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A Computer Aided Diagnostic Tool for Automatic Psoriasis Segmentation and feature extraction from Dermoscopic images

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Abstract –

Background: Psoriasis is a skin disease condition that prevails with red scaly surface along with roughness and requires accurate and precise lesion localization. The subjective methods require more expertize and dermatologist intervention. The time consuming process leads to motivate development of automated tools for detecting psoriasis lesion along with its characteristics which will help in treatment process.

Objective: The study presents the deep learning methodology for detection of psoriasis lesion present in dermoscopic images.

Methods: A Grad-CAM is applied to highlight discriminative lesion regions from pre-trained classification models. A pseudo ground truth mask is generated with attention maps in order to train U-net segmentation. The attention maps are post-processed to generate pseudo ground truth masks, which are then used to train a U Net segmentation model to detect psoriatic part. The approach eradicates the dependence on pixel-level annotations, aiding scalable lesion mapping.

Result: The proposed methodology is applied on dermoscopic psoriasis images obtained from benchmark Dermnet database. The dice coefficient obtained as 95.6. The method accurately localizes and detects the characteristic of psoriasis for further calculate Psoriasis Area Severity Index score.

Our approach suggests the potential to help dermatologist as well as patients to detect psoriasis and provide treatment accordingly.

Key Words: Psoriasis, Grad-CAM, Lesion, Dice-coefficient

1. INTRODUCTION

It is a well-known statistic that psoriasis is a long-lasting, inflammatory, and autoimmune disease of the skin which has affected all age group people worldwide. The disease becomes unbearable leading to affect person's social, metal well-being. The disease is excessively characterized by the rapid growth of skin cells, which, in turn, leads to skin thickening and the formation of scales, reflecting a local reaction of the body [1-3]. This type of psoriasis is usually covered with silvery white scales and red, and its appearance causes the feeling of itching, irritation, and pain. Psoriasis typically begins with the elbows, knees, scalp, and lower back but may appear anywhere else on the body [4]. It has been found that the exact cause of psoriasis has not been discovered yet; that being said, the disease appears to be associated with genetic predisposition. An error or a delay in the diagnosis process might result in the adoption of ineffective treatment methods, patient suffering for longer extended periods, and the development of the disease. That is why building up automatic and smart diagnostic systems is so important in the process of supporting and enhancing the skills of dermatologists involved in the diagnosis, enabling them to carry out their job much faster and more accurately at the same time. The essential point is that the structure of these networks mimics the human visual system. In other words, CNNs are able to perform automatic detection, including edges, textures, and complex patterns of the image, without any human intervention. It has been found that by using CNN models in dermatology, it is absolutely possible to make a distinction between benign and malignant tumors and, at the same time, to be able to recognize skin diseases like melanoma, eczema, and psoriasis. One of the most pertinent benefits of Deep Learning is its capability to manage these enormous and complicated datasets, which in turn increases the accuracy of classifying the data and lesion segmentation.

Advances in deep learning have improved the automated lesion segmentation and psoriasis classification [5-7]. However, most of the methods require the enormous amount of pixel annotated images which require time and computational cost as well most significantly in case of psoriasis where lesion boundaries are not properly defined as shown in Fig.1.In order to mitigate the manual lesion segmentation weakly supervised learning have gained popularity in recent times. Class Activation Maps (CAMs) is one of the approaches, which enable spatial localization of features from image-level labels. Whereas, Grad-CAM an enhanced version of CAM, envisages discriminative areas used by CNNs for classification, contributing both interpretability and potential segmentation. Although extensively used for interpretability, Grad-CAM has been applied in application as a pseudo-labeling tool for lesion segmentation [8].

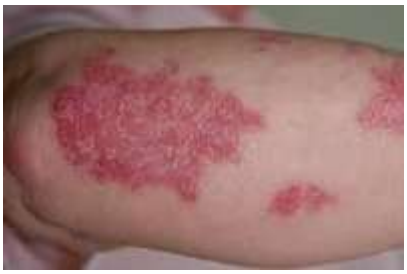


Fig.1: Plaque Psoriasis image showing scalp on hands [19].

In this study, we a novel pipeline that leverages Grad-CAM to generate pseudo-masks for psoriasis lesions is proposed, which is further refined using a U Net-based segmentation model. This system bridges the gap among weak supervision and precise lesion segmentation by altering class-discriminative heat maps into usable training labels. We evaluate the performance of this approach on dermoscopic images, demonstrating that the proposed methodology can effectively segment psoriatic regions with accuracy, despite the absence of pixel-wise annotations. Moreover the redness, roughness and lesion detection will enable dermatologist to evaluate PASI score effectively.

2. RELATED STUDY

Deep Learning (DL) is one of the subfields of Machine Learning (ML), and it has changed the way image-based diagnosis works thanks to automatic feature extraction from raw data. Among the most popular methods used for image classification are Convolutional Neural Networks (CNNs), with their hierarchical architecture in image classification and segmentation [9]. In particular, deep learning-based techniques have been applied to a widespread range of skin conditions, including melanoma, eczema, and psoriasis, with favorable results.

Traditional methods in dermatology for lesion segmentation relied profoundly on handcrafted features, such as edge detection algorithms, color histograms, and texture descriptors. Though, these approaches are often unsuccessful to generalize due to variability in skin tone, lesion morphology, and lighting circumstances. The introduction of fully convolutional networks (FCNs) and U-Net [10] significantly improves the segmentation performance by empowering lesion boundaries detection in effective way. Numerous surveys have utilized U-Net and its derivatives on skin lesion datasets like ISIC and PH2, resulting in elevated Dice coefficients and IoU scores. Bi et al. [11] introduced a multi-task U-Net that instantaneously adopts segmentation and classification, indicating improved performance for multifaceted lesions. Nonetheless, these methods typically require dense annotations at the pixel level, which are rarely accessible for conditions such as psoriasis. However, several researchers have explored methods for segmenting psoriasis lesions from digital images captured across various body regions of patients exhibiting multiple lesions. Bidaki et al. [12] introduced an automated approach for assessing psoriatic lesion areas by means of an optimum thresholding technique within the YCbCr color space with an accuracy of 72% which lack complex skin background and other lesion features. In related works [13], in order to segment lesion and color texture features K-means clustering algorithms were utilized.

Patidar et al .[14] extracted features such as color histograms, texture energy, and fractal dimensions from psoriasis images and classified lesions using support vector machines (SVMs)**.** Their method achieved 87.6% classification accuracy, but segmentation precision was not directly measured, and spatial localization of lesions remained coarse. Moreover they used hand crafted method which was time consuming. Ronneberger et al.'s U-Net [10] has become a widely adopted backbone in medical image segmentation due to its encoder-decoder architecture and skip connections. When applied to skin lesion datasets like ISIC, U-Net variants regularly achieve dice coefficients above 0.90.The method do not include psoriasis images. Shaikh et al. [15] applied a residual U-Net model for psoriasis segmentation and reported a Dice score of 0.87 on a dataset which is collected from hospitals, but required pixel-level annotations for training, which limits scalability. Wang et al. [16] combined Grad-CAM with Conditional Random Fields (CRFs) and trained a U-Net model using the refined masks. On a melanoma dataset, they achieved a dice score of 0.82, demonstrating that attention maps can effectively guide segmentation with limited supervision. Kumar et.al. [17] in 2025 worked with dermoscopic psoriasis images with dice coefficient 0.91 with U net and Deep Lab v3. The lack of bench mark dataset and works mostly on skin cancer images as summarized in Table I have motivated the work for psoriasis images collected from DermNet bench mark dataset.

Table I Summarized literature work for lesion segmentation

Author	Method	Dataset	Performance metices	Limitation
Bidaki et al. [12]	YCbCr Thresholding	ISIC 2017	72%	Low accuracy
Patidar et al. [14]	SVM with handcrafted features	Private clinical sources	87.6%	Only classification without segmentation
Shaikh et al. [15]	Residual U-Net	Private hospital dataset	0.87 Dice coefficent	Annoted masking not specified
Wang et al. [16]	Grad-CAM + CRF + U-Net	Melonama dataset	0.82 Dice coefficient	Psoriasis images not taken into account. Weak supervision
Kumar et al. [17]	UNet , DeepLAb V3	Clinical dermoscopic images of psoriasis	Dice coefficient 0.91	Further the dice co-efficient can be improved

3. METHODS AND MATERIALS

All experiments were conducted using Google Colaboratory (Google Colab) cloud-based Jupyter notebook environment with free GPU access with all key libraries imported. The dataset of psoriasis plaque dermoscopic images was collected from DermNet dataset available for educational purpose. As the images includes of different body parts and different sizes, which were re dimensioned to 224x224 pixels for model adaptability. The image quality and uniformity is improved by adapting pre-processing steps that includes normalization, Resizing, data augmentation.

Since the manual annotated mask wass unavailable, in order to overcome the lack of manual segmentation masks, Grad-CAM (Gradient-weighted Class Activation Mapping) was used to produce pseudo-labels [18]. Grad-CAM is a visualization methodology that uses the gradients of any target class flowing into the output convolutional layer of a CNN to create a heat map that highlights the discriminative regions of an input image. The steps involved in the process includes

1. A pre-trained EfficientNet-B0 model was fine-tuned on the psoriasis classification task using image-level labels. It is used as efficient classifier for separating psoriasis images from other skin ailments [4].
2. Grad-CAM heat maps were generated to localize psoriatic regions. The spatial information of pixels are detailed in this layer.
3. Heat maps were threshold to extract binary pseudo-masks for segmentation.

A U-Net architecture using the generated pseudo-masks is trained to perform pixel-wise lesion segmentation. This approach allows segmentation without manually labeled data,

reducing annotation burden. The workflow diagram is depicted in Fig.2

- Input**:** Original RGB images (224×224)
- Target**:** Grad-CAM-derived binary masks
- Loss Function**:** Dice Loss + Binary Cross-Entropy
- Optimizer**:** Adam (learning rate = 0.0001)
- Epochs**:** 30
- Batch size**:** 16

To transform the continuous-valued Grad-CAM heat map into a binary mask appropriate for training, a threshold (empirically set to 0.6) is applied as shown in equation (1) as:

$$M(x,y) = \{1 \; if \; Grad\; CAM\; (x,y) \geq 0.6\} \quad (1)$$

$$0 \; otherwise$$

This creates pseudo ground truth masks demonstrating possible lesion area.

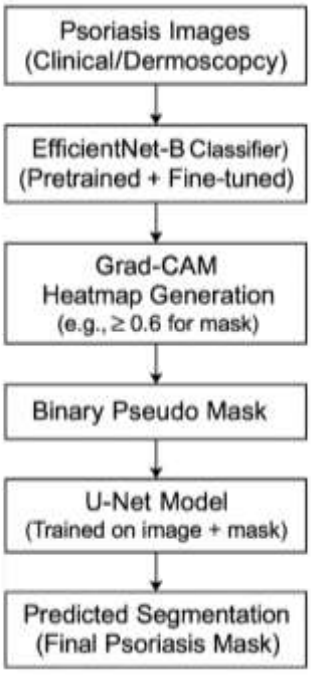


Fig.2 Work flow for supervised psoriasis lesion segmentation

The U-Net architecture is implemented in this work for segmenting psoriatic lesions from dermoscopic images, using pseudo-masks derived from Grad-CAM outputs as training labels. U-Net is a broadly used encoder–decoder network specifically designed for biomedical image segmentation tasks due to its capability to confine and outline fine-grained structures.

The standard U-Net used in this methodology has the following alignment as stated in Table 2.

Table 2: U-Net architecture details for proposed work

Block	**Layers**
Encoder	4 convolutional blocks (Conv2D → ReLU → Batch Norm → Max Pooling), doubling filters each step: 64 → 128 → 256 → 512
Bottleneck	2 Conv2D layers (512 filters)
Decoder	4 up-convolutional blocks (Up Sampling → Conv2D → ReLU), halving filters: 512 → 256 → 128 → 64
Output	1×1 Conv2D + Sigmoid to produce final binary mask (0–1 range)

4. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed model for psoriatic lesions segmentation. The results are analyzed both quantitatively using standard metrics and qualitatively through visualizations. The trained U-Net is verified on set of dermoscopic images. Performance metrics such as Dice Coefficient, IoU, and Pixel Accuracy are computed. Additionally, the model's qualitative performance is marked using over layed masks on test images.

The segmentation performance is measured using the following metrics:

(1) Dice Coefficient (F1 Score): The Dice Coefficient processes the intersection between the predicted and ground truth masks.

$$\text{Dice} = \frac{2(A \cap B)}{A+B}$$

A: Predicted mask

B: Grounded Mask

(2) Intersection over Union (IoU): Also called the Jaccard Index, this metric computes the overlap between the predicted and true masks over their union.

$$IoU = \frac{A \cap B}{A \cup B}$$

(3) Pixel Accuracy: Pixel accuracy measures the ratio of appropriately predicted pixels to the total number of pixels.

$$Pixel\; Accurcy = \frac{TP + TN}{TP + TN + FP + FN}$$

TN: True Positive

TP: True Negative

FN: False Positive

FP: False Negative

Table 3 Quantitative Performance metrics of proposed model

Metrics	U-Net Grad CAM model
Dice	95.68
IoU	89.56
Pixel accuracy	90.00

The Dice score of 0.95 shows a high degree of overlap between predicted and ground truth lesion regions, especially notable given the absence of pixel-level annotations during training. The IoU score of 0.89 also confirms robust performance in distinctive psoriatic areas from surrounding skin as shown in Fig 3 and Table 3.

Fig. 3 Result of Pixel accuracy of 0.90 and IoU of 0.89 for dermoscopic psoriasis image.

Qualitative analysis of proposed method depicts the representative segmentation outputs are shown in Fig.4 (a)-(c). The U-Net model effectively defines lesion boundaries, even in the presence of texture differences and lighting changes. The generated masks capture not only the core plaque areas but also peripheral scaling regions, which are often missed in traditional thresholding-based methods. These visual results demonstrate that even with weak supervision, the model learns to generalize lesion features across diverse skin tones and lighting conditions.

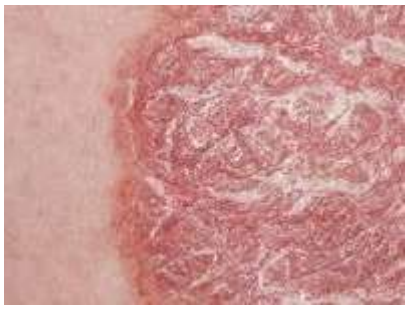


Fig. 4 (a) Original plaque psoriasis image

Fig.4 (b) Grad-CAM lesion localization showing the psoriatic lesion part

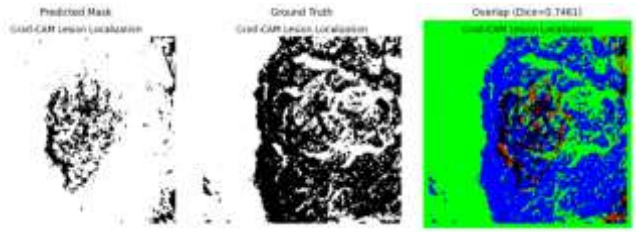


Fig.4 (c) The Dice coefficient with predicted mask and overlay image.

The sample image of small lesion part with less texture features is also depicted with the proposed method as shown in Fig.5 (a)-(c)

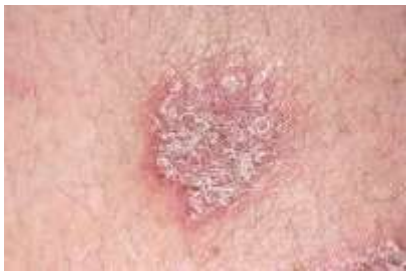


Fig. 5 (a) Original plaque psoriasis image with less features and small lesion size

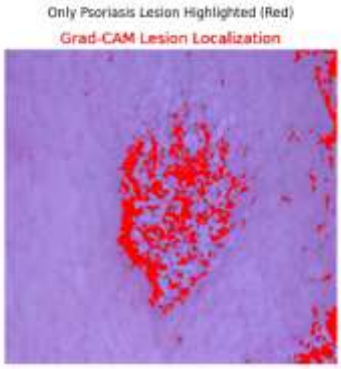


Fig.5 (b) Grad-CAM lesion localization showing the psoriatic lesion part highlighted in red

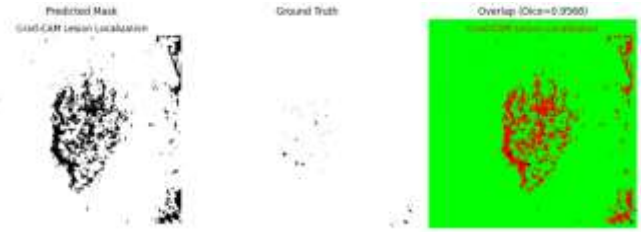
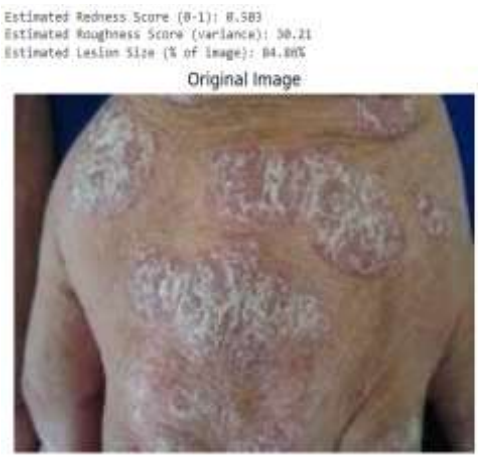


Fig.5 (c) The Dice coefficient with predicted mask and overlay image with dice coefficient 0.95.

Compared to traditional segmentation approaches such as K-means clustering or thresholding in YCbCr or HSV color space (Dice ≈ 0.55–0.65), as cited in literature survey the proposed method offers significant improvements in both precision and boundary localization.

Further the typical lesion all over the body parts, redness, roughness and lesion size prediction is being done to help dermatologist for proper treatment process.



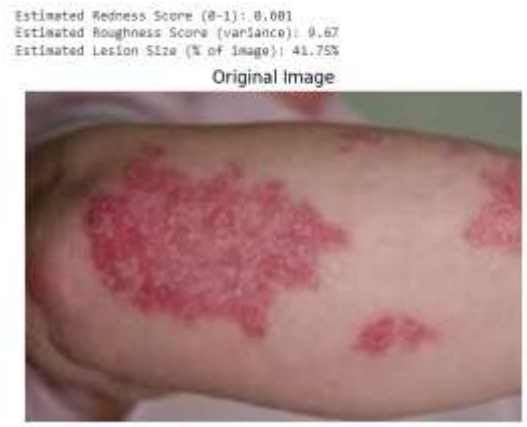


Fig 6 The redness roughness and scale along with lesion depicted for psoriasis images [20]

The results confirm that Grad-CAM is a viable tool for generating weak annotations in dermatological tasks. By integrating these activation-based pseudo-labels into a segmentation model like U-Net, we can build reliable lesion detectors without expensive manual annotations. This approach not only reduces the cost of annotation but also makes it feasible to train on large-scale datasets with only image-level labels.

However, the method is not without limitations. The Grad-CAM masks may miss subtle lesions or highlight non-lesion areas, especially in cases of mild psoriasis. Further refinement of the activation maps in order to improve initial mask quality. Additionally, the features depicted from psoriasis images will provide an aid to medical imaging. .

5. CONCLUSIONS

In this study the proposed work for the segmentation of psoriatic lesions from dermoscopic skin images have proved to be effective in depicting lesion size, redness, roughness. The approach utilized Grad-CAM to create class activation maps from a classification model, which are used as pseudo-labels for training a U-Net segmentation model. The u Net proves its efficiency in achieving a Dice coefficient of 0.95 and an IoU of 0.89 on the test set though the annotated mask are not present.
The findings indicate that supervision based on Grad-CAM can proficiently direct deep segmentation networks in recognizing lesion boundaries, as it incorporates color and texture signals associated with psoriasis, like redness and scaling.. The method suggests the substantial improvement by reducing reliance on labor-intensive manual annotations, which are often a blockage in dermatological image analysis.
This work highlights the potential of combining explainable AI techniques with segmentation models to facilitate more scalable and accessible skin disease diagnosis tools. Future directions include refining the quality of pseudo-masks using attention mechanisms, validating the model on diverse datasets, and extending the framework to multi-class segmentation involving different psoriasis sub types.

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