Chronic wound segmentation methods: A brief systematic review

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Abstract.
Chronic wounds are a leading cause of mortality and morbidity, and they are considered a significant public health and economic burden. In recent years, the development of noninvasive imaging technologies along with the growth in the field of Artificial Intelligence, especially, Deep Learning, have resulted in the implementation of different studies for the automatic assessment of chronic wounds. In this review, we summarize some of the works that can be found in the literature for the task of chronic wound semantic segmentation. For this purpose, we used two databases to find studies between 2010 and November, 2021, which meet certain eligibility criteria and contain specific keywords. In this regard, 16 articles that met the established conditions were selected. All of them addressed chronic wound segmentation; however, some of them were not limited to that task. These were classified in two big classes: Machine Learning methods, and Deep Learning methods. The use of noninvasive imaging technologies was a common factor in all of them; however, the majority of the works was focused on color images. Lastly, the results reported for all of them are above 80%, i.e., satisfactory. In conclusion, the proposed methods outperform the traditional visual inspection for wounds assessment in terms of accuracy and time, and represent a potential alternative for supporting the medical decision-making process of such task.

1. Introduction

Chronic wounds are one of the most complex type of injuries, and are associated with high mortality and morbidity rates. These wounds can be caused by underlying diseases, such as diabetes and obesity, limited mobility, prolonged pressure or shear forces on the skin, lack of blood perfusion, presence of biofilm, significant trauma to the skin, deep burns, and poor nutrition Atkin (2019); Moreo (2005). In The United States, it is estimated that 2% of the population experience chronic wounds, and their treatment results in elevated medical costs, approximately $28.1 to $96.8 billion per year, representing a major economic burden Sen (2021).

Wound care is essential for promotion and acceleration of the healing process, decreasing the risk of mortality and the impact on the patient's quality of life that the wound can have. Prompt and accurate wound assessment is critical to plan an effective and advanced treatment strategy to achieve anatomical and functional recovery of the skin and underlying tissues. In this regard, said assessment should include wound measurements, such as perimeter, length and width, surface area, volume, and the type of tissue inside the wound region. Additionally, the condition of the wound could also be described by other complimentary attributes like blood flow, oxygen, infection, inflammation, among others. However, this assessment task continues to constitute a clinical challenge due to the dynamic nature and highly variability of chronic wounds Tottoli et al. (2020).

The normal healing process is usually described by four phases that lead to the regeneration of the skin: hemostasis, inflammatory, proliferative, and maturation. This process is disrupted in chronic wounds, which are characterized by a prolonged inflammatory phase that prevents the wound from healing in a period of eight weeks. Among the most common chronic wounds we find: pressure ulcers, diabetes ulcers, foot ulcers, and venous ulcers Goldberg and Diegelmann (2020). Their wound site presents one or more of the following tissue types: a) *necrotic*, a black eschar or dead tissue; b) *slough*, a yellow-white non-viable tissue; c) *unhealthy granulation*, a dark read infected tissue; and d) *ischemic tissue*, a blueish tissue without proper blood supply. Grey et al. (2006).

Traditionally, the size, area, and type of tissue present in the wound bed are determined by visual examination performed by the clinician. However, such methods contribute to the inter-subject variability and increment on the workload of the medical personnel. For this reason, and considering the development and adoption of novel non-invasive imaging technologies in the past few decades, several Computer-Aided Detection or Diagnosis (CAD) systems have been proposed to achieve a more accurate and consistent wound assessment while decreasing the time taken in the process. These systems support the medical decision-making process, serving as a second opinion for the clinician Fauzi et al. (2015).

This work focuses on automatic semantic segmentation of chronic wounds, which is the first step for the implementation of CAD systems, and can be used for further wound characterization and classification. Semantic segmentation is a technique that classifies each pixel of an image into the corresponding class. Therefore, in this case, it is possible to identify the healthy skin and the chronic wound Guo et al. (2018). As a result, it enables the obtention of critical information for assessment, and continuous monitoring and treatment, such as wound location, area, and shape Hesamian et al. (2019).

In this paper, we present a brief systematic review on methods for automatic semantic segmentation of chronic injuries that include different Image Processing, Computer Vision, and Artificial Intelligence techniques, with a particular emphasis on Deep Learning models. The rest of the paper is organized as follows. In Section 2, the search and selection methodology is described. Section 3 presents different categories of wound segmentation techniques, including a summary of such techniques and the corresponding results. In Section 4, we analyze and summarize the trends in wound semantic segmentation. Last, the conclusions of the work are presented.

2. Methods

The review was performed according to the instructions provided in class and the information provided by the different resources and examples shared with us.

2.1. Searched Databases

Two databases were used to find peer reviewed articles published between January 1, 2010, to November 25, 2021: PubMed and Google Scholar.

2.2. Searched Keywords

The following relevant terms associated with semantic segmentation of chronic wounds were used: *wound assessment, wound segmentation, chronic wound segmentation, wound semantic segmentation.*

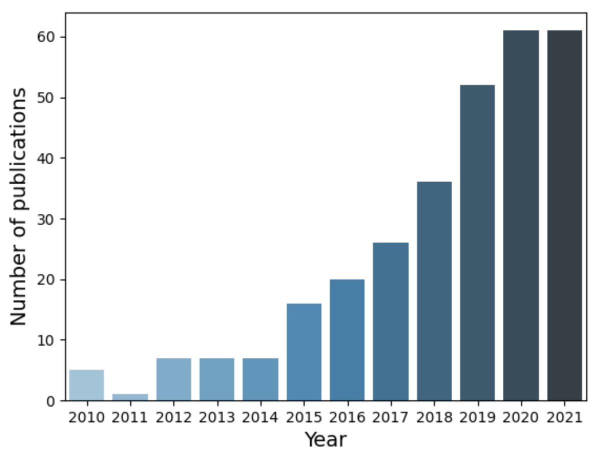

Figure 1: Number of publications by year since 2010

2.3. Exclusion Criteria

Research papers and studies were not included in the review if they met one or more of the following criteria: (1) lack of evaluation metrics (i.e., accuracy, specificity, sensitivity, f1-score, confusion matrix); (2) special emphasis on the classification task rather than the segmentation task; (3) lack of readibility, clarity, and provided details in the proposed method; (4) missing information on the collected or selected dataset; (5) studies from the same author or authors that only presented improvements on the same model. In that case, the previous model was discarded; (6) Reviews and surveys; and (7) inclusion of invasive imaging techniques.

2.4. Data Extraction

The following information was extracted from the selected papers: Authors and year, addressed wound assessment tasks, dataset information, type of wounds included, type of images, image processing techniques, extracted features if applicable, summary of the semantic segmentation methodology, performance evaluation metrics, and statistical results.

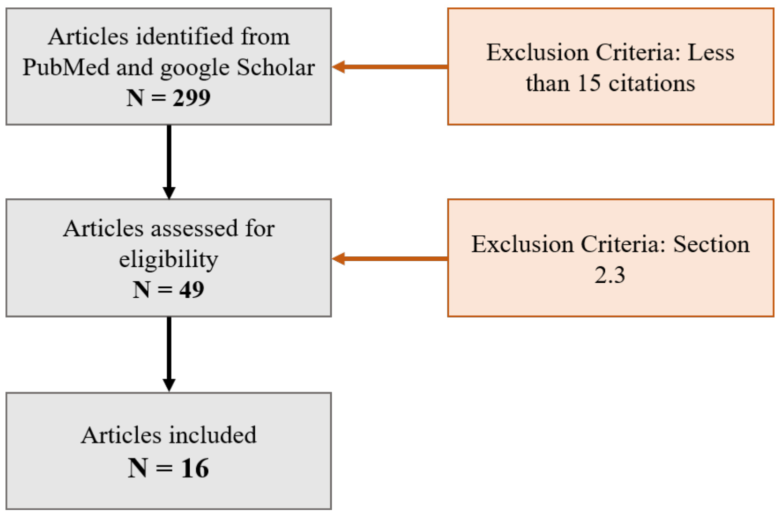

Figure 2: Review selection methodology

3. Results

In the last decade, several researchers have studied the application of semantic segmentation for chronic wound assessment. More specifically, 299 studies were identified since the year 2010. However, it is possible to observe (See Figure 1) that most of these studies were conducted in the last 4 years. From this total number of studies, 250 were excluded as they had less than 15 citations and were considered not relevant for the review. Lastly, from the 49 assessed studies, 16 of them were selected according to the exclusion criteria explained in Section 2.3 (See Figure 2).

The methods proposed in the included studies can be classified in two main categories: Machine Learning models and Deep Learning models. While Deep Learning is a subcategory of Machine Learning, given its dramatic impact in the field, and the number of studies in the literature based on such methods, it is considered as an independent category. For each category, we will briefly describe some of the the reviewed methods, and besides, important information from all the reviewed methods is provided in a succinct manner in Table 1.

3.1. Machine Learning methods

Bockho et al. used near-infrared (NIR) images to segment the chronic wounds in the lower extremity of 30 patients. To achieve this, they trained a Support Vector Machine classifier with color and edges features extracted from the NIR images, using basic image processing techniques, such as the Canny filter Bochko et al. (2010). Song and Sacan proposed an automatic wound segmentation approach based on K-means Clustering, Edge Detection, Thresholding, and Region Growing integrated together to enhance the robustness of the system. They conducted a study to evaluate their method on 92 images containing diabetic foot ulcers, and obtained an overall accuracy of 85.7%. Song and Sacan (2012). Wantanajittikul et al. proposed a method based on Fuzzy C-Means Clustering specifically for burn injuries segmentation, First, they converted the image to the Cr-space and applied clustering to separate the skin from the background. Subsequently, they transformed the color image to the Luv-space and applied clustering again to obtain the burn region. The method was finalized with a closing morphology operation. Five burn images were used to evaluate their approach, obtaining a sensitivity of 84.3% when comparing to two experts Wantanajittikul et al. (2012).

Similarly, Mukherjee et al. (2014) used color spaces and machine learning techniques to segment wound images. However, their proposed method was based on HSI color space and Fuzzy Divergence Based Thresholding. This method highlighted the wound region initially, which increased the accuracy of the segmentation task. The validation was conducted with 76 images selected from a publicly available dataset. They also used a Support Vector Machine (SVM) model to segment the wound according to the different types of tissue present Mukherjee et al. (2014). Following the use of color spaces, Cirillo et al. combined CIELab color space, Tucker tensor decomposition, grey-level co-ocurrence matrix (GLCM), and Fuzzy C-Means Clustering. The satisfactory performance of the proposed method was evaluated on a small dataset of burn patients, and it was demonstrated that the method can be highly effective when there is a lack of data with a sensitivity of 96.85% Cirillo et al. (2019).

3.2. Deep Learning methods

The methods proposed in this subsections do not rely heavily on Image Processing and Computer Vision techniques to achieve the wound segmentation. The reason is that one of the most important characteristics of Deep Learning models is the ability to take raw data and output the desired results. In this regard, Wang et al. proposed a Convolutional Network with 5 encoding layers, 4 decoding layers, and Rectified Linear Unit (ReLU) as the activation function. The features that could be extracted from the bottleneck of the proposed architecture were used for further wound assessment. For the validation of the model, 150 color images of chronic wounds were used, resulting in an overall pixel accuracy of 95% Wang et al. (2015). Jiao et al. implemented a model based on the Mask-RCNN architecture, using ResNet101 with atrous convolution as the backbone. For this purpose, they created their own annotated dataset composed of RGB

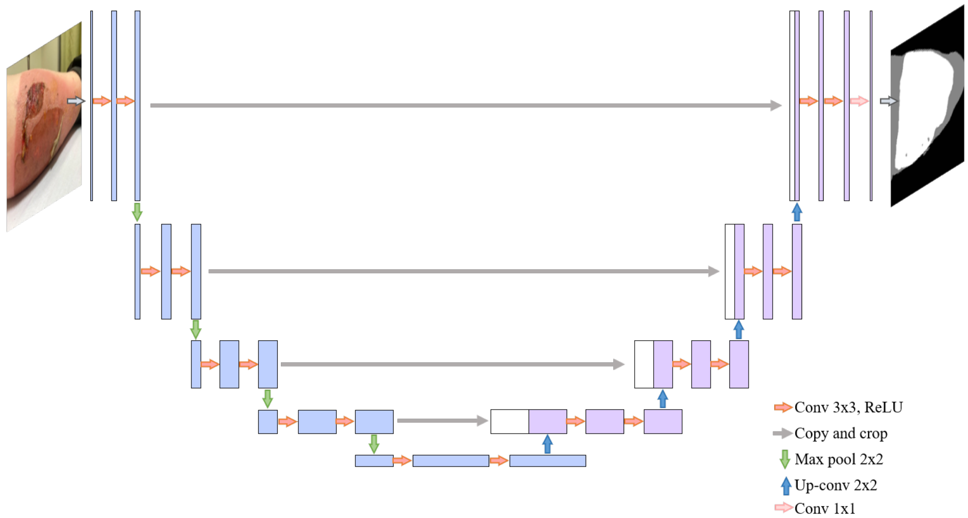

Figure 3: U-Net Example for Burn Injuries. Adapted from Ronneberger et al. (2015)

pictures obtained with smartphones at the Wuhan Hospital; however, such dataset is not publicly available. This method achieved an accuracy of 94.2% for 150 color images Jiao et al. (2019).

Chino et al. proposed an architecture based on U-Net for the segmentation of skin ulcers from RGB images. An adaptation of U-Net from the original study is presented in Figure 1 for a chronic wound segmentation example. Since the introduction of this architecture in 2015, it has been used several times in the medical image analysis field leading to satisfactory results in diverse applications with different type of 2D and 3D data, such as color images, ultrasound, infrared, among others (See Figure 3). For the reviewed study, two publicly available datases were used: ULCER and ULCER-2, leading to a segmentation sensitivity of 91%. In addition, the segmented region was used for automatic calculation of the wound area Chino et al. (2020). Recently this year, Mahbod et al. proposed an ensemble model constituted by LinkNet and U-Net, in which the encoder network or contracting path of both models was pretrained on Medetec dataset, mentioned above. In order to evaluate the model, 200 images of the FUSeg dataset were used, resulting in a precision of 92.68% Mahbod et al. (2021).

4. Discussion

In this brief review, we evaluated 16 studies focusing on the semantic segmentation of different types of chronic wounds, using a variety of image processing techniques, and artificial intelligence techniques. From this systematic search, it is possible to identify the significant growth in the importance of non-invasive imaging techniques during the last years. All the reviewed studies used such techniques in order to implement their proposed solutions. It was also possible to identify a shift in the attention of researchers in the medical image analysis field in recent years. According to the initial articles

Table 1: Summary of reviewed chronic wound semantic segmentation works

Author	Task	Image type	Wound type	Segmentation method	Number images (Testing)	Performance metrics Accuracy (%)	Sensitivity (%)
Machine Learning Methods							
Bochko et al. (2010)	Wound segmentation	NIR images	Lower extremity ulcers	Image processing and SVM	30	-	-
Song and Sacan (2012)	Wound segmentation	Color images	Diabetic foot ulcer	K-means, edge detection thresholding and region growing ensemble	92	85.7	-
Wantanajittikul et al. (2012)	Wound segmentation and classification	Color images	Burn injuries	Fuzzy C-Means clustering and Color spaces	5	-	84.3
Mukherjee et al. (2014)	Wound segmentation and classification	Color images	Chronic wounds	Fuzzy Divergence SVM and Color spaces	76	-	-
Dhane et al. (2016)	Wound segmentation	Color images	Pressure Ulcers	Color spaces Clustering	40	86.73	-
Cirillo et al. (2019)	Wound segmentation	Color images	Burn injuries	Fuzzy C-Means clustering, Color spaces GLCM, and tensor decomposition	13	-	96.85
Deep Learning Methods							
Wang et al. (2015)	Wound segmentation and infection detection	Color images	Chronic wounds	Encoder-Decoder CNN	150	95	-
Liu et al. (2017)	Wound segmentation	Color images	Chronic wounds	Mobile-Net	200	98.12	-
Lu et al. (2017)	Wound segmentation	Color images	Chronic wounds	Encoder-Decoder CNN	40	91.3	-
Li et al. (2018)	Wound segmentation	Color images	Chronic wounds	Mobile-Net	190	-	94.94
Jiao et al. (2019)	Wound segmentation	Color images	Burn injuries	Mask-RCNN	150	94.2	-
Ohura et al. (2019)	Wound segmentation	Color images	Ulcers	U-Net with VGG16	40	-	94.3
Chino et al. (2020)	Wound segmentation area measurement	Color images	Venous ulcers	U-Net	217	-	91
Wang et al. (2020)	Wound segmentation area measurement	Color images	Foot ulcers	MobileNetV2	-	-	91.01
Blanco et al. (2020)	Wound segmentation	Color images	Ulcers	ResNet and Superpixel methods	150	-	97.04
Mahbod et al. (2021)	Wound segmentation	Color images	Foot ulcers	U-Net and LinkNet ensemble	200	-	92.68

retrieved by the searched keywords, in the last four years there has been an increasing attention to wound care in the medical image analysis field. For example, it is easy to notice that the number of works in the literature for topics such as breast cancer or lung cancer is huge. This is despite the fact that for those mentioned fields, even more specialized imaging technology is needed; however, given the interest of the community in these topics in the last decade, it is easier to find available resources and datasets to work on those problems. The opposite happens with wound care, finding a dataset to complete studies or develop new assessment techniques represents a significant hurdle. This can be one of the reasons why the proposed and implemented studies in the assessment of chronic wounds were scarce before the year 2015. From that moment, it is possible to find more studies, especially, the ones developed with Deep Learning techniques.

This increment in the literature demonstrates that the topic is starting to catch researchers' attention and we will continue to see an increment in the studies related to wound care and wound assessment. Therefore, with the constant progress in the non-invasive imaging tools, which provide a high resolution view of he skin, beneficial for this task; the increment in computational capabilities; and the newest Deep Learning methods that lead to satisfactory and consistent results and high accuracies, it will be possible to implement a wound assessment and monitoring system that can be adopted in hospitals and can be incorporated into the clinical routine. I.e., in the next years, the efforts in this field should be focused towards the creation of a big dataset of different types of wounds, annotated by a group of experts, which can be used in the development of advanced semantic segmentation techniques. This will allow the the impact of Image

Processing, Machine Learning and Deep Learning to continue growing and provide an alternative solution to the current clinical assessment that can lead to better results and have a positive impact in the patient's life.

5. Conclusions

The review identified and summarized different methods for automatic semantic segmentation of chronic wounds. These included color images and NIR images combined with different Image Processing, Machine Learning and Deep Learning techniques that resulted in satisfactory results. Therefore, considering the high accuracy and the readily availability of the proposed systems, it is beneficial for both, the patient and the clinician to study the possibility of adopting and incorporating said systems in the clinical routine, with the goals of serving as a second opinion to the clinician, and avoiding unnecessary delays in the assessment and monitoring process of chronic wounds.

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