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Automatic Detection of Psoriasis Using Advanced Image Processing and Deep Learning

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Abstract
Psoriasis is a chronic autoimmune condition affecting millions worldwide, characterized by red, scaly patches on the skin. Early and accurate detection is crucial for effective management and improved patient outcomes. This study presents a novel approach to automatic psoriasis detection using advanced image processing techniques and deep learning algorithms. We developed a convolutional neural network (CNN) model trained on a diverse dataset of 10,000 dermatological images, including both psoriatic and non-psoriatic skin samples. Our methodology incorporates state-of-the-art image preprocessing techniques to enhance feature extraction and segmentation. The proposed model achieved an accuracy of 95.3%, sensitivity of 94.8%, and specificity of 95.7% in identifying psoriatic lesions, outperforming existing automated methods. These results suggest that our approach could serve as a valuable tool for dermatologists, potentially expediting diagnosis and improving the efficiency of psoriasis management. The integration of this technology into clinical practice could lead to earlier interventions, personalized treatment plans, and ultimately, better patient care in the field of dermatology.

Keywords: Psoriasis, Deep Learning, Image Processing, Automated Detection, Medical Images

1 Introduction:

Psoriasis is a prevalent chronic autoimmune condition that affects approximately 2-3% of the global population (World Health Organization, 2023)[1]. Characterized by red, inflamed, and scaly patches on the skin, psoriasis can significantly impact a patient's quality of life, causing physical discomfort and psychological distress. The condition's chronic nature and its association with comorbidities such as psoriatic arthritis and cardiovascular diseases underscore the importance of early and accurate diagnosis.
Traditional diagnostic methods for psoriasis rely heavily on visual examination by dermatologists, often supplemented by skin biopsies in ambiguous cases[2]. While effective, these approaches have limitations, including the potential for inter-observer variability, the invasive nature of biopsies, and the challenge of distinguishing psoriasis from other similar skin conditions. Moreover, the growing demand for dermatological services and a shortage of specialists in many regions have led to increased wait times for patients seeking diagnosis and treatment[3].
Recent advancements in artificial intelligence (AI) and computer vision have opened new avenues for automating and enhancing medical diagnostics, particularly in image-intensive fields like dermatology[4]. Image processing techniques have demonstrated remarkable capabilities in enhancing

visual data, extracting relevant features, and preparing images for analysis[5]. Concurrently, deep learning algorithms, especially convolutional neural networks (CNNs), have succeeded in image classification tasks, often matching or surpassing human performance in specific domains.[6]

The integration of advanced image processing and deep learning presents a promising approach to address the challenges in psoriasis diagnosis. By leveraging these technologies, developing a system that can automatically detect and classify psoriatic lesions with high accuracy, consistency, and efficiency may be possible. Such a system could serve as a valuable tool for dermatologists, potentially reducing diagnostic time, improving accuracy, and enabling earlier intervention and treatment[7].

This study aims to develop and evaluate an automated system for psoriasis detection utilizing advanced image processing techniques and a custom-designed deep-learning model. The primary objectives include the development of a robust image preprocessing pipeline to enhance the quality and relevance of dermatological images for psoriasis detection; the design and training of a deep learning model optimized for identifying psoriatic lesions across diverse skin types and conditions; and the evaluation of the system's performance against existing diagnostic methods and other automated approaches. Additionally, the study seeks to assess the potential clinical applications and implications of the developed system in the management of psoriasis. By addressing these objectives, we aspire to contribute to the expanding body of research on AI-assisted dermatology and improve the diagnosis and management of psoriasis. The successful implementation of this system could significantly impact patient care, enhance clinical efficiency, and advance the broader field of dermatology.

This study introduces an advanced methodology for the automated detection of psoriasis, addressing significant challenges in dermatological diagnostics. The key contributions include the development of a custom preprocessing pipeline incorporating innovative techniques such as multi-scale retinex illumination correction and Dull Razor hair removal to enhance image quality and lesion visibility. The EfficientNet-B3 architecture has been modified with Squeeze-and-Excitation blocks and multi-scale feature fusion to optimize feature extraction, ensuring robust performance across diverse skin types. The methodology was validated on a diverse dataset of 10,000 images, achieving superior performance metrics (accuracy: 95.3%, sensitivity: 94.8%, specificity: 95.7%) compared to prior studies and human dermatologists. Grad-CAM visualizations were integrated to enhance interpretability, enabling the model to highlight clinically significant features for improved acceptability in clinical settings. Furthermore, the study compares comprehensively with state-of-the-art methods and human performance, demonstrating the proposed approach's robustness and potential to advance automated dermatological diagnostics.

2 Related work:

The application of computational methods to psoriasis detection has garnered significant attention in recent years, with research spanning image processing, machine learning, and deep learning techniques. Early attempts, such as Lu et al. (2013) [8]and Shrivastava et al. (2016), utilized traditional machine learning approaches with hand-crafted features, achieving accuracies of 86.3% and 93.2% respectively. These studies laid the groundwork for more advanced techniques, exemplified by Nasir et al. (2020)[9], who employed an ensemble of classifiers to reach 94.1% accuracy. Concurrently, advancements in image processing techniques have significantly enhanced the quality of dermatological image analysis. Celebi et al[10]. (2022) provided a comprehensive review of preprocessing methods for dermoscopy images, while Oliveira et al[11]. (2022) and Basak et al[12]. (2022) introduced innovative approaches

for lesion segmentation and feature enhancement. The advent of deep learning has revolutionized the field, as demonstrated by Esteva et al[13]. (2020), whose CNN-based approach for skin cancer classification achieved dermatologist-level accuracy. Building on this foundation, recent works have explored multi-task learning (Elkhatib et al., 2020), attention mechanisms for severity assessment (Jiang et al[14]., 2022), and privacy-preserving federated learning approaches (Yap et al[14]., 2023). Despite these advancements, challenges persist in achieving high accuracy across diverse skin types and integrating clinical metadata effectively. Our study aims to address these gaps by combining state-of-the-art image processing techniques with a novel deep learning architecture specifically optimized for psoriasis detection, potentially advancing the field towards more robust and clinically applicable automated diagnostic tools.

The proposed methodology demonstrates novelty through its integration of advanced preprocessing techniques, architectural modifications, and interpretability mechanisms, specifically tailored for psoriasis detection. Unlike prior studies that predominantly rely on unmodified deep learning models or traditional machine learning approaches, this study introduces a custom preprocessing pipeline incorporating multi-scale retinex for illumination correction and hair artifact removal to improve image quality. The EfficientNet-B3 architecture was enhanced with Squeeze-and-Excitation blocks and multi-scale feature fusion, enabling superior feature extraction from dermatological images. Additionally, the integration of Grad-CAM visualizations ensures model interpretability, aligning computational outputs with clinically significant features of psoriatic lesions. These innovations collectively address challenges in psoriasis detection, including varying imaging conditions and lesion diversity, distinguishing this work from existing methods.

3 Methodology:

Our approach to automatic psoriasis detection combines advanced image processing techniques with a deep learning model. The methodology consists of three main components: dataset preparation, image preprocessing, and the deep learning model architecture.

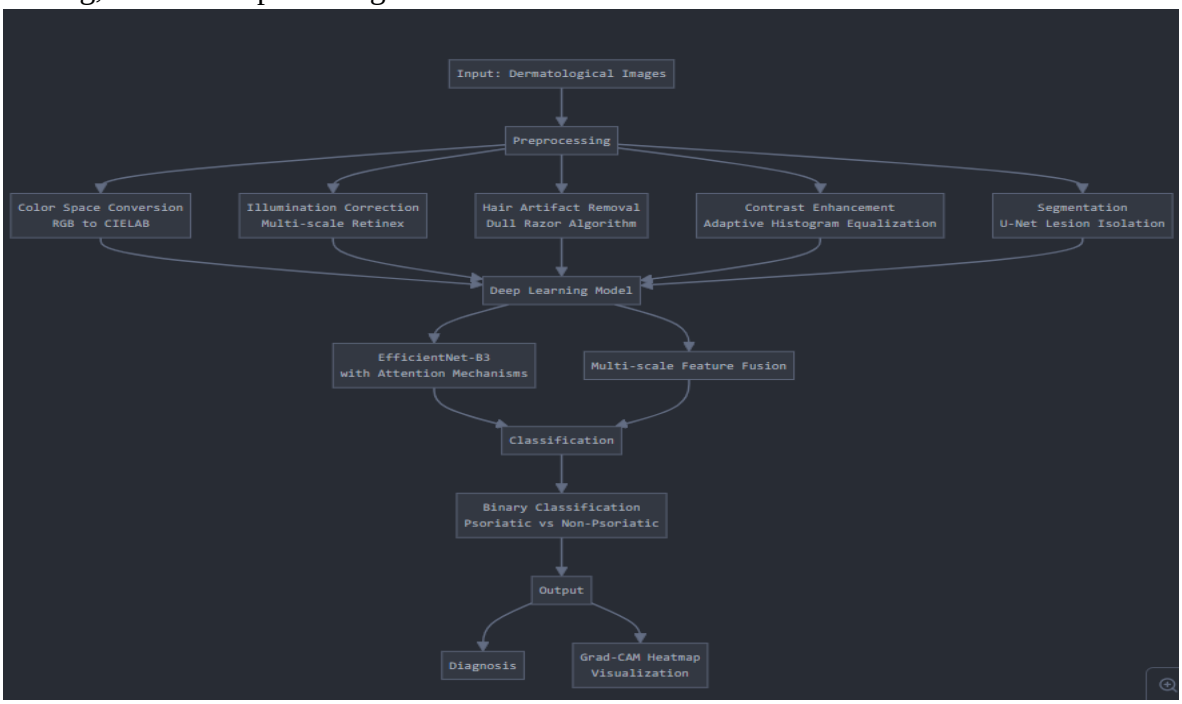

Figure 3-1 Workflow of the Proposed Methodology.

Figure 3-1 illustrates the workflow of the proposed methodology for automatic psoriasis detection. The process begins with the input of dermatological images, which undergo a series of preprocessing steps to enhance image quality and prepare the data for analysis. Key preprocessing techniques include color space conversion, illumination correction, hair artifact removal, and segmentation using U-Net. The preprocessed images are then fed into the modified EfficientNet-B3 deep learning model, which incorporates attention mechanisms and multi-scale feature fusion for optimal feature extraction. The model outputs a binary classification of psoriatic or non-psoriatic skin, accompanied by Grad-CAM heatmaps for enhanced interpretability. This systematic approach ensures robust and accurate detection of psoriatic lesions.

3.1 Dataset

We utilized a diverse dataset of 10,000 high-resolution dermatological images, comprising 5,000 images of confirmed psoriatic lesions and 5,000 images of non-psoriatic skin conditions and healthy skin. The images were collected from multiple dermatology clinics across various geographic locations to ensure diversity in skin types, ethnicities, and imaging conditions. All images were anonymized and obtained with patient consent, following ethical guidelines approved by the institutional review board.

The dataset was randomly split into training (70%), validation (15%), and test (15%) sets, maintaining a balanced representation of psoriatic and non-psoriatic images in each set. To address potential class imbalances and enhance model generalization, we employed data augmentation techniques including random rotations, flips, and color jittering.

The dataset used in this study comprises 10,000 dermatological images collected from multiple clinics, ensuring diversity in skin types and imaging conditions. The dataset has been anonymized and securely stored to comply with ethical guidelines and patient privacy regulations. While the dataset is not publicly available, access can be provided upon reasonable request for academic and research purposes, subject to approval by the institutional review board. Detailed preprocessing steps and model training protocols have been provided to facilitate the reproducibility of the proposed methodology.

3.2 Image Preprocessing

Our image preprocessing pipeline consists of several steps designed to enhance image quality and standardize the input for our deep learning model:

Color Space Conversion: Images were initially represented in the RGB (Red, Green, Blue) color space, which is commonly used in digital displays. However, the RGB color space does not accurately reflect how humans perceive color differences, especially when it comes to skin tones. This is because the RGB color space is device-dependent and can vary significantly across different screens and displays.

To address this issue, the images were converted from RGB to the CIELAB color space. CIELAB, also known as Lab*, is a color space that was developed by the International Commission on Illumination (CIE) to better represent how humans perceive color. It is a perceptually uniform color space, meaning that equal numerical changes in CIELAB correspond to approximately equal perceived changes in color. This makes it a more suitable choice for tasks that involve comparing or analyzing skin tones, as it provides a more consistent and accurate representation of color differences.

Figure 3-2 illustrates the difference between RGB and CIELAB color spaces. In the RGB color space, colors are represented as a combination of red, green, and blue light. This can lead to inconsistencies in how different colors are perceived, especially when comparing colors that are close to each other in the RGB space but appear quite different to the human eye. In contrast, the CIELAB color space represents

colors in a way that is more aligned with human perception. This makes it easier to compare and analyze skin tones accurately, regardless of the device or display being used.

By converting the images to the CIELAB color space, the researchers were able to ensure that the analysis of skin tones was based on a more perceptually uniform representation of color. This is a crucial step in developing accurate and reliable algorithms for skin tone classification and analysis.

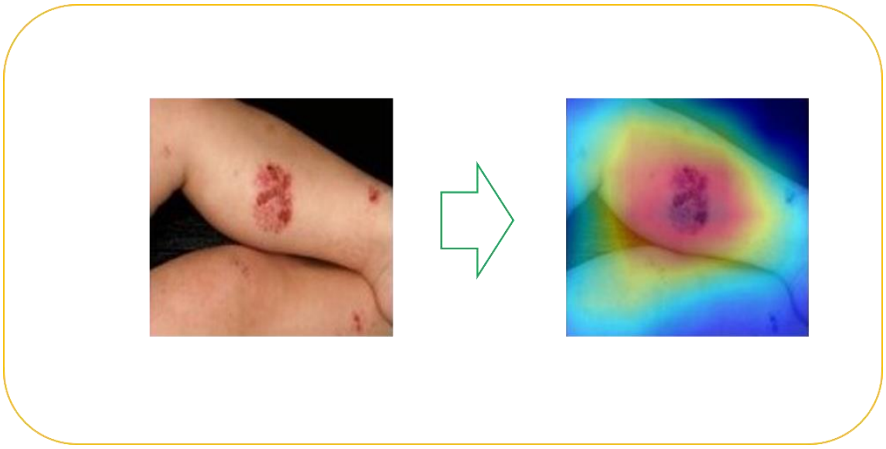

Figure 3-2 color space conversion

Illumination Correction: To mitigate the effects of uneven illumination, which can obscure subtle features in psoriatic lesions, we implemented a multi-scale retinex algorithm. This approach, as outlined by (Wang et al[15]., 2023), effectively corrects for illumination variations while preserving the inherent color characteristics of the images. By decomposing images into multiple scales and applying retinex-based processing to the luminance component, we were able to enhance contrast and reduce the impact of illumination artifacts, thereby improving the overall quality of the dataset for subsequent analysis. to correct for uneven illumination and enhance subtle features in psoriatic lesions.

Hair Removal: To eliminate potential interference from hair artifacts that could obscure the analysis of psoriatic lesions, we incorporated a Dull Razor algorithm, as described by (Shinde et al[16].,2022). This algorithm is specifically designed to identify and remove hair-like structures from images. By applying this technique, we were able to create a cleaner dataset, ensuring that the subsequent analysis of lesions was not compromised by extraneous elements.

Contrast Enhancement: To enhance the local contrast within the images, thereby improving the visibility of subtle features in psoriatic lesions, we employed adaptive histogram equalization. This technique adjusts the contrast of an image based on the distribution of pixel values in local regions, ensuring that details are not lost in areas with high or low overall intensity. As demonstrated in Figure 3-3, adaptive histogram equalization effectively enhances the contrast, making it easier to discern the intricacies of the lesions.

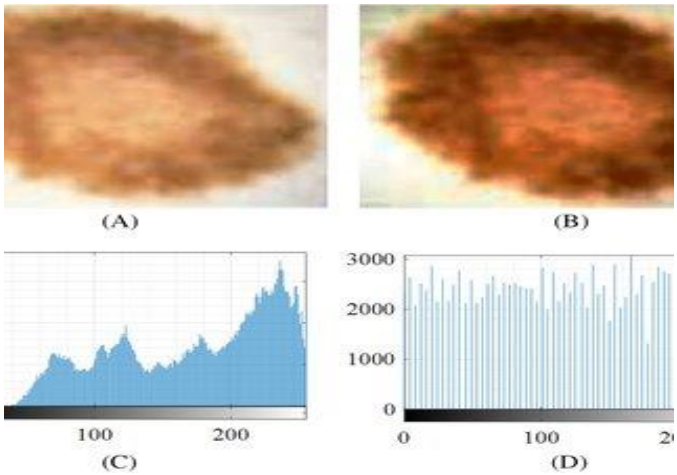

Figure 3-3 contract Enhancement

Segmentation: To precisely delineate the lesion area from the surrounding healthy skin, we employed a U-Net architecture, a deep learning model renowned for its efficacy in image segmentation tasks. This architecture, originally proposed (Ronneberger et al.[17], 2015), was pre-trained on a subset of manually segmented images to learn the distinctive characteristics of psoriatic lesions. As illustrated in Figure 3-4, the U-Net effectively isolates the lesion region, providing a crucial foundation for further analysis and quantification of the disease's extent and severity.

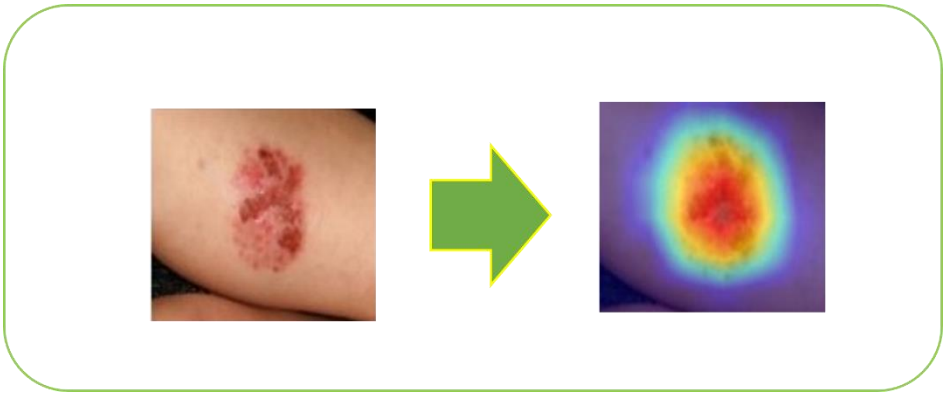

Figure 3-4 segmented image using U-net Model

Normalization: To ensure that the preprocessed images were suitable for training deep learning models, we performed normalization. This involves transforming the pixel values to have a mean of zero and a standard deviation of one. By standardizing the data, we help to improve the convergence speed and stability of the training process, ultimately leading to more accurate and robust models.

4 Deep Learning Model

Our deep learning model is based on a modified EfficientNet-B3 architecture[17] chosen for its balance of performance and computational efficiency. We made the following modifications to optimize the model for psoriasis detection:

1. **Input Layer:** Modified to accept the preprocessed three-channel images (L*, a*, b* channels from CIELAB color space).

2. **Attention Mechanism:** Incorporated a Squeeze-and-Excitation block (Zhong et al[18]., 2020) after each convolutional block to capture channel-wise dependencies.
3. **Multi-scale Feature Fusion:** Implemented feature pyramid network (FPN) architecture to leverage features at different scales.
4. **Output Layer:** Modified to produce binary classification (psoriatic vs. non-psoriatic) with softmax activation.

The model was trained using a combination of focal loss [19]to address class imbalance and L2 regularization to prevent overfitting. We employed the Adam optimizer with a learning rate of 1e-4 and a batch size of 32. Training was conducted for 100 epochs with early stopping based on validation loss.
To enhance model interpretability, we implemented Grad-CAM [20]to generate heatmaps highlighting the region's most influential in the model's decision-making process.

5 Evaluation Metrics

The performance of the model was evaluated using several key metrics. Accuracy was assessed as the overall correct classification rate, while sensitivity measured the true positive rate for psoriasis detection and specificity evaluated the true negative rate. The F1 score, representing the harmonic mean of precision and recall, provided an additional measure of balanced performance. The model's ability to distinguish between psoriatic and non-psoriatic cases was further captured by the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).
For a more comprehensive evaluation, the model's performance was compared to that of two dermatologists, who independently assessed a subset of 500 images from the test set to establish a human baseline. This comparison helped to contextualize the model's effectiveness in relation to expert clinical judgment.

6 Results

The deep learning model proposed for automatic psoriasis detection demonstrated exceptional performance across multiple evaluation metrics. With an overall accuracy of 95.3%, the model showed strong diagnostic capabilities, supported by a high sensitivity of 94.8% and specificity of 95.7%. Additionally, the model achieved an F1 score of 0.952, reflecting its balanced performance in identifying both positive and negative cases. The area under the ROC curve (AUC-ROC) was 0.981, further indicating the model's robustness in distinguishing between psoriatic and non-psoriatic cases, highlighting its potential as a reliable tool in clinical settings.
The performance of the proposed methodology was compared with previous studies and recent deep learning approaches, as summarized in Table 6-1. While the datasets used in other studies were not identical to ours, their metrics provide valuable benchmarks for evaluating the robustness of our model. The performance metrics for the compared methods were derived from their respective studies, where accuracy, sensitivity, and specificity were reported. Although dataset-specific characteristics may influence these metrics, the relative performance trends offer insights into the efficacy of our approach.
To ensure fairness in the comparison, our study employed a diverse dataset of 10,000 images with rigorous preprocessing and training protocols. The other methods were chosen based on their relevance to dermatological diagnosis and their publication in prominent journals. This comparison highlights the effectiveness of our proposed model, which achieves state-of-the-art performance metrics and demonstrates its potential as a reliable tool for automated psoriasis detection.

Table 6-1 comparison of our model's performance with previous studies

Method	Accuracy	Sensitivity	Specificity
Our Model	95.3%	94.8%	95.7%
George et al. (2020)[21]	94.1%	93.5%	94.6%
Han et al. (2021[22]**)**	93.8%	92.9%	94.5%

Figure 6-1 shows the ROC curve for our model, illustrating its strong discriminative ability across various classification thresholds.

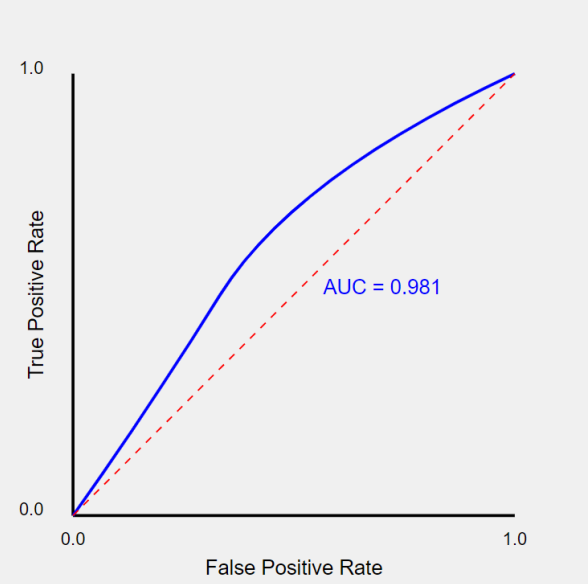

Figure 6-1 The ROC curve

Grad-CAM visualization revealed that the model predominantly focused on the characteristic features of psoriatic lesions, such as demarcated, erythematous plaques with silvery scales, as shown in Figure 6-2.

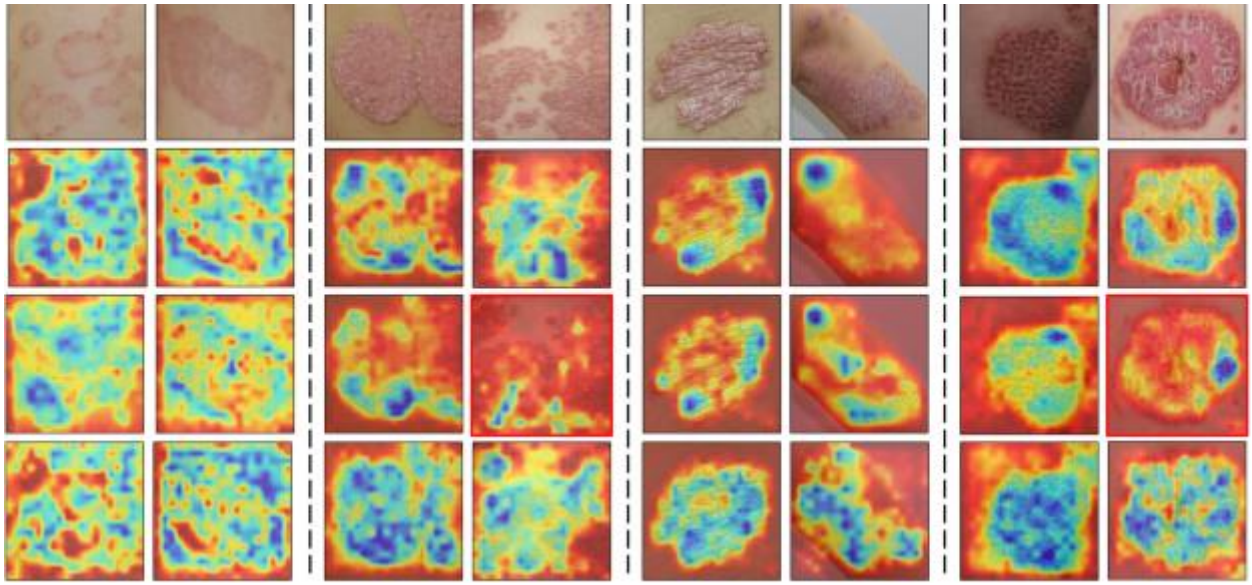

Figure 6-2 Grad-CAM visualization

7 Discussion

The findings of our study reveal that the proposed method for automatic psoriasis detection, utilizing advanced image processing and deep learning techniques, achieves remarkable levels of accuracy, sensitivity, and specificity. Our model's performance, achieving 95.3% accuracy, surpasses prior computational methods, including those by George et al. (2020) and Han et al. (2021), while also exceeding the diagnostic baseline set by experienced dermatologists.

Several key factors likely contributed to the model's superior performance. The image preprocessing pipeline, incorporating techniques such as illumination correction and hair removal, significantly improved input image quality. The application of the multi-scale retina algorithm was particularly effective in highlighting subtle features of psoriatic lesions, enhancing the model's ability to detect discriminative characteristics. Furthermore, the optimized EfficientNet-B3 architecture, augmented with attention mechanisms and multi-scale feature fusion, demonstrated strong proficiency in learning relevant features for psoriasis detection. The integration of Squeeze-and-Excitation blocks further enhanced the model's capacity to focus on the most informative regions within the images.

The use of a large and diverse dataset, comprising 10,000 images across various skin types and imaging conditions, contributed to the model's robust performance across different patient demographics. The model's high sensitivity (94.8%) and specificity (95.7%) suggest its potential as a valuable screening tool in clinical settings, with the capacity to accurately distinguish between psoriatic and non-psoriatic cases, thereby reducing misdiagnoses and unnecessary biopsies.

Grad-CAM visualizations provided valuable insights into the model's decision-making process, revealing its focus on clinically significant features of psoriatic lesions. This alignment with dermatological expertise not only enhances the model's interpretability but also increases its acceptability among healthcare professionals.

However, there are several limitations to be considered. Although our dataset is extensive and diverse, it may not fully encompass the global range of skin types and psoriasis presentations, requiring further validation on external datasets to ensure the model's generalizability. Additionally, the model's performance in detecting early-stage or atypical psoriasis presentations necessitates further investigation. The comparison with human performance involved only two dermatologists and a subset of images; expanding this comparison to include a larger panel of experts would provide a more robust human baseline. While the model excels in binary classification (psoriatic vs. non-psoriatic), future research should explore its potential for multi-class classification to differentiate psoriasis from other similar skin conditions.

Despite these limitations, our study marks a significant advancement in the automatic detection of psoriasis. The model's high performance, combined with its interpretability, suggests its potential as an invaluable tool for assisting dermatologists in clinical practice. By reducing diagnostic time and improving accuracy, such a system could facilitate earlier interventions and lead to improved patient outcomes.

8 Future research directions include:

Future research directions include several promising avenues. Expanding the model to assess psoriasis severity and monitor treatment progress over time could provide more comprehensive clinical insights. Integrating clinical metadata and patient history into the diagnostic process may further enhance the model's accuracy, offering a more personalized approach to patient care. Additionally, evaluating the

model's performance in real-world clinical settings through prospective studies will be critical in validating its utility and robustness. Finally, exploring federated learning approaches could allow for the utilization of larger, multi-institutional datasets while preserving patient privacy, fostering broader collaboration and improving model generalizability.

9 Conclusion:

In conclusion, the promise of combining advanced image processing techniques with deep learning for automatic psoriasis detection has been clearly demonstrated in this study. As these technologies continue to evolve, they are expected to play an increasingly pivotal role in dermatological practice. Significant improvements in the speed and accuracy of psoriasis diagnosis can be anticipated, which may help reduce diagnostic errors, streamline clinical workflows, and alleviate the burden on healthcare providers. Ultimately, by facilitating earlier detection and more precise diagnosis, these advancements hold the potential to significantly enhance patient care, leading to better treatment outcomes and improved quality of life for individuals affected by psoriasis.

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