Skin Disease Segmentation: Current Practices, Techniques, and Emerging Trends

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*Abstract*— Skin disease segmentation is of paramount importance when it comes to early detection and implementation of diagnosis for skin related diseases for the management of proper health interventions. This review aims at stating the current state of affairs in skin disease segmentation, both in terms of existing methodologies and new trends that have emerged in recent years, with an emphasis on the combination of standard image processing methods and state-of-art machine learning and deep learning techniques. The paper discusses the strength and weakness of the above techniques and how annotated datasets, preprocessing techniques, as well as proper metrics contribute to the performance of segmentation. Furthermore, it examines factors like skin tone and lesion variability, the variety of lesions which are difficult to depict, and lighting conditions that may affect the performance of the model. Recorded trends such as multimodal data fusion, transfer learning and explainable artificial intelligence are also discussed as potential directions towards the above challenges. The present review seeks to give a brief comprehensive overview of the dynamic state of skin disease segmentation, and the findings may be useful in facilitating further research and development into this important area.

Keywords— Skin Disease Segmentation, Image Processing, Deep Learning, Dermatology, Medical Imaging.

# Introduction

Disease segmentation of skin is an important feature in dermatological image analysis as it helps in determination of type of lesion and allows for early intervention. For a long time, researches have used conventional techniques like localization using edge detection or region growing techniques but in certain cases these approaches have difficulty in identifying skin lesions in terms of color distribution, texture and size. The segmentation performance has tremendously been enhanced by the recent progress in deep learning, which entail data-driven feature learning. For example, Zhang and Lu [1] present a boundary distillation method to improve the segmentation speed and point out the increased concern with improving the practicability of the model.

Recently introduced deep learning architectures have proved extremely promising while dealing with the challenges associated with the segmentation of skin lesions. More recently, Zhi et al. [2] proposed the configuration of a masked autoencoder network with self-distillation to enhance generalization to heterogeneous datasets whereas Kalaivani and Karpagavalli [3] disclosed that further refinements of the domain adaptation algorithms look highly promising for segmentation purposes. Furthermore, LeaNet [8] as proposed by Hu et al., is another case of lightweight architecture intended for high performance of segmentation and low overhead, thus catering with real time processing. However, the difficulties persist, including data deficiency and bias, which were discussed by Nasreen et al. [13]& Mirikharaji et al. [14].

This paper seeks to review the existing methodologies and most recent research developments that can be implemented to accomplish segmentation of skin diseases using the conventional machine learning methods and other novel deep learning techniques. In this paper, we look at the advantages and drawbacks of these methods and expose limitations of each; we critically analyze the availability of data, the problems with access to it, as well as new features in the field such as multimodal fusion and explainability of AI. In this review, using recent studies such as boundary-aware segmentations [1], multi-scale feature fusion [12] and ensemble methods [15], the different attempts were pooled for future advancements in this important area of medical imaging.

# Overview of Skin Disease

Skin disease segmentation is one of the fundamental procedures in dermatological image analysis that focuses on precisely analyzing the area of interest in a skin image such as that of a lesion or an abnormality. Moles and skin lesions segmentation plays a crucial role in various skin diseases including melanoma, eczema and psoriasis. In the context of this medical imaging modality it assists clinicians to better understand size, shape and location of lesions and further assists in the treatment planning and prognosis. The segmentation process may be more difficult and time-consuming because skin lesions exhibit high variability in terms of morphology, depending on the type or stage and skin color. To map precisely the ideal diagnostic and clinical management, skin disease segmentation must be accurate and stable irrespective of the disease type.

Fig. 1 demonstrates different types of skin diseases which should be segmented: it shows that skin diseases encompass a broad range of conditions. The diseases include:

* Atopic Dermatitis
* Basal Cell Carcinoma
* Benign Keratosis-like Lesions
* Eczema
* Healthy Skin
* Lichen Planus
* Melanocytic Nevi
* Melanoma
* Pityriasis Rosea
* Psoriasis

These images highlight the range of appearances across different skin conditions, each requiring specific segmentation strategies for effective analysis.



1. Skin Disease types

## Key Challenges in Segmentation

The proposed skin disease segmentation raises certain concerns based on the method’s restrictions and dermatological image characteristics. The fact that the lesions shape, texture, color and sizes differ significantly presents a challenge when developing the segmentation models. Skin tone diversity introduces another difficulty that is important because in darker skin types lesions may be less discernible, which creates problems with contrast and identification of lesions. Other challenges include, for example, external factors such as lighting, image quality and image dimensions or if, for instance, hair in an image hinders segmentation. In addition, the task of achieving high performance across different skin diseases, all of which exhibit the distinct features of their type (e.g. melanoma vs eczema) remains an open problem. However, there remains various challenges in achieving skin disease segmentation based on such factors, which has been offset by latest developments in deep learning techniques as offered by U-Net as well as CNN based model solutions.

# Different Methodology

## Traditional Segmentation Techniques

Conventional type of segmentation methods in medical image analysis were employed prior to the realization of deep learning models. Although the methods described here are simple and effective they mostly depend on hand tablename and mathematical operations to segment lesion areas from the background in skin disease images. Even though these techniques are logically less complex and computationally efficient to implement, these fail to incorporate the various and complex nature of skin disease. The most frequent identified conventional approaches are the forms of threshold methods, the region-based segmentation and the contour and edge detection techniques. For every approach used here, there is a benefit that can be offered, as well as demerits that may be incurred in view of the degree of accuracy and further reliability of the software, and the kind of skin lesion that might be under analysis.

**Thresholding Methods:** It is one of the simplest and most employed techniques in the image segmentation process targeting mainly skin diseases. The rationale of the use of thresholding when it comes to image segmentation entails categorizing a grayscale image as a binary image by setting pixel values that are above or below a set of threshold values. This is best applied when the lesion is well demarcated from the skin background or when they are biopsied. However, the method of thresholding could be very dependent on light conditions, contrast in lesion colors and difference in skin color and therefore can be not fully effective while dealing with complex images with slight differences. Zhang and Lu [1] reviewed the latest work of developing more precise thresholding methods with other boundary distillations for detecting the lesion boundaries and alleviation of noise sensitivity. Further, in the case of global thresholding, crucial features as part of the skin lesion may be eliminated rendering the segmentation defected particularly for the lesions that closely resemble the skin intensity level.

**Region-Based Segmentation:** Categorised segmentation techniques group an image based on the pixel characteristics like brightness, texture, and color. These methods assume that skin lesions are poi niform shape, size and intensity within the margins of the lesion. Some of them are region growing and splitting these methods initialize with a seed and then grow or split the region based on certain similarity measures. Region-based methods provide some advancement over the global thresholding but they show difficulties when the texture inside the lesion varies greatly or when the lesions are in indistinct from the surroundings. Reddy et al [6] demonstrate the use of a combination of classification and segmentation carried out through a fusion of fuzzy logic and region-based segmentation to produce improved results in case of skin diseases. Region-based methods can sometimes split an image up too much if there is noise in the picture or if lesions are asymmetrical, as they often are in melanomas and psoriasis.

**Contour and Edge Detection Approaches:** Contour and edge detection techniques mainly deal with distinguishing boundaries of differing density in a picture. These technique include methods such as those like Sobel operator, Canny edge detection and active contours (snakes). The edge detection methods are more relevant to draw the boundary contour of lesions that are essential for the diagnosis process . However, these methods can only be applied in case of high contrast between the lesion and the surrounding skin and often fail in case of eczema or basal cell carcinoma where the edges are often soft or blurred. Nevertheless, both of these approaches can segment lesions with a clear boundary separating them from the background Using an active contour model, which segments an object by gradually deforming a curve toward the object boundary, one can use a more sophisticated type of segmentation for delineating irregularly shaped lesions. However, active contours initially depend on the positioning of the curve and need a huge amount of computation for snakelike evolution. Hosny et al. where quoting in the current study as stating that despite useful results, the application of edge detection techniques is generally poor due to noise and poor contrast of the image especially in low resolution or poor imaging conditions.

Although the thresholding techniques and region-based, as well as contour detection methods have been used as basic approaches to skin disease segmentation, the ample variety of skin lesions and their complex structure often makes segmentation a difficult task. These methods fail to handle problems such as noise, changes in the appearance of the lesion and overlapping of lesion and skin color. To overcome these issues, the scholars have been shifting towards higher levels of machine learning and the deep learning model since they are highly robust and accurate in segmenting skin lesions regardless of the environmental conditions. But still, traditional approaches are used in some situations mainly due to the constraints in computational power or the need for fast results.

## Deep Learning-Based Segmentation Approaches

Segmentation methods with deep learning have dramatically transformed the challenging field of medical image analysis including segmentation of skin diseases. Such approaches notably include CNNs with improved architectures such as U-Net and Transformer paradigms which enhanced segmentation and enhance the accuracy and reliability of lesions detection of the skin. Indeed, deep learning models are capable of extracting features from raw data and optimizing model parameters without the need for human intervention, which is a great advantage in addressing the inherent issues in skin disease segmentation including large variation in lesion size and shape, and variation in skin color. In the following sections, previous and the most sought after deep learning-based segmentation methods such as CNNs, U-Net, and advanced architectures are discussed.

**Convolutional Neural Networks (CNNs) for Segmentation:** The Convolutional Neural Network (CNN) has played a pivotal role in designing the contemporary image segmentation techniques because of their capability to learn features from an image automatically at different levels of abstraction. Indeed the CNNs are very essential for segmentation of skin diseases; this is because the CNN extracts local area features such as edges, textures, and shapes which are very useful in segmenting skin diseases in order to identify the various types of skin lesions. CNN’s have a layer of convolution where the image is filtered, and a layer of pooling which reduces the dimensionality of the image and a layer of classification which makes the final decision about the image. A large volume of data can be handled by CNNs and it is capable of learning plenty of annotated skin images that in turn increases its ability to generalize. As discussed by Liu et al. [12], convolutional neural network based approaches present a high performance in segmenting skin lesion through automatically detecting important visual patterns, which makes it to be considered as the default strategy for skin disease diagnosis. However, CNNs still struggle with cases of complex lesion boundaries for which detecting finer details is significant for segmentation.

**U-Net and Encoder-Decoder Architectures:** U-Net and all encoder-decoder have become very popular in medical image segmentation tasks for several reasons; The networks are capable of producing excellent segmentation results especially when few training samples are available. The architecture of U-Net model is thus based on a contracting encoder which finds context and a expansive decoder to reconstruct the segmentation map with the use of max pooling downsampling and deconvolution up sampling. The principal design of U-Net is that there are short connections from encoder to decoder where features at the encoder side are directly connected to the decoder side so that spatial information is retained and segmentation is more precise. Most of such a design has been useful in skin disease segmentation since the boundary detail of lesions matters most. Mirikharaji et al. [14] reported on skin lesion segmentation where U-Net proved capable of producing high-resolution segments with small as well as distorted lesions, including melanoma and basal cell carcinoma. Alternative U-Net derived architectures with attention mechanisms or multi-scale features remains the standard approach for segmentation of skin diseases, as the flexibility of the models allows to address the variations in lesion morphology and size.

**Advanced Architectures (Transformers, Attention Mechanisms):** Recent approaches in deep learning for image segmentation are Architectures based on Transformer and attention, which are promising approaches in the improvement of the segmentation task. Transformers, initially used for text input data for the NLP task, have been introduced to the vision tasks because of their favorable property of processing long-distance relations in images. Another transformer family, the Vision Transformer (ViT), relies on self-attention to capture relations between the distant pixels that can facilitate learning of the lesion context and high-resolution details. As it is seen in skin disease segmentation, when lesions have irregular shapes and texture differences, Transformers generalization and outstanding feature extraction, and a focus on critical areas contribute to higher performance. The proposed spatial attention and channel attention enable the models to pay more attention to the area in need and ignore the areas that are conducive to segmentation. For example, Zhang and Lu [1] conducted one of the studies on combining attention mechanisms with CNNs to enhance the performance of the image segmentation regarding the skin lesion boundary by pointing out that such integration yielded notably high sensitivity and specificity levels. These advanced architectures specifically preferable for the problem solving of extending ambiguous lesion boundaries and skin variety, and have the potential for the future improvement of skin disease segmentation.

Several deep learning based segmentation strategies proposed for skin disease segmentation have significantly improved the quality of the segmentation technique. CNNs, U-Net, and the latest Transformer-based methods exemplify such developments provide high-precision segmentation consistent with various skin diseases. These methods have greater advantages as compared to the conventional methods in terms of lesion, irregularity and skin type. Despite the issues related to the differentiation of the uncertain boundaries or noises within the images, the advancement of the deep learning architectures is persistent; these methodologies are unerasable tools for dermatological applications.

# Comparative Analysis

1. Comprative Analysis

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| --- | --- | --- | --- |
| **Method** | **Accuracy** | **Advantages** | **Limitations** |
| Thresholding Methods [9,11] | Low to moderate | Easy to use, short time to complete operations | High IR, low APL, cannot handle complicated texture, the printer is sensitive to noise. |
| Region-Based Segmentation [6,13] | Moderate to high | Suitable for the region where the population density is relatively high and is homogeneous in nature, relatively easy to apply. | Somewhat has difficulties with delineating complex lesions, slow in large amounts of data |
| Edge Detection (Canny, Sobel, etc.) [5,9] | Moderate | Is best used for the identification of edges, suitable for clear shapes. | It appears not to be resilient to noise; the approach fails when the lesions have irregular contours. |
| Convolutional Neural Networks (CNNs) [11,13] | High | Bidirectional and multilingual models perform very well on different data sets, flexibility | They are very sensitive to noise and require large, labeled datasets, as well as a high computational cost. |
| U-Net [3,5] | Very high | Resistant to noise, useful for the precise partitioning of regions. | Needs big training samples, may be overtrained |
| Fully Convolutional Networks (FCNs) [2,10] | High | Segmentation possible, especially pixel-level required due to end-to-end approach. | Excessive training data is needed to implement this filter, and its computational load is high. |
| Mask R-CNN [1,14] | Very high | It performs very well, for instance segmentation, and a minimal accuracy rate. | Hierarchical model, longer time in predicting a single image |
| Transformer-based Models (e.g., Swin Transformer) [12,13] | Very high | Good in handling long range dependencies, high accuracy | Very large computational costs, needs a lot of data |
| Attention Mechanisms (e.g., SENet, CBAM) [7,12] | Very high | Refines feature select direction, increases the quality of the segmentation analysis | Complication of the main model; susceptibility to overtraining |
| Multimodal Fusion Networks [14,13] | High | Compiles data from different sources to increase the accuracy of results | It needs multiple modalities’ data; it is more challenging to train. |

* **Traditional Methods:** There are many methods such as threshold, region-based segmentation, and edge detection that are comparatively more feasible and faster but might be more difficult when it comes to handling many noises in lesions compared to the modern day and age deep learning algorithms. Such methods, in general, offer less precision in the interpretation of more complex images of the affected skin conditions.
* **Deep Learning Methods:** Techniques such as CNN, U-Net, FCN, Mask R-CNN, and Transformer models are 3–5 times more accurate than plain images and especially for complex lesions. These methods learn directly from a large set of data and offer good performance in segmentation, but they are costly in terms of time computational and needs large data set for training labeled.
* **Multimodal Fusion Networks:** These approaches involve the integration of different forms of imaging data, and this includes clinical images and dermoscopic images hence improving the segmentation efficiency. They are very accurate, but also slow and relied on the presence of several kinds of data.

Table I offers a summary format overview of the various segmentation algorithms with pros, cons and how suitable they are for skin disease segmentation.

# Challenges and Emerging Trends

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| --- | --- | --- | --- |
| **Category** | **Parameter** | **Challenges** | **Emerging Trends** |
| Variability | Lesion Types and Skin Conditions | Lesions in skin diseases can be smooth, rough, flat or raised, small or large and may come in a variety of colors in different people. | Multimodal Techniques: Technical adjustments in image pre-processing and analysis approaches such as Dermoscopy images, clinical photographs, and histopathological images avoiding problems related to skin lesion heterogeneity [13]. |
| Image Quality | Illumination and Imaging Conditions | As seen from the light variations, shadows, and variations through the different imaging conditions, images may be distorted, and segmentation may be hard. | Explainable AI: Improvement of segmentation performance under different conditions is achieved through the use of attention mechanism of the AI models [1]. |
| Data Availability | Annotated Data Scarcity | Small, annotated datasets, particularly in cases or specific lesion types, become a problem during model training. | Lightweight Models: Improvement in the miniature models which can be trained on fewer annotations and the effectiveness of the model for real-time or mobile [12]. |
| Segmentation Accuracy | Boundary Detection and Fine Details | It is well known that skin lesions can have rather blurred and, in most cases, inconclusive margins, which makes it challenging for models to bound in a very accurate way. | Advanced Architectures: Transformer-based models and attention mechanisms which enable us to capture detailed features and dependencies at a distance [12] Enhancing boundary detection. |
| Model Generalization | Bias in Training Datasets | This is because existing datasets have more samples of certain skin types or lesions than others which leads to low performance for the latter types. | Multimodal and Transfer Learning: Adding together the data from the source or the data from pre-trained models to increase generalization across multiple skin conditions |

The topic of skin disease segmentation contains several problems that explain why it has not been adopted and implemented widely in clinical practice. However, the irregularity of the skin lesions and textures is one of the greatest challenges because skin diseases present themselves in all forms and sizes, shapes, and colors. Segmentation models for lesion image analysis have a problem of coming up with a single model that works well for different skin types and lesion presentation. It is also limiting by segmentation since illumination and imaging conditions influence the measure of contrast between healthy skin and lesions since some regions will have bad lighting, others shadows, or poor camera quality. In addition, lack of annotated data and selection bias that persists in available datasets is a major issue. Annotation of medical images is a task that can only be done by professionals, and the lack of large labeled datasets of high quality for training deep learning systems results in poor accuracy, especially in rare skin diseases or syndromes.

Nevertheless, there are new trends which can help address these issues in the context of skin disease segmentation models. Overlapping different techniques like Dermoscopy, clinical images and histological images are the trending approaches of segmentation for better overall segmentation. Also, explainable AI is becoming another key direction since it provides clinicians with insights into how the corresponding model makes segmentation decisions, which increases its acceptability in clinical context. The latest trend includes creating lightweight models for real-time, and the purpose of these lightweight models include achieving operational efficiency in limited resource or mobile hardware, which makes for quicker and more accessible skin disease identification. These trends are believed to solve many of the current problems associated with skin disease segmentation, and provide a more accurate, powerful, and convenient means for clinicians.

##### Conclusion

Therefore, skin disease segmentation still remains an essential component in medical image analysis and has open problems such as variations of skin lesions, illumination changes, and minimal labeled data. However, recent studies through CNNs, U-Net architectures, and multimodal techniques assume new and exciting opportunities to increase segmentation precision and resilience. Trending technologies like XAI, light-weight models, real time application and incorporation of new architectures including transformers and attention mechanisms call for more opportunities. There is still so much to learn about the potential of these methods for the future, so more data is needed, generalizations need to be made over populations other than old white males, and these models need to work in clinical contexts, or they are of little use. All these advances offer an opportunity to improve the overall diagnostics and offer strong tools for skin diseases identification to clinicians.

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