracy (93.00%) and sensitivity (91.19%). Style transfer emerged as a valuable technique, enabling the creation of skin tone representative datasets that improved model generalizability. These findings align with existing literature. They demonstrate that augmentation techniques can overcome data limitations and enhance model robustness. This study introduces a novel use of style transfer techniques. These are applied to generate augmented datasets that represent Thai skin tones, addressing a critical gap in publicly available dermatology data. By enhancing dataset diversity, style transfer significantly improves the generalizability and accuracy of AI-based psoriasis classification models. These advancements have important implications for clinical practice. They are especially relevant in Thailand and other resource-limited regions, where AI-assisted diagnostics can improve dermatological care access and effectiveness.

***Keywords***: *deep learning models; image augmentation; psoriasis classification; skin disease; style transfer*

## 1. Introduction

Psoriasis is a chronic, immune-mediated skin disease that affects millions of people worldwide (Mpofana et al., 2024). It is a global health concern, with prevalence rates varying significantly across regions. In Western countries, the prevalence is reported to be higher, ranging from 2% to 3%, whereas Asian countries, including Thailand, generally show lower prevalence rates (Agarwal et al., 2022; Pothisat et al., 2021; Rajatanavin et al., 2022).

Characterized by red, scaly patches on the skin, psoriasis can significantly impair quality of life. This disease has a significant genetic component, with a heritability of up to 60-90% (Raharja et al., 2021). Psoriasis is also a common skin disease in Thailand. It affects approximately of 0.13% of the population in Thailand (Chaiyamahapurk, & Warnnissorn, 2021). Globally, psoriasis affects approximately 2-3% of the population (Agarwal et al., 2022; Mpofana et al., 2024), with prevalence varying by region. In Thailand, the prevalence is estimated to be lower than the global average (Akaraphanth et al., 2013; Prasitpuriprecha et al., 2022), yet the disease imposes a significant burden on affected individuals due to its visible symptoms, stigma, and the costs of long-term management.

Effective treatment and management of psoriasis often require detailed monitoring of lesion distribution, as the extent and pattern of lesions can provide critical insights into disease progression and treatment efficacy (Charoenying et al., 2024; Neema et al., 2022). However, in AI-based diagnostic systems, the impact of lesion distribution on model performance remains relatively underexplored (Smith et al., 2024).

Accurate and timely diagnosis of psoriasis is critical for effective treatment, yet it remains a challenge in resource-limited settings. Dermatologists rely heavily on clinical evaluation and, in some cases, skin biopsies, which can be invasive and time-consuming (Sharma et al., 2023; Yélamos et al., 2021). The advent of artificial intelligence (AI) has the potential to revolutionize dermatology by providing automated, accurate, and accessible diagnostic tools. AI models have demonstrated remarkable success in disease image classification. However, the effectiveness of these models depends on the availability of large, annotated datasets, a resource that is scarce in psoriasis research. Deep learning has shown great potential in psoriasis diagnosis by enabling automated lesion detection and classification with high accuracy, thereby reducing reliance on invasive procedures like biopsies (Srivastava et al., 2022). Proposed deep learning models can assist dermatologists with early detection, disease progression monitoring, and personalized treatment planning, ultimately improving patient outcomes.

To address limited data availability, image augmentation techniques have been widely used to synthetically expand datasets. These techniques generate diverse variations of existing images, enabling AI models to generalize more effectively with unseen data. Previous studies have addressed dataset scarcity in medical AI by employing traditional augmentation techniques such as rotation, flipping, and color adjustments to artificially expand training datasets (Esteva et al., 2017; Islam et al., 2024; Tschandl et al., 2020). Although these methods enhance data diversity, they fail to fully capture variations in skin tone or lesion characteristics across populations. In contrast, this study applies style transfer to generate synthetic images simulating Thai skin tones, thereby enhancing better representation and improving the generalizability of AI models for psoriasis classification. Despite the widespread adoption of augmentation, the extent to which various techniques influence model performance remains underexplored, particularly in psoriasis classification. Furthermore, interactions between augmentation methods and specific AI model architecture warrants further investigation.

Another challenge in developing AI models for skin disease classification is the scarcity of annotated datasets, particularly those representing diverse populations such as Thai patients. To address this issue, the study utilized Roboflow (2024), a platform for dataset annotation and management, to delineate lesion areas in the original dataset. Additionally, a style transfer technique was employed to generate synthetic additional images simulating Thai skin tones (Nakpan, & Sirinkraporn, 2023; Tanantong et al., 2024b). By integrating these steps, the study not only expanded the dataset but also ensured that the generated images reflect the unique characteristics of Thai skin tones, thereby contributing to the development of AI models that are both accurate and generalizable to the Thai population. Localized datasets play a crucial role in enhancing the performance and generalizability of AI diagnostic tools, not only in dermatology but also in other medical fields such as radiology, ophthalmology, and pathology. By incorporating region-specific data, AI models can better account for variations in disease presentation across populations, ultimately improving diagnostic accuracy and clinical applicability in diverse healthcare settings (Willemink et al., 2020).

Focusing on psoriasis, a condition with significant medical and social implications, this research addresses the dual challenges of diagnostic accuracy and data scarcity in dermatology. Style transfer techniques, combined with conventional image augmentation, were used to generate synthetic psoriasis images representative of Thai skin tones. This methodology aims to enhance the performance and generalizability of AI models for psoriasis classification. By creating a more diverse and localized dataset, the study contributes to the development of clinically relevant diagnostic tools, particularly in resource-limited settings, and underscores the importance of population-specific data in medical AI applications.

## 2. Objectives

This study addresses the scarcity of Thai skin disease data by focusing on the area assessment of psoriasis lesions, using image augmentation techniques to enhance AI models for lesion localization and size estimation. Due to the limited availability of Thai skin images in dermatological datasets, this research utilizes standard skin disease datasets and applies both traditional and skin tone augmentations to generate realistic Thai skin simulations. Four state-of-the-art CNN architectures EfficientNetB4, MobileNetV3-Large, ResNet50, and DenseNet-201 are trained and tested on augmented datasets to improve lesion boundary detection.

The study aims to:

1. Address the lack of Thai skin disease data by integrating skin tone variations.

2. Evaluate the impact of image augmentation on AI models for psoriasis lesion localization.

3. Train and assess four CNN architectures to improve segmentation accuracy.

By incorporating image augmentation and skin tone adaptation, this research contributes to the development of AI-driven tools tailored for psoriasis assessment in Thai populations, supporting improved diagnosis and treatment monitoring.

## 3. Materials and Methods

### 3.1 Data Collection

The images used in this study were obtained from a publicly available dataset hosted on the Roboflow (2024) platform, titled “Dermnet Computer Vision Project” (version 17) (Roboflow, 2024). Dermnet is a publicly accessible dataset focused on skin diseases (Dermnet, 2024). The Dermnet dataset includes 23 types of skin conditions and contains 19,500 expert-verified images (Alipour et al., 2024). This dataset serves as a valuable resource for dermatological image analysis, offering annotated images for developing and evaluating computer vision models. In this study, the “Dermnet Computer Vision Project” dataset was selected because, unlike the original Dermnet dataset, it includes expertly annotated psoriasis lesions with precise bounding boxes. This aligns with the study’s objective of identifying lesion locations and measuring their size, enabling AI models to detect psoriasis and assess disease progression for more accurate monitoring and treatment evaluation.

This study specifically focused on the subset of psoriasis images from the original dataset, comprising 291 images. Each image is accompanied by bounding box annotations that indicate the locations of skin lesions, totaling 2,442 annotated regions across the dataset. Since a single image may contain multiple lesions, each image can have several bounding boxes. These bounding boxes provide critical information for localizing skin lesions, making the dataset suitable for both classification and object detection tasks. The average image resolution is 290 x 195 pixels, reflecting the dimensions of skin lesion images in practical dermatological settings.

### 3.2 Data Preparation

A major challenge in this study is the lack of annotated Thai psoriasis images prepared by dermatologists, which limits the availability of high-quality training data. Additionally, the diversity of skin tones among Thai individuals introduces further complexity, necessitating the inclusion of representative images to ensure robust AI model development. To overcome the limited size of this subset and enhance the dataset diversity, image augmentation techniques were applied.

#### *3.2.1 Augmentation Techniques*

This study employed two traditional augmentation techniques: data augmentation with blurs and without blurs. These techniques apply various transformations, including adjustments to brightness, contrast, and color, along with specific blur and noise effects to simulate real-world variability in images. The augmentation parameters were carefully chosen to introduce meaningful diversity while preserving the key visual characteristics of psoriasis lesions. Brightness and contrast were modified within controlled ranges to reflect lighting variations typical in clinical environments. These ranges were based on prior dermatology AI studies (Tschandl et al., 2020), ensuring the augmentations added meaningful variability without distorting critical lesion features.

**Data Augmentation with Blurs**: This technique combines brightness and contrast adjustments with multiple blur effects and additional transformations. Brightness is randomly adjusted between -0.2 and 0.1, while contrast is varied between 0.2 to 0.3. Four types of blurs are applied randomly: Motion Blur (simulating motion, blur limit = 5), Median Blur (using a median filter to reduce noise, blur limit = 5), Gaussian Blur (reducing image detail with Gaussian filtering, blur limit = 5), and Gaussian Noise (adding random disturbances based on a Gaussian distribution, noise limit = 5 to 30). Contrast limited adaptive histogram equalization (CLAHE) enhances image contrast with a clip limit of 4.0 and is applied with a 70% probability. Additional transformations include adjustments to hue, saturation, and value (hue shift limit: -10 to 10; saturation shift limit: -20 to 20; value shift limit: -10 to 10, applied with a 50% probability). Finally, Coarse Dropout randomly blacks out pixels with maximum patch size set to 5% of the image dimensions (640 x 640) and 1 to 8 patches applied at a 70% probability.

**Data Augmentation without Blurs**: This technique excludes blur effects but retained transformations affecting image color and lighting. Brightness varies between -0.2 to 0.1, while Gaussian Blur is applied with a softer intensity (blur limit = 3 to 7). Hue, saturation, and value adjustments are performed with wider limits (hue shift: -20 to 20; saturation shift: -30 to 30; value shift: -20 to 20). Additionally, RGB Shift randomly modifies the intensities of red, green, and blue channels within a range of -20 to 20 for each channel. Additionally, all images were resized to a uniform dimension of 640 x 640 pixels with three color channels (RGB format), ensuring compatibility with the input requirements of the selected AI models.

Following the resizing of the original images to 640 x 640 pixels, grid lines were overlaid onto the images to segment them into smaller regions, 64 x 64 pixels. This process was designed to aid in precise lesion localization and provide a structured framework for analyzing lesion distribution. This was critical for assessing the impact of localization on AI model performance. This method enhanced the dataset's utility for training models capable of understanding lesion patterns in different regions of the skin. Figure 1 illustrates the process of image patch generation. The left side shows the original psoriasis lesion image with a resolution of 640×640 pixels. The right side displays the image after grid lines were applied, dividing it into 100 patches of 64 × 64 pixels each. This grid-based division enables more detailed analysis and annotation.

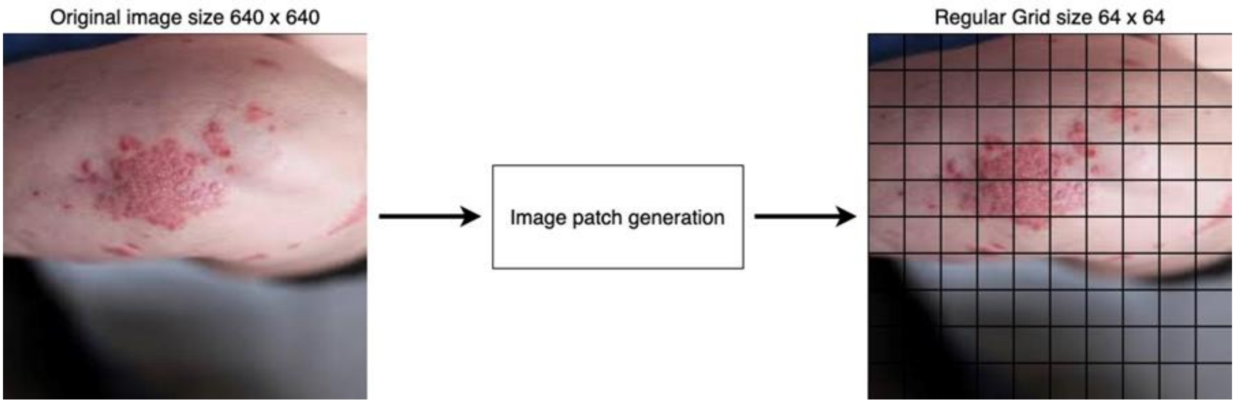


**Figure 1** Grid-based segmentation of a psoriasis lesion image

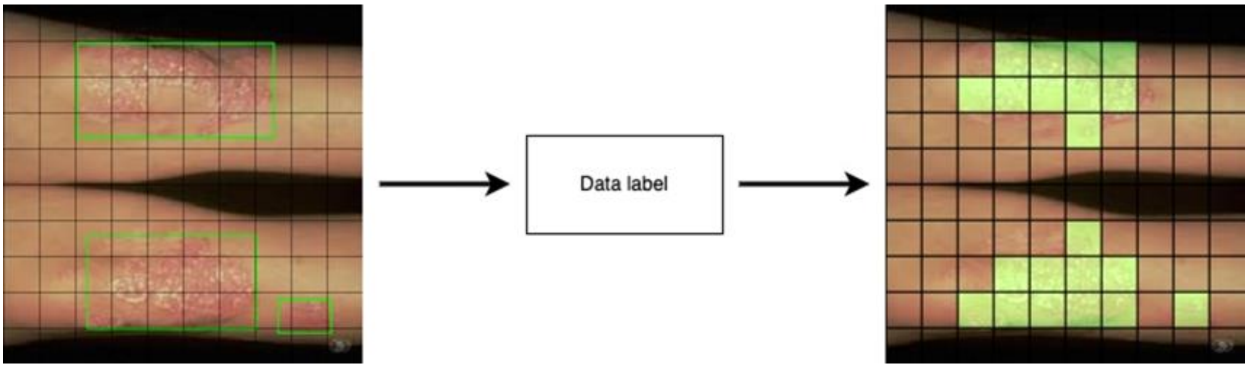


**Figure 2** Lesion annotation using grid-based labeling

During the annotation step, each grid cell was examined and labeled if it contained visible skin lesions. Each grid cell containing a lesion was marked to highlight its location, providing granular detail about lesion distribution, as depicted in Figure 2. The left side of the figure shows the original psoriasis image divided into 64×64 pixels patches, with green bounding boxes indicating the ground truth lesion areas. The right side presents the result after the re-labeling process. In this step, each grid cell was evaluated based on lesion coverage: cells with more than 40% of their area containing lesions were classified as lesion cells, while those with less than 40% coverage were labeled as non-lesional skin. This approach enabled precise lesion localization and labeling to support AI model training and evaluation.

*3.2.2 Style Transfer Techniques*

In addition to traditional augmentation techniques, style transfer was employed as a novel approach to enhance the dataset. Style transfer involves transforming the visual characteristics of images to match the skin tone and texture of a target population, in this case, generating Thai skin images from non-Thai skin images present in the original dataset.

This study employs the Fitzpatrick skin type classification to guide skin tone adjustments through style transfer (Nakpan, & Sirinkraporn, 2023). This system classifies skin tones into six types based on UV sensitivity: pale white, white, light brown, medium brown, dark brown, and black (Nakpan, & Sirinkraporn, 2023). Most of the Thai population falls into the light brown and medium brown categories (Nakpan, & Sirinkraporn, 2023). Therefore, the study focuses on Thai-relevant skin tones including pale white, white, light brown, and medium brown, while excluding dark brown and black skin tones, which are rare in Thailand. Although widely used, the Fitzpatrick classification mainly represents lighter to medium skin tones, limiting diversity in AI training (Gupta, & Sharma, 2019). Excluding darker skin tones may reduce model generalizability, affecting accuracy for more pigmented skin. Figure 3 depicts the common Thai skin tones used in the style transfer process, as referenced in (Nakpan, & Sirinkraporn, 2023). These skin tones were selected based on data from a study that analyzed skin color variations across Thailand's four main regions (north, northeast, central, and south) using a sample of 400 participants per region. To ensure broader representativeness, levels 2, 3, 4, and 5 were selected for the style transfer process, as these shades reflect the most common Thai skin tones. This selection ensures that the synthesized images are realistic and inclusive of regional skin tone variations.

The style transfer method used is fast neural style transfer, inspired by a study that applied style transfer to diversify skin tones in melanoma datasets (Rezk et al., 2022). In this study, four style transfer models were created, each corresponding to one of the targeted skin tone categories. The models were trained using style images resized to 640 x 640 pixels and content images resized to 224 x 224 pixels, with a content loss weight of $10^7$ and a style loss weight of $10^{10}$. Each model was trained over 1,000 epochs for each skin tone style. By applying these models to 601 psoriasis images from the dataset, the style transfer process generated 601 additional images for each of the four skin tone styles, resulting in 2,404 augmented images. These augmented images were incorporated into the experimental dataset to improve diversity and enhance the robustness of the AI model.

**Figure 3** Fitzpatrick skin types representative of the Thai population used in style transfer

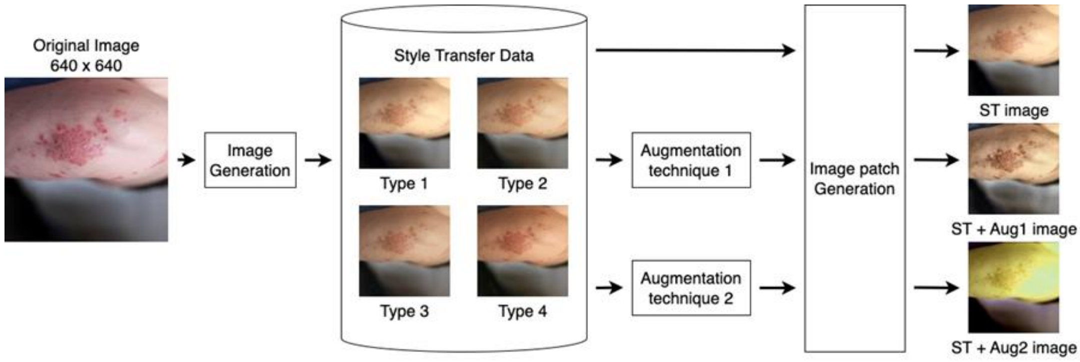


**Figure 4** Workflow of dataset preparation. The process includes style transfer application, traditional augmentation (with and without blur), and grid-based segmentation to produce 12 unique training datasets

*3.2.3 Augmented Datasets*

The data preparation process resulted in a total of 12 datasets. First, the original images underwent a style transfer process to simulate four different skin tones, creating four distinct datasets including, Type 1, Type 2, Type 3, Type 4 (Style Transfer Data). Next, each of these skin tone datasets was further processed with "Augmentation technique 1," generating four additional datasets. Similarly, "Augmentation technique 2" was applied to each skin tone dataset, resulting in another four datasets. Finally, the four original skin tone datasets without any additional augmentation were included, completing the collection of 12 diverse datasets (4 sets of style transfer, 4 sets of style transfer + Augmentation technique 1, 4 sets of style transfer + Augmentation technique 2). Figure 4 depicted the data preparation process.

These manipulations aimed to maximize the dataset's utility for training AI models, allowing for more accurate and reliable classification of psoriasis. The augmentation techniques were carefully selected to preserve the integrity of the original images while introducing meaningful variability to improve model generalization.

**3.3 Deep Learning Models**

In this study, four AI models were selected based on prior research (Tanantong et al., 2024a), which demonstrated their effectiveness classifying skin lesions using 64 × 64 pixel images. EfficientNetB4 and DenseNet-201 were chosen for their strong performance in image classification tasks, particularly in medical imaging. EfficientNetB4 is known for its optimized scaling of depth, width, and resolution, achieving high accuracy with fewer parameters, making it suitable for handling complex dermatological patterns (Tan, & Le, 2019). DenseNet-201, with its dense connectivity, enhances feature propagation and reuse, reducing redundant parameters while maintaining robust learning, which is particularly beneficial for distinguishing intricate psoriasis lesions (Huang et al., 2017). The selected models are as follows:

**EfficientNet Model**, introduced in 2019, was designed specifically for image classification tasks (Tan, & Le, 2019). Subsequent research (Rafay, & Hussain, 2023) applied EfficientNet models, EfficientNetB0 to EfficientNetB6, to classify skin diseases using the Atlas Dermatology and ISIC datasets. The study reported classification accuracy exceeding 80% across these models, highlighting their efficacy for skin disease identification.

**MobileNetV3 Model**, with advancements in mobile technology and the need to implement deep learning on mobile devices under resource constraints, Howard et al., (2019) developed MobileNetV3 as an enhancement of MobileNetV2. MobileNetV3 includes two variants, MobileNetV3-Small and MobileNetV3-Large, differentiated by their resource utilization, making them well-suited for mobile deployment (Howard et al., 2019).

**ResNet50 Model** was first introduced in 2016, featuring a unique "Residual Learning" architecture. This approach enables deeper network structures while minimizing training errors. ResNet50 has become widely recognized for its robust performance in a variety of image classification tasks (He et al., 2016).

**DenseNet Model** was developed to address challenges in deep learning networks, such as vanishing gradients and redundant parameters. DenseNet employs "dense connectivity," in which each layer connects directly to all previous layers through concatenation. This structure enhances gradient flow and feature reuse, reducing the number of parameters while improving memory efficiency and training performance (Huang et al., 2017).

### 3.4 Experiment Setting

The datasets were divided into 80% for training, 10% for validation, and 10% for testing, using only images containing psoriasis lesions. The generated datasets are collectively referred to as "Style Transfer data," while the original dataset is referred to as "Original data." Next, the Style Transfer data underwent augmentation using two techniques: one with blur and the other without blur. These augmented datasets are referred to as "Style Transfer data with Augmentation technique 1" (with blur) and "Style Transfer data with Augmentation technique 2" (without blur). Subsequently, all images, including the original data and the augmented Style Transfer data, were divided into smaller patches of size 64 x 64 pixels using an image patch generation process. Each patch was labeled to indicate whether it contained a lesion or a non-lesion area. Finally, the datasets were used to train deep learning models. The models were configured with a batch size of 32 and enhanced with additional layers including global average pooling 2D layer and followed by dense layer with softmax activation function. The Adam optimizer was used with a learning rate of 0.0001, and the models were trained for 30 epochs.

The experiments in this study were conducted on a high-performance computing system with the following specifications: an Intel Gen14th Core i5-14500 processor (24 MB cache, 14 cores), an NVIDIA RTX 4000 Ada Generation GPU with 20GB GDDR6 memory, and 32GB of DDR5 UDIMM RAM. This configuration provided computational power for model training and evaluation.

### 3.5 Evaluation Metrics

The evaluation metrics employed in this study include accuracy, sensitivity, and specificity, as outlined in prior research by Tanantong et al., (2015). Accuracy measures the proportion of correct predictions out of the total predictions, providing a general assessment of model performance. Sensitivity indicates the model's ability to correctly identify positive results (true positives), reflecting how well it detects lesion areas. Specificity, on the other hand, evaluates the model's capability to identify true negative results, demonstrating how effectively it distinguishes non-lesion areas. These metrics were calculated based on the testing datasets.

## 4. Results

The training and evaluation of the AI models followed a systematic process to ensure robust performance assessment across varying datasets. Initially, the models were trained using combinations of original, style-transferred, and augmented images, designed to enhance the diversity and representation of training data. The datasets were divided into training and testing sets, with the testing set held constantly to evaluate the models' ability to generalize. Performance metrics such as accuracy, sensitivity, and specificity were calculated for each experiment. Additionally, models were tested using both original and style-transferred datasets to examine their adaptability to data variations. A comprehensive evaluation allowed for the comparison of model performance across different augmentation scenarios and dataset types. Figure 5 depicts different datasets used for training, testing, and evaluating the models.

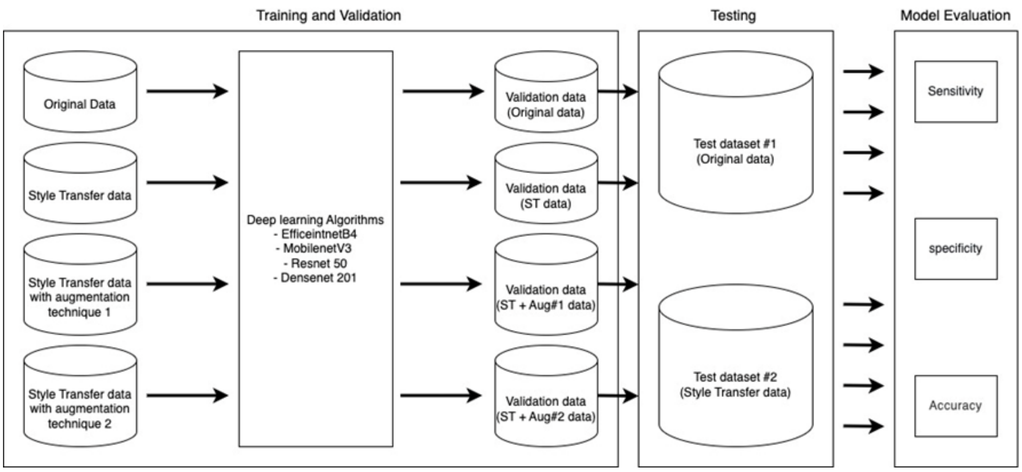


**Figure 5** Dataset partitioning strategy for model training and evaluation

The experimental results are summarized across four AI models including EfficientNetB4, MobileNetV3-Large, ResNet50, and DenseNet-201, evaluating their performance under varying training and testing conditions. The evaluation metrics include accuracy, sensitivity, and specificity. The experiments are categorized as follows:

**Experiment 1.1:** Training and testing on the original dataset (48,000 training images, 6,000 testing images).

**Experiment 1.2:** Training on the original dataset (48,000 training images) and testing on the style transfer images (6,000 testing images)

**Experiment 2.1:** Training on the original dataset augmented with style transfer images (240,000 training images) and testing on the original dataset (6,000 images).

**Experiment 2.2:** Training on the original dataset augmented with style transfer images (240,000 training images) and testing on the style transfer images (24,000 images).

**Experiment 3.1:** Training on the dataset augmented with style transfer and the first augmentation method (432,000 training images) and testing on the original dataset (24,000 images).

**Experiment 3.2:** Training on the dataset augmented with style transfer and the first augmentation method (432,000 training images) and testing on the style transfer images (24,000 images).

**Experiment 4.1:** Training on the dataset augmented with style transfer and the second augmentation method (432,000 training images) and testing on the original dataset (6,000 images).

**Experiment 4.2:** Training on the dataset augmented with style transfer and the second augmentation method (432,000 training images) and testing on the style transfer images (24,000 images).

The experiments evaluated the performance of four AI models, EfficientNetB4, MobileNetV3-Large, ResNet50, and DenseNet-201, under varying data augmentation setups and testing scenarios. Across all models, augmentation techniques involving style transfer and additional methods (Augmentation technique1 and Augmentation technique2) improved overall performance metrics. EfficientNetB4 consistently achieved the highest accuracy (93.00%) and specificity (93.80%) in Experiment 1.1, which used only original data for training and testing. When style transfer was added, the model maintained strong accuracy (92.00%). DenseNet-201 showed competitive performance with up to 93.00% accuracy in Experiment 4.2, where all augmentation techniques were applied. MobileNetV3-Large and ResNet50 exhibited moderate performance gains, with MobileNetV3-Large showing improved specificity under augmented datasets. Style transfer and augmentation techniques had a notable impact on enhancing model performance, particularly in experiments involving larger augmented datasets, as shown in Table 1. The results reveal that EfficientNetB4 consistently outperformed other models in terms of accuracy and sensitivity, while DenseNet-201 exhibited competitive specificity.

As shown in Table 1, the experimental results demonstrate that models trained on augmented datasets maintained comparable performance when tested on the original dataset. Accuracy, sensitivity, and specificity remained consistently high across all models, indicating that the use of augmentation and style transfer techniques did not degrade model performance. This suggests that the augmented data did not introduce significant distribution shifts and can be effectively used to enrich training without compromising generalizability to real-world data. The experimental results reveal that when the models were trained using a combination of the original dataset and the style transferred datasets (representing Thai skin tones), and subsequently tested on the style transferred dataset, they maintained a consistent level of accuracy across different skin tones, as shown in Table 2. This finding highlights the robustness of the models in handling diverse skin tones, which is critical for practical applications in dermatology. The ability of the models to generalize well to style transferred datasets demonstrates their potential for broader applicability, particularly in scenarios where annotated datasets for various skin tones are limited. These results underline the effectiveness of integrating style transfer techniques in data augmentation to enhance model robustness and performance.

**Table 1** Performance of AI models tested on the same original dataset after training on different combinations of original, augmented, and style-transferred data

| Experiment | Performance (%) | *EfficientNet B4* | *MobileNetV3-Large* | *ResNet 50* | *DenseNet-201* |
|---|---|---|---|---|---|
| Experiment 1.1 | Accuracy | 93.00 | 92.00 | 91.00 | 92.00 |
| | Sensitivity | 91.19 | 83.56 | 87.38 | 86.29 |
| | Specificity | 93.80 | 95.49 | 92.92 | 94.47 |
| Experiment 2.1 | Accuracy | 92.00 | 90.00 | 90.00 | 92.00 |
| | Sensitivity | 90.30 | 84.82 | 86.71 | 89.58 |
| | Specificity | 93.08 | 92.59 | 90.98 | 92.82 |
| Experiment 3.1 | Accuracy | 92.00 | 91.00 | 89.00 | 92.00 |
| | Sensitivity | 91.00 | 90.33 | 87.92 | 88.47 |
| | Specificity | 91.66 | 92.22 | 89.15 | 93.37 |
| Experiment 4.1 | Accuracy | 92.00 | 91.00 | 87.00 | 92.00 |
| | Sensitivity | 88.62 | 86.98 | 83.59 | 86.65 |
| | Specificity | 92.83 | 92.72 | 88.22 | 93.66 |

**Table 2** Model performance on style-transferred datasets representing Thai skin tones.

| Experiment | Performance (%) | *EfficientNet B4* | *MobileNetV3-Large* | *ResNet 50* | *DenseNet-201* |
|---|---|---|---|---|---|
| Experiment 1.2 | Accuracy | 85.00 | 87.00 | 82.00 | 85.00 |
| | Sensitivity | 93.64 | 88.86 | 93.45 | 94.18 |
| | Specificity | 83.42 | 86.55 | 80.60 | 83.57 |
| Experiment 2.2 | Accuracy | 92.00 | 92.00 | 91.00 | 92.00 |
| | Sensitivity | 91.55 | 88.13 | 90.26 | 91.55 |
| | Specificity | 92.74 | 93.12 | 90.59 | 92.36 |
| Experiment 3.2 | Accuracy | 92.00 | 92.00 | 89.00 | 92.00 |
| | Sensitivity | 90.74 | 88.38 | 89.53 | 91.32 |
| | Specificity | 92.27 | 91.54 | 89.25 | 92.14 |
| Experiment 4.2 | Accuracy | 92.00 | 92.00 | 89.00 | 93.00 |
| | Sensitivity | 88.87 | 89.42 | 87.33 | 90.17 |
| | Specificity | 93.45 | 92.69 | 89.39 | 93.76 |

According to Table 2, the results from Experiment 1.2 clearly indicate that when models were trained using the original dataset, which did not include Thai skin tones, and tested on the style transferred dataset (representing Thai skin tones), the model performance was the lowest compared to other experiments. Specifically, the accuracy for EfficientNetB4, MobileNetV3-Large, ResNet 50, and DenseNet-201 were 85.00%, 87.00%, 82.00%, and 85.00%, respectively. Sensitivity and specificity also showed relatively lower values when compared to experiments where the datasets included a combination of original data and style transferred data with Thai skin tones.

The variation in model performance suggests that model selection should align with specific clinical needs. EfficientNetB4's high accuracy makes it suitable for general psoriasis classification, ensuring reliable overall predictions. In contrast, DenseNet-201's higher specificity is beneficial in reducing false positives, making it more suitable for applications requiring precise lesion differentiation. The choice of model should consider the balance between sensitivity and specificity based on the intended use case. In addition, EfficientNetB4, which is often cited as the most effective model in prior studies, performed less well in Experiment 2.1. This is likely due to the use of small 64×64 image patches for training, which were specifically designed to locate lesion areas rather than provide full-context skin images. The reduced image resolution may have limited EfficientNetB4's ability to leverage its complex feature extraction capabilities, affecting its performance in this experiment.

The high accuracy of each model can be attributed to its unique architectural advantages. EfficientNetB4 benefits from compound scaling, optimizing depth, width, and resolution, allowing it to extract fine-grained features effectively. DenseNet-201 leverages dense connectivity, improving gradient flow and feature reuse, enhancing learning efficiency. MobileNetV3-Large is designed for optimized efficiency with depthwise separable convolutions, making it effective despite its lightweight architecture. ResNet50, with its residual learning framework, mitigates vanishing gradient issues, enabling stable learning in deep networks. These design strengths contribute to their high classification accuracy in psoriasis lesion detection.

The results of this study align with recent research (Li et al., 2024; Xing et al., 2024), demonstrating the effectiveness of deep learning for psoriasis classification. Prior studies have shown that EfficientNet and DenseNet architectures achieve high accuracy in dermatological image analysis, consistent with our findings. However, this study extends previous work by incorporating style transfer for skin tone adaptation, addressing dataset limitations, and improving model generalizability for diverse populations. These findings underscore the importance of incorporating diverse skin tones during the training process to enhance the adaptability and robustness of the models for real-world scenarios. The results highlight the limitations of using datasets that lack representation of diverse skin tones, which can significantly impact the model's performance in applications requiring generalization, such as dermatological diagnostics for individuals with varied skin tones.

In summary, the results presented in Table 2 emphasize the effectiveness of incorporating style transferred datasets into the training process for psoriasis classification. Models trained on a combination of original images and style transferred images, specifically those adapted to represent Thai skin tones, consistently achieved higher accuracy, sensitivity, and specificity compared to models trained exclusively on the original dataset. This improvement in performance highlights the benefit of enhancing dataset diversity, particularly for populations that are often underrepresented in existing dermatological image datasets. The use of style transfer techniques helps simulate realistic skin tone variations, enabling the models to generalize more effectively when applied to real-world clinical scenarios. Furthermore, the reduction in performance disparity across skin tones suggests that style transfer can serve as a practical and scalable method for mitigating skin tone bias in AI systems. These findings reinforce the critical importance of developing inclusive datasets in medical AI and suggest that integrating population-specific features during training is essential for creating equitable, accurate, and widely applicable diagnostic tools in dermatology.

As depicted in Table 3, the training and testing times varied significantly across models and experiments due to the increasing size of training datasets. EfficientNetB4 and DenseNet-201, while offering high performance, demonstrated the longest training durations for the largest dataset (432,000 images). EfficientNet B4 required approximately 9 hours and 12 minutes in Experiment 4.1, while DenseNet-201 took 11 hours and 14 minutes. Comparatively, MobileNetV3-Large, and ResNet50 exhibited shorter training times, with MobileNetV3-Large completing Experiment 4.1 in 4 hours and 47 minutes and ResNet50 in 5 hours and 20 minutes.

Testing times across all models were relatively brief and stable regardless of dataset size. EfficientNet B4 and DenseNet-201 exhibited slightly longer testing times, with DenseNet-201 taking up to 15 seconds for style-transferred test data. MobileNetV3-Large and ResNet50 showed faster testing times, often completing within 9 seconds for style-transferred datasets. These results underscore the balance between computational demands and accuracy, highlighting the suitability of certain models for rapid deployment scenarios.

**Table 3** Training and testing durations (in hours, minutes, and seconds) for each AI model across different experimental setups.

| Experiment | Time (HH:MM:SS) | *EfficientNet B4* | *MobileNetV3-Large* | *ResNet 50* | *DenseNet-201* |
|---|---|---|---|---|---|
| Experiment 1.1 | Training | 0:54:44 | 0:39:06 | 0:32:29 | 1:16:16 |
| | Testing (original) | 0:00:03 | 0:00:02 | 0:00:02 | 0:00:04 |
| | Testing (style transfer) | 0:00:12 | 0:00:08 | 0:00:08 | 0:00:15 |
| Experiment 2.1 | Training | 4:41:42 | 2:35:58 | 2:58:17 | 6:18:08 |
| | Testing (original) | 0:00:03 | 0:00:02 | 0:00:02 | 0:00:04 |
| | Testing (style transfer) | 0:00:11 | 0:00:09 | 0:00:09 | 0:00:15 |
| Experiment 3.1 | Training | 9:00:25 | 4:08:21 | 4:35:31 | 11:12:11 |
| | Testing (original) | 0:00:03 | 0:00:02 | 0:00:02 | 0:00:04 |
| | Testing (style transfer) | 0:00:12 | 0:00:09 | 0:00:08 | 0:00:14 |
| Experiment 4.1 | Training | 9:12:49 | 4:47:01 | 5:20:55 | 11:14:49 |
| | Testing (original) | 0:00:12 | 0:00:08 | 0:00:02 | 0:00:04 |
| | Testing (style transfer) | 0:00:03 | 0:00:02 | 0:00:08 | 0:00:15 |

Complex models with longer training times generally perform better with high-quality, large datasets, but require more computing resources. However, advancements in HPC technology and competitive pricing make scaling more accessible. Researchers can fine-tune models on local machines and utilize cloud services for large-scale training, optimizing cost and efficiency.

In summary, Table 3 highlights the trade-offs between model complexity, training duration, and computational efficiency. EfficientNet B4 and DenseNet-201 required the longest training times, especially when handling the largest dataset, reflecting their complex architectures. However, these models consistently delivered high performance in earlier experiments, making them suitable for applications where accuracy is a top priority. In contrast, Mobile NetV3-Large and ResNet50 demonstrated significantly faster training and testing times, indicating their potential for rapid deployment and use in resource-constrained environments.

## 5. Discussion

This study explored the impact of image augmentation techniques, including traditional and style transfer techniques on the performance of AI models for skin disease classification. By training four state-of-the-art CNN models, EfficientNetB4, Mobile NetV3-Large, ResNet50, and DenseNet-201, on progressively augmented datasets, several insights were derived. These findings contribute to existing knowledge in the domain of skin disease image augmentation and AI model development. An important observation is that EfficientNetB 4 consistently delivers superior performance due to its advanced architecture, which balances network depth, width, and resolution for effective feature extraction. However, this complexity requires greater computational resources and longer training times, indicating that while EfficientNetB 4 is well-suited for high-accuracy applications, it may be less practical for resource-limited settings.

The results of this study provide valuable insights into the effectiveness of AI models for psoriasis classification, particularly in addressing dataset limitations through augmentation and style transfer. By demonstrating how lesion distribution, image resolution, and model architecture impact performance, these findings contribute to the development of more accurate and generalizable AI-driven diagnostic tools. Additionally, the study highlights practical considerations for real-world applications, such as the importance of dataset diversity and model selection, making the results relevant for both researchers and clinicians.

### 5.1 The Role of Augmentation in Addressing Dataset Scarcity

The consistent improvements observed across all models, particularly in sensitivity, demonstrate the effectiveness of image augmentation in overcoming data scarcity. Previous studies have shown that augmentation techniques help enhance model generalization by introducing variability in the training data. This study supports these findings, with EfficientNetB4 achieving its highest sensitivity (91.00%) when trained on datasets augmented with both style transfer and additional augmentation. Notably, the use of style transfer to generate images reflective of Thai skin tones represents a novel approach to enhancing dataset diversity. This aligns with research advocating for localized dataset adaptation to improve AI model applicability across diverse populations.

Overfitting is a common risk when using heavily augmented datasets, as models may learn augmented patterns rather than generalizable features. To mitigate this, the experimental design outlined in Tables 1 and 2 ensures that testing data is completely separated from training data from the beginning. This approach simulates real-world applications by evaluating model performance on unseen data, preventing data leakage and ensuring that the models generalize well beyond the training set.

### 5.2 Impact of Augmentation Techniques on Model Performance

The obtained experimental results indicate that the use of augmentation techniques, such as style transfer with blur, did not significantly improve model performance compared to using style transfer alone. While accuracy remained stable across most experiments, the sensitivity improvements expected from the addition of blur were minimal, suggesting that the technique provided no substantial benefit for detecting positive cases. This finding underscores that the effectiveness of augmentation techniques may depend more on the quality of the original data and model architecture than on the addition of specific transformations like blur. However, the impact of blur effects remains inconclusive, as this study did not include specific visual comparisons or quantitative breakdowns dedicated to the blur augmentation alone. Future work should incorporate visual illustrations and detailed metric comparisons to clarify the precise contribution of blur effects on model performance. Consistent with previous research, deeper models such as EfficientNetB4 and DenseNet-201 continued to outperform others due to their advanced architecture and superior feature extraction capabilities, regardless of whether blur was included in the augmentation process. However, style transfer plays a crucial role in reducing bias in AI models trained on limited or non-representative datasets by generating synthetic images that better reflect diverse skin tones. This technique enhances model generalizability by ensuring that AI systems learn from images that more accurately represent underrepresented populations, such as Thai skin tones in this study. By incorporating style transfer, the dataset becomes more balanced, helping to mitigate bias and improve the model's reliability across different demographic groups.

Compared to similar studies (Shorten, & Khoshgoftaar, 2019; Wang, & Perez, 2017), our findings suggest that certain augmentation techniques, such as blur, had a limited impact on model performance. This is likely due to the small image size (64×64), where augmentation may not significantly alter image resolution or introduce meaningful variations. In such cases, the effectiveness of augmentation depends on the scale of input features, and smaller images may not benefit significantly from transformations that primarily affect texture or fine details. In addition, one possible explanation for the minimal impact of blur augmentation in this study is that psoriasis lesions typically exhibit distinct color contrasts and well-defined edges, which are not entirely obscured by mild blurring. Additionally, the textural patterns of psoriasis, such as scaling and redness, remain visible even when blur is applied, making this augmentation somewhat redundant for feature extraction. This suggests that the models primarily rely on broader structural and color features rather than fine-grained textures, which blur augmentation may not significantly alter to enhance learning. As a result, the application of blur does not introduce significant variation or additional learning value for the models, especially when dealing with images of psoriasis lesions.

### 5.3 Generalizability of AI Models with Augmented Datasets

The enhanced performance metrics observed when using augmented datasets suggest that augmentation contributes to model generalizability, enabling better performance on unseen data. This finding is in line with existing literature emphasizing the importance of augmentation for building robust medical AI systems. However, the slight performance decline in specificity for certain models (e.g., ResNet50) during experiments with extensive augmentation suggests that balancing augmentation techniques is critical to avoiding overfitting or data distribution shifts. Future studies should explore advanced augmentation methods, such as GAN-based approaches, to further improve model generalizability without compromising specificity.

The findings of this study have broader implications for AI-driven diagnostics in low-resource settings and for other diseases beyond psoriasis. In regions with limited access to dermatologists or annotated medical datasets, style transfer and augmentation techniques can help generate more diverse training data, improving AI model performance. This approach can be extended to other medical imaging fields, such as tuberculosis detection in chest X-rays or diabetic retinopathy screening, where dataset scarcity and demographic variability present similar challenges.

Moreover, these findings highlight practical implications for clinical use, where AI models trained on diverse, augmented datasets could support dermatologists in early detection and monitoring of psoriasis, particularly in primary care settings or regions with limited specialist access. By improving generalizability, such models can assist in triaging patients more effectively, reducing diagnostic delays, and optimizing resource allocation in clinical workflows.

This study demonstrates that augmentation techniques, particularly when tailored to address regional and dataset-specific challenges, play a pivotal role in enhancing the performance of AI models for skin disease classification. The integration of regionally relevant transformations, such as style transfer for Thai skin images, underscores the potential of augmentation to bridge the gap between limited datasets and real-world applications. Specifically, for deployment in Thai clinical settings, such AI models can assist general practitioners and healthcare workers in early screening and triaging of psoriasis cases, helping to reduce diagnostic delays and ensure timely referrals to dermatologists, especially in rural areas where specialist access is limited. These findings provide a foundation for future research on leveraging augmentation to develop scalable and inclusive AI solutions in dermatology.

Several challenges were encountered in this study, including dataset limitations, variations in skin tone representation, and the potential risk of overfitting with augmented data. Additionally, the small image size (64×64) may have affected model performance for certain augmentation techniques. While these challenges were addressed through careful experimental design, future research should focus on expanding dataset diversity and exploring advanced augmentation methods to further enhance model robustness.

## 6. Conclusion

This study proposes an effective strategy to address data scarcity in AI-based skin disease classification by integrating conventional augmentation techniques with style transfer, specifically designed to simulate Thai skin tones. Leveraging a public dataset of psoriasis and eczema images, we created enriched training sets that support the development of robust AI models, including EfficientNetB4, MobileNetV3-Large, ResNet50, and DenseNet-201. Rather than focusing solely on performance improvements already detailed in the results, this conclusion emphasizes the broader contributions of our approach. Importantly, style transfer provides a practical method for diversifying datasets to better represent underrepresented populations, enabling AI models to perform reliably across varied demographic groups. Beyond improving model accuracy, this process also contributes to reducing bias and enhancing fairness in medical AI applications.

For practical clinical deployment, especially in Thailand, these AI models could complement existing healthcare systems by assisting non-specialist providers in early-stage psoriasis identification and referral. Integration into mobile platforms or cloud-based systems could further extend diagnostic capabilities to remote or underserved areas, empowering healthcare workers with decision-support tools that function in real-time. Such advancements can help alleviate bottlenecks in dermatology services and ensure that patients receive timely care. While promising, this study acknowledges limitations in dataset size and diversity, and the scope of augmentation methods employed.

### 6.1 Limitations of the Study

Despite its contributions, this study has some limitations. First, the dataset used, while enhanced through augmentation, remains relatively small compared to datasets commonly used for deep learning. This may limit the generalizability of the findings to larger and more diverse datasets. Second, the augmentation techniques employed were limited to style transfer and blur. Additionally, the focus on psoriasis images means that the results may not generalize to other skin conditions without further validation.

### 6.2 Future Research Directions

Future research should explore more advanced augmentation techniques, such as synthetic image generation using generative adversarial networks (GANs) and context-aware transformations, to further improve dataset diversity and model performance. Expanding the dataset to include more classes of skin diseases and images from different demographic groups would enhance the generalizability of the findings. Moreover, incorporating explainability techniques into model evaluation could provide insights into how AI models make decisions, enabling better trust and adoption in clinical settings. Finally, evaluating the impact of augmentation on multi-task models that integrate lesion classification and localization could open new avenues for comprehensive diagnostic tools.

Future studies could integrate generative AI techniques, such as GANs, to complement style transfer by generating more realistic and diverse synthetic skin disease images. GANs can help create high-fidelity lesion variations, improving dataset diversity and enhancing AI model robustness for psoriasis classification. However, implementing GANs requires high computational power, as training deep generative models involves significant processing and memory resources.

Additionally, future data collection should prioritize diversity by incorporating images from various ethnicities, skin tones, and geographic regions. Collaborations with global dermatology centers will be essential for building more representative datasets, ultimately enhancing AI model generalizability.

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