International Journal of
Image Processing and Pattern Recognition

ISSN: 2456-6985
Volume 10, Issue 1, 2024
January—June
DOI (Journal): 10.37628/IJIPPR

https://journalspub.com/journal/ijippr

Review IJIPPR

A Study of Segmentation Techniques for Diagnosing Melanoma in Dermoscopic Images

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Abstract

Skin cancer remains among the deadliest forms of cancer, with an average survival rate ranging from 18% to 20%. Detecting and segmenting melanoma early is a challenging yet crucial undertaking. To effectively segment the lesions, several studies have presented automated and standard techniques. Likewise, traditional methods for segmentation frequently require inputs from humans and cannot be applied in automated systems. The aim of this article is to provide a comparative analysis of a various number of segmentation methods. The methods are explained along with their benefits and drawbacks. In numerous studies, effective methods for image segmentation of skin lesions have been successfully explored. Therefore, based on an analysis of the various segmentation approaches, intensity-based segmentation performs the best in segmenting the lesion region and produces more accurate findings.

Keywords: Skin cancer, image segmentation, intensity-based segmentation, skin lesions, dermoscopic image

INTRODUCTION

Malignant or benign pigmented skin lesions frequently present as an abnormal overgrowth of a certain group of cells in a particular area. Compared to malignant tumors, benign lesions behave more meticulously. Examples of benign lesions include seborrheic keratosis (Figure 1(b)) and nevus such as congenital (Figure 1(a)), common, dysplastic, blue, miescher, and halo. With an incredibly high mortality rate, melanoma (Figure 1 (c)) is an especially fatal form of skin cancer [1]. In India's north, both males and females had the highest rates of melanoma of the skin (1.62 and 1.21, respectively). In men, the highest incidence of non-melanoma skin cancer or other skin malignancies was observed in the eastern region (6.2), whereas in women, the highest incidence was recorded in the northeast region (3.49). The northeast area has the highest frequency of non-melanoma skin cancer in both the male (75.6) and female (43.6) sexes [2]. The good news is that the substantial amount of melanin in Indian skin protects it; the bad news is that tropical nations like India are exposed to higher amounts of ultraviolet (UV) radiation, which increases the risk of skin cancer. Because the saltwater in the sea scatters UV radiation, those who live in coastal areas must also cope with this issue.

Data sourced from the National Cancer Registry Programme and GLOBOCAN 2018 provided age-specific rates and age-adjusted rates (AARs) for the occurrence of skin cancer across all age groups (0–75 years) in India and globally, respectively, as shown in Table 1.

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Received Date: April 14, 2024
Accepted Date: April 24, 2024
Published Date: May 30, 2024

Citation: Jasmine Samraj, R. Pavithra. A Study of Segmentation Techniques for Diagnosing Melanoma in Dermoscopic Images. International Journal of Image Processing and Pattern Recognition. 2024; 10(1): 1–10p.

Figure 1. Three examples of lesions: (a) congenital nevus, (b) seborrheic keratosis, and (c) melanoma.

Table 1. Number of cases as per age-adjusted rate (AAR) for all ages across the globe.

Place	Male	Female
North region	1.62	1.21
Northeast region	6.2	3.49
Western Pacific region	225.4	68.6

Melanoma may be identified from dermoscopic images using a computer-aided diagnostics (CAD) system. Dermatology uses dermoscopy as a non-invasive diagnostic method for the in-person examination of pigmented skin lesions. An entirely new perspective on the clinical morphologic characteristics of pigmented skin lesions is now possible due to this diagnostic tool, which improves the visualization of both surface and underneath structures and enables the identification of morphologic structures that are invisible to the naked eye [3]. Prior to image recognition, image segmentation is a crucial stage involving the division of an image into meaningful segments or components.

SEGMENTATION OF THE SKIN LESION

Imaging Methods

Dermatologists have employed diverse non-invasive imaging techniques to assist in diagnosing skin lesions. These methods encompass dermoscopy, photography, continuous scanning laser microscopy (CSLM), optical coherence tomography (OCT), ultrasound, magnetic resonance imaging (MRI), and spectral imaging [4]. The process in telemedicine is known as remote clinical diagnosis, in which macroscopic images of the concerned skin region are submitted to the doctor via the internet for remote evaluation. Using images captured with standard cameras, suspected skin lesions are prescreened in this way, and if image analysis reveals a lesion that requires particular care, the patient is promptly directed to a dermatologist [5].

Digital imaging tools made specifically for this purpose are used to acquire the nevus image. These typically comprise of an integrated illumination system, a digital camera, and an optical system designed specifically for acquiring skin images. Using this method, nevus images are captured and sent to a specialized system for processing them, which is often a personal computer with specialized image processing software [6]. Dermoscopy is a non-invasive skin imaging method that uses optical magnification and optics that decrease surface reflection to make sub-surface features more easily apparent than on traditional clinical pictures. It is one of the primary tools for the detection of melanoma.

As a result, screening mistakes are decreased and there is better discrimination between difficult lesions such pigmented Spitz nevi and tiny, clinically ambiguous lesions. Dermoscopy has been shown to decrease diagnostic accuracy in the hands of unfamiliar dermatologists, nevertheless as shown in Figure 2(a–d). Therefore, the development of computerized image analysis tools is of utmost importance in order to reduce diagnostic mistakes caused by the complexity and subjectivity of visual interpretation [7]. The images are captured using a nevoscope device, which enables the acquisition of images with varying amounts of transillumination or cross-polarized surface light. While the surface pigmentation is highlighted by both modalities, the transillumination modality has the benefit of also displaying the blood flow and underlying vascular. To better identify the skin lesions, it is necessary to remove hairs and air bubbles from the images afterwards [4].

Pre-processing of Images

In order to locate and remove any visible hairs on the skin, some preprocessing on the photos is the initial step that has to be done. The presence of hairs in the skin imaging data raises the possibility of categorization mistakes. As a result, during this stage of preparation, the DullRazor hair removal process is used [8]. Similar to this, dermoscopic images' uneven lighting and low contrast are frequently corrected using image enhancing preprocessing techniques. Contrast adjustment, filtering, adaptive histogram equalization, and contrast limited adaptive histogram equalization (CLAHE) are the foundations for these enhancing techniques. CLAHE is largely acknowledged as the top technique among the currently used enhancement techniques for preparing medical images [9]. Accurately identifying characteristics for automated cancer classification is significantly hindered by the presence of hairlines and the low resolution of the skin pictures. The first method, called intensity adjustment–based hair removal (IA-HR), aims to occlude hairlines by adjusting intensity levels using morphological operators and detecting and removing hair pixels using closest neighbor criteria. The second method employs a multiscale context aggregation convolutional neural network (MCACNN) to improve dermoscopy picture resolution and lessen high-frequency content loss [10].

Pre-processing an image is done to get rid of unnecessary specimens like noise, air bubbles, and fine hair. Various filtering methods, such as median and Gaussian Filtering, can be used to eliminate hair from the skin. Enhance filtering may form out image borders and increase the precision of image segmentation in addition to contrast. Compared to dermoscopy, medical images require additional pre-processing since they have different image quality, conditions of illumination, and angle of image acquisition [11]. Enhancing the form and scaling of an image are both aspects of post-processing an image.

Following are the problems encountered while pre-processing skin images [12]:

- If the pre-processing phases are not appropriately followed, there is a considerable probability of inaccurate cancer diagnosis. An effective pre-processing method must be used as a consequence.
- The majority of real-world medical images exhibit different types of noise distortion, which makes image denoising difficult.

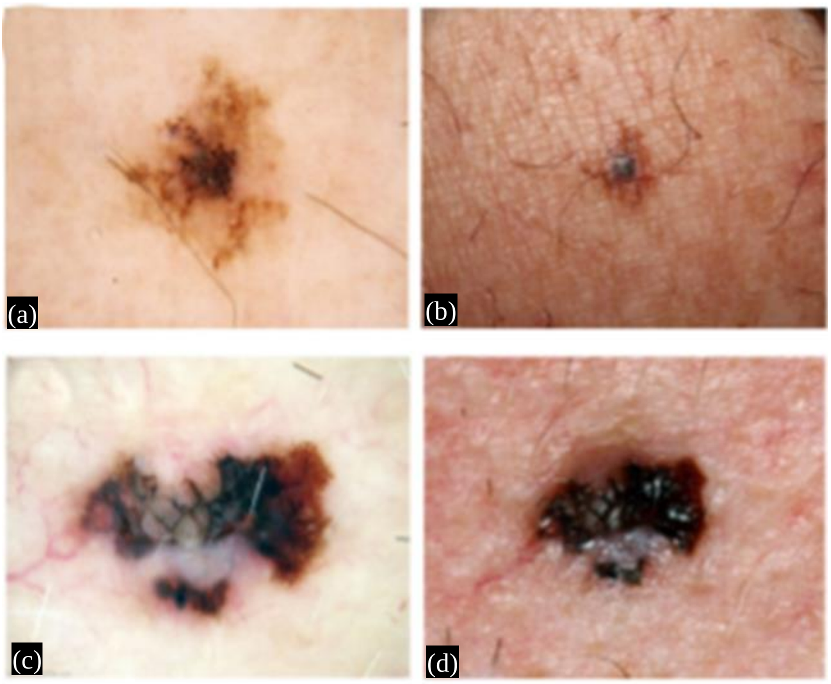

Figure 2. Examples for macroscopic (b and d) images and dermoscopic (a and c) images [4].

- It could be challenging to distinguish between bright and dark lesion sites in low contrast skin photographs.
- Another sign of melanoma is an irregular lesion border on the skin. Due to hair and low contrast photographs, border detection might be difficult.
- Specific image enhancement techniques, such as using a dull razor, can introduce noise into the image.

Abbas et al. [13] proposed an effective preprocessing approach to minimize various artifacts in both dermoscopic and macroscopic images, leading to improved detection of lesion boundaries. This method contrasts with many techniques proposed in the literature aimed at mitigating the impact of hair on images of skin lesions.

Image Segmentation

The capacity to segment an image enables the extraction of the region of interest (ROI). The segmentation process should persist until the skin lesion is fully distinguished from the background of the image or until another specified criterion is met, with the understanding that the skin lesion constitutes the ROI in the examined image. The segmentation process can be affected by distortions like hairs, reflections, shadows, skin lines, and bubbles, which makes it a challenging computation work [4].

Over the years, many computational approaches for the segmentation of skin lesions have been presented. Generally speaking, the techniques may be divided into supervised and unsupervised segmentation procedures. Unsupervised techniques typically undergo training during the segmentation process, whereas supervised segmentation methods necessitate prior knowledge of the ground truth obtained from a substantial training dataset of images. The primary objectives of supervised segmentation approaches involve training, learning, and extracting hierarchical image features from extensive image datasets using supervised machine learning techniques such as support vector machines (SVMs) and convolutional neural networks (CNNs) [14]. When compared to their unsupervised parallels, supervised segmentation algorithms perform better, but their computational cost is the major drawback. For the examination of skin lesions, unsupervised image segmentation techniques that integrate techniques for pretreatment to improve performance outcomes are frequently used. Despite research efforts to eliminate image preparation in supervised image segmentation, progress is still being made with notable results.

Segmentation, also known as image partitioning, is the process of dividing an image into many pieces based on its form, color, and texture. Segmentation is often used to eliminate skin that is of less value, which is to locate the region of interest, usually the picture of a cancer cell, and remove it from the image. The performance of image classification will be enhanced by effective skin cancer image segmentation [11]. Edge detectors are the most prevalent cases of edge-based segmentation techniques. The segmentation method may also be based on similarity criteria, such as comparable hues, textures, or greyscales. Using similarity criteria, techniques like thresholding and region-based segmentation may be used to identify skin lesions in images [4].

In the subsequent sections, we will examine the suitability of various approaches commonly employed in the literature for segmenting pigmented skin lesions in images, which include edge-based, thresholding-based, and region-based methods, as well as techniques based on artificial intelligence (AI) and active contours. Furthermore, additional methods will be discussed in the subsequent section. Table 2 outlines the reviewed studies.

Region-Based Segmentation

In this segmentation, recursively include the nearby pixels that are related to and comparable to the seed pixel in order to develop areas. When comparing regions with uniform gray levels, researchers employ similarity metrics like the variance in grey levels. To avoid linking various areas of the picture, we employ connectedness.

Region-based segmentation comes in two forms:

1. *Top-down approach:* The predetermined seed pixel must first be defined. We may categorize all pixels as either seed pixels or randomly selected pixels. Grow areas until they contain all of the image's pixels.
2. *Bottom-up approach:* Select only intriguing objects for the seed. Grow areas are only permitted if the matching condition is met.

The Selected reaction monitoring (SRM) method is founded on an image generation model that models picture segmentation as an interpretation challenge. On the basis of an unknown theoretical image, it is the reconstruction of areas from the observed images. The SRM method uses statistical tests to determine whether to merge areas and is a subset of region expanding algorithms and region merging techniques. Therefore, in order to verify the merging of areas, the combined predicate and the merging order are two factors that affect performance [15]. The suggested technique extracts the regional features of an input image using an algorithm from. It was emphasized that the initial segmentation should be obtained using one of the over-segmented methods since the accuracy of the final segmentation depends greatly on it. In order to get superior over segmentation results, a number of techniques have been presented in the literature, including watershed, mean shift (MS), normalization cut (Ncut), and tuberpixel. MS is utilized to extract the over-segmented data [16].

Artificial Intelligence–Based Segmentation

Current performance for automated medical image segmentation has been demonstrated using convolutional neural networks (CNNs). One of the earliest deep learning (DL) architectures trained from beginning to end for pixel-wise prediction is a fully convolutional network (FCN), which is used for semantic segmentation tasks. The U-Net architecture consists of two main components: the analysis path and the synthesis path. Deep features are learnt in the analysis phase, and on the basis of the learned features, segmentation is conducted in the synthesis path [17].

We suggest an architecture that employs modified U-Net and VGG-19 in the encoder section of the network in response to the success of U-Net and its modifications for medical picture segmentation. We refer to the design as Double U-Net since it uses two U-Net topologies in the network. Utilizing the VGG network is primarily motivated by comparing to other pre-trained models; VGG-19 is a lightweight model [17].

Fuzzy logic proves highly advantageous in resolving the ambiguity present in images. Several parameters can influence an image. One of the most prevalent uncertainties is light illumination. Because of the light, colors in images might change. Fuzzy logic also operates well when there is a shadow effect. Fuzzy logic is a well-known strategy to get around these kinds of problems [18].

Active Contour Based Segmentation

A fixed mask is used to begin the "Region-Based Active Contour Segmentation." A region of interest in the skin lesion dermoscopic pictures is the foreground, thus the main goal of the binary mask creation is to distinguish it from the backdrop. Here, the backdrop is represented by a pixel value of 0, with the region of interest denoted by a pixel value of 1. In order to map this binary mask image onto the input picture, the segmented binary image must first be obtained. Then, where it was discovered, it begins to encircle the contour's active form [19].

The active contour techniques cause the starting curves to deform appropriately as they advance near the borders of the objects of interest. A deformable model can be either geometric or parametric, depending on the method employed to monitor the movement of the curve. Traditional active contour models, such as snake models, are among the parametric models [20]. The current region-based active contour approach can only handle homogeneous (one color) data; however, since low contrast images need working with various colors, the method is modified by include heterogeneity. K-means clustering, gradient vector flow level set, region-based active contour algorithm, and active contour without edges are some of the active contour segmentation techniques [21].

The Chan-Vese model has been used to segment skin lesions in images [22]. The active contour model without edges suggested by Chan and Vese is based on the average of image pixel intensities rather than the image gradient. As a result, the model combines the Mumford–Shah [23] and level set [24] segmentation approaches.

Edge-Based Segmentation

Edge-based techniques aim to emphasize the variance in the image whereas region-based approaches concentrate on grouping pixels using a measure of similarity. Since the majority of them have supported and enhanced picture contrast in the region immediately surrounding the edges, several researchers have expanded this method within various theoretical frameworks. Traditional approaches frequently use classical edge detectors like Canny, Roberts, and Prewitt to compute the gradient picture. The most frequent issues with edge-based segmentation include edge presence when there is no boundary and absence of edge presence where an actual border is present.

Based on differences in contrast, texture, color, and saturation, edge-based segmentation algorithms locate edges. They can use edge ropes which are made up of the individual edges, to precisely depict the boundaries of objects in an image.

Intensity-Based Segmentation

Intensity-based segmentation refers to thresholding-based segmentation in which the image is divided into sections using a range of intensity values as the threshold value. Segmentation methods both supervised and unsupervised existent.

Thresholding segmentation can be classified into various types based on different threshold values, including:

1. *Simple thresholding:* This method involves replacing the pixels of the image with either white or black based on a specified threshold value. If the intensity of a pixel at a certain point is less than the threshold value, it will be replaced with black. If it is higher above the threshold, it will be replaced with white. This is a basic thresholding method that is ideal for beginners in image segmentation.
2. *Otsu's binarization:* While the range of intensity values is predetermined for supervised segmentation algorithms, unsupervised segmentation methods just divide the image into two groups: low intensity values and high intensity values. For instance, an image is typically composed of numbers ranging from 0 to 255 for intensity. Here, is set to be low intensity if 0 is used, and high intensity if 1 for 255 is used. High intensity levels are observed above 0.5 while low intensity values are seen above 0.2.

The simplest segmentation method is thresholding. By rotating all pixels below a certain threshold to zero and all pixels within that threshold to one, it creates binary pictures from grayscale ones. The right grey level threshold must be chosen in order to separate objects from their backgrounds. An automated threshold selection region-based segmentation technique is the Otsu algorithm. It is extensively utilized since it is straightforward, efficient, and anticipated in determining the ideal value for the global threshold [20]. A global image thresholding approach that is often used for thresholding, binarization, and segmentation is presented by Otsu's segmentation method. Instead of concentrating solely on the image boundaries, this method primarily examines the image histogram, analyzing pixel values and regions for segmentation. By enhancing the variance within each of the minimum classes, it attempts to perform segmentation. This approach [20] is particularly effective for images characterized by two classes of pixels and exhibiting a bimodal histogram distribution. In actuality, the algorithm takes the foreground and background of a picture as given.

To determine the required threshold value, a thresholding approach based on Renyi's entropy has also been used, producing segmentations that maintain the geometry and form of the lesions [4]. The suggested multilayer thresholding method segments the pigmented skin lesion with acceptable results. Several methods for multilayer thresholding have been presented. Researchers oppose its usage in multilevel thresholding because of Otsu's method's computing cost and exhaustiveness as shown in Figure 3(a, b) [21].

DISCUSSION

In general, segmentation results are further processed in order to increase accuracy of the lesion edges acquired. Morphological filters are frequently used to smooth the borders, eliminate isolated parts, and/or fill the interior of segmented lesion regions. With fundamental facts determined by one or more professionals. The accuracy of segmentation is dependent on the model and approaches employed to address the problem. Table 3 shows the distribution of the approaches covered in this article, according to the relevant concept, that have been generated to separate pigmented skin lesions in images.

Figure 3. Results of segmentation using Otsu's approach on the (a) dermoscopic image and (b) the macroscopic image, publicly available in reference [4].

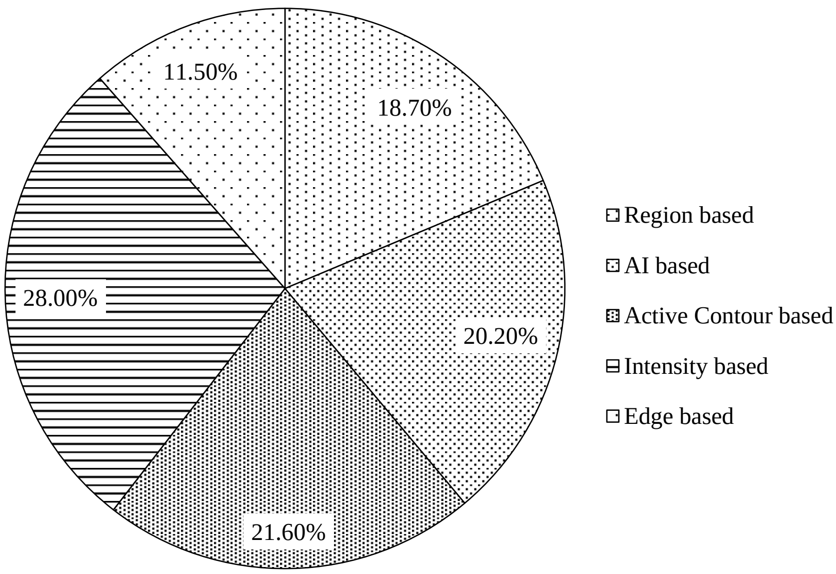

Figure 4. Comparison chart for the segmentation methods employed on skin lesion images.

Table 2. Research done on segmentation of skin lesions in images.

Segmentation Method	Techniques	References
Region based	• Generalized statistical region merging (GSRM) method • Watershed, mean shift (MS), normalization cut (Ncut), and tuberpixel	[15, 16]
Artificial intelligence based	• Fuzzy logic • Fully convolutional network (FCN)	[17, 18]
Active contour based	• K-means clustering • Region-based active contour method • Chan-Vese model	[19, 22]
Edge based	• Sobel operator • Prewitts operator • Canny operator	[25]
Intensity based	• Simple thresholding • Otsu's thresholding • Renyi's entropy	[4, 20]

Table 3. Comparison of reviewed methods for segmentation of skin lesions.

Segmentation Method	Techniques	Accuracy	Recall	F-measure
Region based	Generalized statistical region merging (GSRM)	84%	83%	83%
Artificial intelligence based	Double U-Net	94%	87%	78%
Active contour based	Region based method	95.3%	94.6%	95.9%
Edge based	Canny Edge Operator	75%	72%	69.1%
Intensity based	Otsu Thresholding	97%	95%	96.2%

Clustering techniques have also been used to segment skin lesion pictures [26]. Castillejos et al. [27] for example, employed the k-means clustering technique. Threshold-based methods are frequently employed, owing to their simplicity, operational economic performance, and high performance. The popularity of AI-based techniques is justified by the benefits they provide, such as the ability to learn from sample cases provided by artificial neural networks, the search and optimization for the best segmentation results provided by genetic algorithm (GA)–based methods, and the ability to deal with unclear values supplied by fuzzy logic [4]. For the segmentation of skin lesions, algorithms dependent on the active contour model have also often been developed. Nevertheless, topological shifts and significant curvatures are challenging for parametric models to handle. Geometric models, on the other hand, avoid such problems, but their computing complexity might be excessive. Region-based methods are also being utilized since they have demonstrated effective performance despite the presence of a number of challenges, such as lighting and color fluctuation. Edge-based segmentation algorithms are typically not used independently since it may not be possible for them to fully detect the edges of the lesions, which is essential for the study of lesions of the skin in images.

Pre-processing methods, including color space transformation, lighting correction, contrast enhancement, and artifacts removal, have been utilized to get improved segmentation results from dermoscopic and macroscopic pictures. Smooth images are typically processed using the median filter and anisotropic diffusion filter to minimize noise. However, some obstacles, like variations in lighting and very thick, black hair, are too significant for these filters to overcome [4]. To solve this problem, hair removal algorithms might be used. Edge-based methods should not be applied when splitting up skin lesions since they may result in divisions with partially closed edges. Nevertheless, both threshold-based and AI-based segmentation techniques can effectively detect the lesions present in Figure 4. Due to its capacity to effectively divide both low contrast and high contrast images, intensity-based segmentation may be a beneficial option. Since only the darker area of the skin indicates melanoma, we can more accurately identify the lesion from the image based on its intensity values.

CONCLUSION

The effective computational recognition of pigmented skin lesions in images requires image segmentation as an essential step. Skin lesion diagnostics is an important topic of research since it is important for both prevention and early identification of skin cancer. In this article, the most modern techniques for segmenting skin lesions are examined, as well as methods for capturing and pre-processing images with the goal of later segmenting them. According to the review, dermoscopic images have been proposed for use in the computational diagnosis of skin lesions since they have less distortions and more detailed characteristics, perhaps leading to more accurate lesion segmentation and analysis. Edge-based, thresholding-based, region-based, AI-based, and active contour-based are some of the investigated segmentation methods. Intensity-based models can produce a positive result on images with color variations and low contrast of the lesion borders. As a result, such models are a feasible choice for segmenting skin lesions. However, other methods with enhancements or in association with other methods might give accurate lesion detection. In summary, future advancements in skin lesion image segmentation will strive for enhanced precision in detecting lesion boundaries while also tackling other challenges such as computational efficiency, noise reduction in images, and image enhancement.

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