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Review

A Systematic Investigation of Models for Color Image Processing in Wound Size Estimation

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Abstract: In recent years, research in tracking and assessing wound severity using computerized image processing has increased. With the emergence of mobile devices, powerful functionalities and processing capabilities have provided multiple non-invasive wound evaluation opportunities in both clinical and non-clinical settings. With current imaging technologies, objective and reliable techniques provide qualitative information that can be further processed to provide quantitative information on the size, structure, and color characteristics of wounds. These efficient image analysis algorithms help determine the injury features and the progress of healing in a short time. This paper presents a systematic investigation of articles that specifically address the measurement of wounds' sizes with image processing techniques, promoting the connection between computer science and health. Of the 208 studies identified by searching electronic databases, 20 were included in the review. From the perspective of image processing color models, the most dominant model was the hue, saturation, and value (HSV) color space. We proposed that a method for measuring the wound area must implement different stages, including conversion to grayscale for further implementation of the threshold and a segmentation method to measure the wound area as the number of pixels for further conversion to metric units. Regarding devices, mobile technology is shown to have reached the level of reliable accuracy.

Keywords: wound measurement; image processing; mobile devices; medicine; size; technology

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1. Introduction

The treatment, care, and prevention of wounds represent high costs for health services [1]. In [2], Landi et al. showed that mortality rates associated with specific wound pathologies have increased in the last few years. This has significant consequences for health, especially for populations at risk, such as older adults.

Accurate wound assessment is critical to determine the correct diagnosis and assign treatment. Ordinarily, this evaluation is performed by visual inspection, using standardized scales or indexes. Nevertheless, this approach has been shown to be an inaccurate method to deal with wound diagnosis [3,4].

Information and communications technology (ICT) advancements, particularly in mobile technology, have led to new applications in health and medicine [5,6]. Mobile development has led to various applications in health [7], such as teaching and learning in clinical medicine [8], documenting medical findings using eyewear devices [9], and applying markerless augmented reality in forensic medicine [10], among others. Within this scope, a specific class of novel applications related to wound analysis has emerged that leverages the capabilities of mobile devices' cameras. By utilizing the continuous improvements in processing power and battery capacity, these applications are used to assess and evaluate the wound's different characteristics.

Novel approaches in wound diagnosis are critical, as wound healing can be highly demanding in many diseases such as diabetes, tuberculosis, allergies, or ulcers [11,12]. The challenges of working with wound images lie in their very heterogeneous colorations related to the patient's skin color and anomalies such as erythema and striations. Additionally, the tissue segmentation process's complexity is increased further, as the boundaries between different tissue regions are often vague and highly irregular. Hence, image processing and computational intelligence techniques have been applied in several studies to address various aspects of wound diagnosis.

The main focus of wound-related approaches is on non-intrusive or less-intrusive telematic procedures for measurement and monitoring [13]. In [14], Pal et al. proposed early detection and monitoring of chronic wounds using low-cost, omniphobic, paper-based smart bandages. Alternatively, the authors proposed predicting and monitoring the chronic dermal wounds' therapeutic responses [15]. Another class of problems is related to wound area identification. It has been tackled with different techniques such as contour detection with histogram segmentation [16], active contours modeling [17], clustering approaches [18], and skin texture models [19]. It is further extended to the classification and triage of identified wounds [20]. The applications rely on optical character recognition to characterize and measure injuries, depending on multispectral images capturing the color, temperature, and geometry of the wounds [21].

With the exponential growth of smartphone and tablet devices, these processes have become even more reliable and agile, especially in techniques that utilize mobile devices for wound measurement [22] and wound area assessment [23]. Furthermore, in [24], Gupta presented a method for providing real-time mobile wound segmentation and management. Additionally, mobile devices have been used for performing 3D wound imaging [25] or using machine learning within a pipeline relying on mobile images [26]. Within the context of machine learning, deep learning approaches for image segmentation have been proven to be successful [27] and versatile, as well as applicable to different learning tasks with adaptable learning rates [28].

It is essential to perform research in which the color model qualities of image processing techniques are evaluated to enable adequate wound size estimation methods in the future. Furthermore, it would provide information on whether the particular technique and subsequent results can be trusted. Although other systematic reviews were performed previously, these reviews did not consider the application of image processing techniques in wound size estimation. Therefore, this review aims to analyze the technological advances and the dissemination of new solutions that allow for the automatic identification of wound sizes using image processing techniques. In addition, mathematical formulas enable establishing a border between the healthy skin and the part that contains the wound area. The main contribution is providing a summary and best evidence synthesis on each technique's properties by presenting different levels of research.

The structure of this paper follows with Section 2, where we present the strategy used to conduct this systematic review, the description of the research questions, and the literature selection criteria. Subsequently, in Section 3, we present the results with a detailed discussion and classification of the retrieved studies. The results are discussed and placed within Section 4 before concluding the paper with Section 5.

2. Methods

2.1. Research Questions

This review's leading research questions were the following: (RQ1) Which are the techniques that can be applied in a mobile application to measure a wound's area? (RQ2) What are the most significant features to define a method for the automatic calculation of a wound's size? (RQ3) What are the benefits that this kind of study can bring to the medical profession?

2.2. Inclusion Criteria

The inclusion criteria of studies and assessing methods for this review were as follows: (1) studies that focus on measuring the size of a wound; (2) studies using a mobile application and image processing to detect and calculate the area of a wound; (3) studies that present methods of segmentation and the use of color to identify the area of a wound; (4) studies that seek to present the medical evolution for the detection of features from a chronic wound through a photo; (5) studies that utilize at least motion or magnetic sensors; (6) studies that were published between 2010 and 2020; and (7) studies written in English.

2.3. Search Strategy

The team searched for studies meeting the inclusion criteria on the following electronic databases: IEEE Xplore, ScienceDirect, Google Scholar, and PubMed Central. The research terms used to write this systematic review were as follows: wound, measurement, size, image processing, and mobile device. Four reviewers independently evaluated every study, and their suitability was determined with all parties' agreement. The studies were examined to identify the different approaches relative to measuring a wound's size using mobile devices and image processing methods.

2.4. Extraction of Study Characteristics

After examining the different studies, the following data were presented in Table 1: year of publication, population, purpose, devices, methods, and analyzed diseases. As some studies did not show some data, we contacted the different corresponding authors of each study by email, asking about the implemented methods. The contact with the various authors was also related to the source code's request in the different studies. All of the studies were analyzed to measure the different methods used for the measurement of wound size.

Table 1. Study analysis.

Paper	Year of Publication	Population	Purpose of the Study	Devices	Dataset Availability	Methods	Diseases
Casal-Guisande et al. [29]	2020	N/A	Monitor and analyze the chronic wound treatment process	Desktop	Not available	Segmentation, threshold, color detection	Pressure ulcers
Zahia et al. [30]	2020	N/A	Measure the depth, area, volume, main axis, and secondary axis of chronic wounds	Smartphone	MS COCO [31] and ImageNet [32] datasets	Mask recurrent convolutional neural networks (RCNN) model	Chronic wounds
Cazzolato et al. [33]	2020	People with chronic wounds	Segment and measure skin ulcers	Smartphone	Datasets from [34,35]	Rule-based ulcer segmentation and measurement (URule) framework	Pressure ulcers
Wu et al. [36]	2019	Voluntary people	Detection of wounds with image processing techniques	Smartphone	Not available	Segmentation, threshold, color detection	N/A
Liu et al. [37]	2019	54 patients	Detection and measurement of the wound area	Smartphone	Available by request	Least squares conformal map (LSCM) algorithm	N/A
Huang et al. [38]	2018	N/A	Measurement of wound size	Smartphone	Not available	Enhance local contrast (CLAHE) algorithm	Chronic wounds
Naraghi et al. [39]	2018	People with tuberculosis	Detection of wounds in people with tuberculosis	Smartphone	Not available	Photogrammetric reconstruction	Tuberculosis infection
Chen et al. [40]	2018	N/A	Evaluation of a surgical wound	Smartphone	Dataset available in [41]	Segmentation, threshold, color detection	Surgical wounds
Gupta et al. [24]	2017	20 wound images	Mobile system for the segmentation and identification of a wound	Smartphone	Not available	Segmentation, threshold, color detection	Chronic wounds

Table 1. *Cont.*

Paper	Year of Publication	Population	Purpose of the Study	Devices	Dataset Availability	Methods	Diseases
Sirazitdinova et al. [25]	2017	N/A	Automatic wound reconstruction	Smartphone	Not available	Color correction, tissue segmentation	Skin Lesions
Tang et al. [42]	2017	N/A	Analysis of the evolution of wounds	Smartphone	Not available	Scaling method	Chronic wounds
Zapirain et al. [43]	2017	24 clinical images of pressure ulcers	Segmentation and identification of chronic wounds	Desktop	Not publicly available	Linear combination of discrete gaussians (LCDG) model	Chronic wounds
Dendere et al. [44]	2017	10 subjects	Measure the size of a wound	Smartphone	Not available	Tuberculin skin test (TST)	Tuberculosis infection
Yee et al. [45]	2016	N/A	Measurement, tracking, and diagnosis of wounds	Smartphone	Not available	Seymour wound model 0910	Chronic wounds
Satheesha et al. [46]	2015	People with skin cancer	Segmentation and analysis techniques of wounds for the detection of the shape	Smartphone	Not available	PH2 dermoscopy image information, D-quick Fourier rework	Melanoma
Cheung et al. [47]	2015	N/A	Diagnosis and treatment of chronic wounds	Smartphone	Not available	Photogrammetric reconstruction	Melanoma
Pires et al. [23]	2015	N/A	Calculation of the wound area	Desktop	Not available	Segmentation, threshold, color detection	N/A
Bulan et al. [48]	2014	36 patients with allergic diseases	Identification of a wound in images	Desktop	Not available	Linear discriminant analysis (LDA)	Allergic diseases
Hettiarachchi et al. [22]	2013	20 patients	Measurement of wound area with segmentation techniques	Smartphone	Not available	Segmentation, threshold, color detection	Chronic wounds
Kanade et al. [49]	2010	Wide range of people	Restore, detect, and track cells and cellular tissues	Desktop	Not available	HCRF model	N/A

3. Results

As illustrated in Figure 1, our review identified 208 articles that included nine duplicates, which were removed. The remaining 199 studies were evaluated in terms of title, abstract, and keywords, resulting in the exclusion of 161 papers. The remaining 38 studies were analyzed in terms of the purpose of the study. Full-text evaluation was performed, resulting in 18 studies that did not match the inclusion criteria. The remaining 20 papers were included in the qualitative synthesis and quantitative synthesis. In summary, we examined 20 scientific articles.

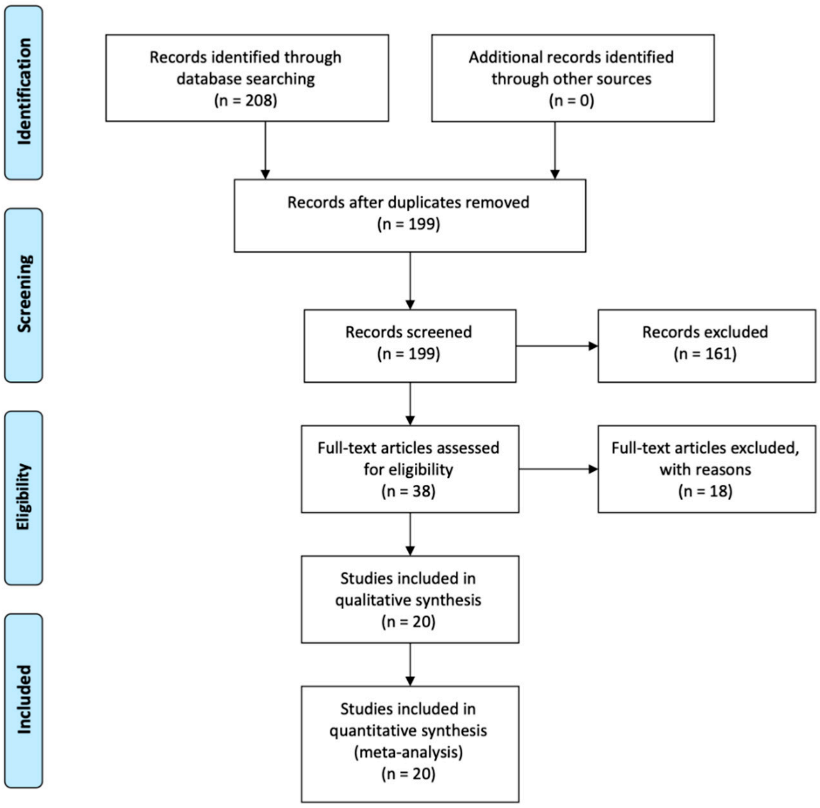

Figure 1. Flow diagram of the identification and inclusion of papers.

To analyze the different studies and get more relevant information regarding wound measurement in the different studies, the interested reader must read the original works. Based on the results presented in Table 1, the analyzed studies were published between 2010 and 2020, reporting three studies in 2020 (15%), two studies in 2019 (10%), three studies in 2018 (15%), five studies in 2017 (25%), one study in 2015 (5%), three studies in 2016 (15%), three studies in 2015 (15%), one study in 2014 (5%), one study in 2013 (5%), and one study in 2010 (5%). Regarding the studies that reported the number of images used in the study, the average reported was approximately 27 images. For the devices used, five studies used desktop computers (25%), and fifteen studies used mobile devices (75%). None of the studies published a proprietary dataset regarding the dataset availability of the images used for the different experiments. Three studies (15%) used datasets already published in other studies, as mentioned in Table 1. The studies considered different types of diseases that corresponded to the different types of wounds. All studies referenced in Table 1 used supervised learning and were model-based approaches. The presented analyses only summarize the results of each research paper. The interested readers must read the full text for more detailed information.

Casal-Guisande et al. [29] analyzed pressure ulcers to measure the size and evolution of wounds using the hue, saturation, and value (HSV) model. The population studied had chronic wounds. The proposed system used MATLAB software (R2020a, MathWorks', Natick, MA, USA), which implemented different image processing algorithms as a decision support system with concurrent fuzzy inference engines. After analyzing the various points, the decision factor's growth was reversed, reporting that the corrections prevented abnormal behaviors. For the measurement of the wound, the steps performed were selecting the saturation plan, the inversion and filtering of saturation values, and the performance of segmentation with a threshold.

Zahia et al. [30] also calculated the size of a wound. They used the mask recurrent convolutional neural network (RCNN) model to classify chronic wounds, reporting results with an accuracy of around 87%. The authors used Python 3.6 with Keras 2.0 [50] and TensorFlow 1.3 [51] for the segmentation of the images and measurement of the different features, which were processed with MATLAB software (R2018b, MathWorks', Natick, MA, USA). Internally, the proposed system extracted all quantitative information by matching the 2D image with its 3D mesh. Finally, they captured the depth, volume, area, and major and minor axes of each wound. The final method was achieved by applying the mask recurrent convolutional neural network (RCNN) model to segment the injury. In continuation, the 3D mesh was rasterized, generating a top view image and the matrix of face indices. The expectation–maximization (EM) approach was implemented, and a projective transform matrix of the image was calculated. Next, the image was segmented, and the RANdom SAmple Consensus (RANSAC) algorithm was used to calculate the best fitting hyperplane. Finally, the authors calculated the faces and the wound's boundary, computing its depth, area, volume, and axes. For example, one of the images available in the authors' dataset was tested in grayscale and is presented in Figure 2.

Figure 2. Foot ulcer image available in the MS-COCO dataset [31].

In [33], Cazzolato et al. proposed the rule-based ulcer segmentation and measurement (URule) framework for the segmentation and measurement of the wound area. The results obtained reported an F-measure of 0.8 in the measurements performed with ulcer wounds. The method was implemented in the URule app, which included capturing and processing the images with a mobile device. The method starts with dividing a mobile application into a matrix, continuing with the interior seed region's estimation considering the user's annotation. Next, the threshold is applied to the areas, and the pixels are filled. Sequentially, the different mathematical models are used for the measurement of the wound area. Thus, the implemented method is composed of the segmentation of RGB images into the foreground and background. After that, the minimum bounding rectangle (MBR) of the region of interest is cropped. Next, the image is binarized and converted to grayscale. After that, the ISODATA algorithm was used to find a threshold for the image, and the line segment detector (LSD) approach was implemented to find the ticks of the measurement tool. Initially, the ticks were grouped by angle. Next, the authors considered the segments with angles greater than or equal to five degrees of difference for the group with more elements. Finally, the wound area was measured by the computation of the distance between ticks in pixels, which were converted to centimeters. For example, one of the images available in the authors' dataset was tested in grayscale, and it is presented in Figure 3.

Figure 3. Fibrin skin ulcer available in [34].

Wu et al. [36] also used the HSV color model to detect the wound area in images captured by a Redmi6A smartphone with volunteers. The authors also used the grabCut algorithm in four images, reporting an accuracy of 50%, and the color threshold approach in the same images, reporting an accuracy of 100%. The color threshold approach was also more efficient than the other algorithms. Thus, the OpenCV library was used to apply a coin detection algorithm. After that, the image was segmented, and a rectangle was created around the wound. Next, the grabCut algorithm was used to measure the wound area. Still, the intensity values of colors with the OpenCV histogram were calculated. Finally, the coin detection algorithm was implemented to improve the wound area measurement.

Liu et al. [37] proposed a system to perform 3D measurement of wounds with mobile device images. The smartphone collected 2D images, and a 3D model was constructed with these images. With these images, the authors unwrapped the texture coordinates, transforming the 3D model to a 2D plane with the least squares conformal map (LSCM) algorithm, segmenting and scaling it to extract and measure the wound area with the conversion between pixels and the actual length. After analyzing 118 wounds on 54 patients, the implemented method reported an accuracy of 97%. The implemented method was constituted by the 3D reconstruction of the body's wound part, and they mapped the 3D model to the 2D plane. After applying the image segmentation techniques, the scale conversion algorithm was implemented to measure the wound area.

Huang et al. [38] implemented a python-based user interface to measure a wound's size with the enhance local contrast (CLAHE) algorithm's implementation. The system reported a reliable accuracy in estimating the size of chronic wounds, but it needed the correct definition of each pixel's size. The proposed system implemented different techniques, including white balance, anti-glare, the enhance local contrast (CLAHE) algorithm, the level set algorithm to find the wound's boundary, and the snakes model algorithm to define an energy function of the image and detect the size of an injury.

Naraghi et al. [39] proposed photogrammetric 3D reconstruction, induration segmentations, and segmented depth maps to measure the wound size with a mobile application to measure tuberculosis infections. The authors started with the scaling of the image and photogrammetric 3D reconstruction. Next, the position and orientation of each image in the 3D space were estimated. With these features, the authors performed the feature matching process. In continuation, the authors evaluated the surface of the object by a dense point cloud. After applying histogram equalization, the Otsu's thresholding algorithm was used to enhance the image's contrast. The induration was cropped for the identification of the margin of the rough. Finally, the elliptical approximation of the induration margins was calculated, and the wound area was measured. In general, the proposed system reported reliable accuracy.

Chen et al. [40] also used the HSV color space when measuring the wound size in surgical wounds, reporting an accuracy of 91%. The system was implemented with a non-professional system that identified the injury in an image, distinguished the state of the surgical wound, and assessed the symptoms. It combined machine learning techniques with image processing techniques to compare the textures of the skin and wounds. Thus, the authors normalized the images. After that, they applied the SEED algorithm for superpixel segmentation to identify the superpixels that were skin. The skin area was reconstructed with superpixels, and the area was detected.

In [24], Gupta converted the image to the HSV color model while measuring a chronic wound area. Next, they performed the segmentation. Next, they extracted the saturation space from the color space and implemented the threshold to enhance the image's contrast with Otsu's thresholding algorithm and the dilation operation. After that, the implemented method found the contours from the binary image using the Suzuki85 algorithm. The number of black pixels inside the segmented image was calculated to design a healing curve plot. Thus, the results reported an accuracy of 70% in the tests performed with 20 photos from various healthcare centers.

Sirazitdinova and Deserno [25] measured the size, depth, volume, rate of healing, color, presence of necrosis, and types of a skin lesion with several techniques. Initially, the authors started with color correction and color calibration on the original 2D images to measure the wound area. Next, 3D reconstruction, color correction, tissue segmentation, and HSV were applied to compute the wound perimeter. Finally, the authors designed the contour in a 2D plane, calculated the area as the number of pixels between the outlines, and translated the measured pixels to real-world measurement units. The system reported a reliable accuracy.

Tang et al. [42] used a scaling method to measure chronic wounds' sizes with a mobile device, reporting reliable results. The scaling method included calculating the approximate size of an injury and inserting and adjusting a rectangular box in the image.

In [43], Garcia-Zapirain et al. mainly implemented the linear combination of discrete Gaussians (LCDG) model to measure the sizes of the wounds, reporting an accuracy of 90.4% in the tests with 24 clinical images of pressure ulcers. Thus, the authors' images of injuries were segmented in the ulcer region, with image decomposition using the parametric equations that defined the toroidal geometry. After that, the resulting image was decomposed in different contrast levels. Next, the threshold technique was performed to enhance the contrast of the image with Otsu's thresholding algorithm, and the contours of the wound were detected. In continuation, the resulting image was transformed from RGB to grayscale, creating an appearance model using linear combinations of discrete Gaussians (LCDG) and minimizing the noise with a generalized Gauss–Markov random field (GGMRF) image model for the calculation of the areas of the wounds.

Dendere et al. [44] proposed a mobile system to evaluate the sizes of wounds from tuberculosis infection with the Mantoux tuberculin skin test (TST), reporting an accuracy of 96.5%. The TST method performs the round-off of the induration size to the nearest millimeter. It starts with the application of a mask to select the relevant part. Next, the matching of common points to the input images is found, estimating each image's camera positions. In continuation, the camera calibration parameters are refined, building the point cloud model, a polygonal mesh, and the texture. Finally, the 3D reconstruction is performed for the measurement of the wound area.

Yee et al. [45] implemented a mobile application for remote wound measurement, tracking, and diagnosis which implemented the Seymour wound model 0910 with granulating, necrotic, and slough, reporting an accuracy of 99.13%. The core of the method includes the extraction of images from videos, and they compute the absolute scale of the wound with optics equations. Finally, the methods trace the contour with wound boundary detection for the calculation of the wound area. The authors tested different known areas from a constant distance of 20 cm from the wound to the smartphone, various specialized tissue types within wounds with known areas, and actual wound simulations.

Saathesha et al. [46] implemented PH2 dermoscopy image information and a D-quick Fourier rework to measure shape geometry asymmetry, border irregularity, color, and the diameter of a melanoma, reporting reliable accuracy. Thus, the authors started with the extraction of RGB channels from images, extracting the blue channel. Next, histogram equalization was performed. Before the application of segmentation techniques, the picture was converted from RGB to grayscale. Next, the average low pass filter was applied, and the threshold was calculated. In continuation, the degree intensity image was converted to a binary image, and Otsu's thresholding algorithm was used to enhance the contrast of the picture. After that, the asymmetry, border irregularity, color, and diameter were extracted, and the image was denoised for the extraction of the region of interest (ROI) of the wound. Finally, the support vector machine (SVM) was implemented for the classification of the wounds.

Furthermore, Cheung et al. [47] estimated the wound size. They classified the tissue with color variation, asymmetry, maximum distance, texture, and border irregularity, based on a 3D model using structure from light, photogrammetry, or motion. The implemented methods were for feature extraction and segmentation.

Pires et al. [23] used the OpenCV library for the measurement of the sizes of wounds. The implemented method consisted of three stages, including preprocessing, segmentation, and wound area measurement, implementing the HSV color model with a Gaussian filter 31×31 in size, reporting reliable results. The OpenCV library was used for the implementation of segmentation, threshold, and color detection techniques.

Bulan [48] used a method for detecting wounds in 36 patients with allergic diseases that included the HSV color space and linear discriminant analysis (LDA) with a reported accuracy of 94%. This paper presented the detection of a wound. Initially, the authors inserted calibration marks to identify the localization of the region of the injury. Next, the image was converted to grayscale, and it was transformed from an RGB to YCbCr color space. After that, principal component analysis (PCA) was performed on the Cb and Cr color channels. Thus, it was possible to find the fly's subspace with the maximal contrast between the wheel and the surrounding erythema. The authors performed the dimensionality reduction by finding an orthogonal projection of the high-dimensional data into a lower-dimensional subspace. The implementation finished with the median filtering, the threshold to enhance the contrast of the image with Otsu's thresholding algorithm, the erosion operation on the binarized image, and the suppression of the structures connected to the image border dilation operation.

Hettiarachchi et al. [22] also implemented the HSV color space while measuring the wound size based on segmentation, camera distance, angle, and lighting conditions. It implemented preprocessing techniques to reduce errors from artifacts and lighting conditions, reporting an accuracy of 90%. The method started with the crop of the center of the wound and removed the unnecessary artifacts. Next, the image was resized and resampled to extract the saturation plane of the HSV color model. In continuation, the authors calculated the contour with the contrast between infected and normal skin, and the authors smoothed the image with a Gaussian filter. After that, the authors applied the snakes model algorithm to define the image's energy function, and they transformed it into a grayscale image. The grayscale image was segmented, building the contour of the wound for further measurement of the wound size.

Kanade et al. [49] measured the cell population, cell cycle, mitotic cell rate, and tree synchrony with microscopic images and performed segmentation of the images. Thus, they performed several actions, including the detection of small, bright rectangular regions in each image using thresholding and convolution, overlapped areas combined into one patch, the detection of candidate patch sequences based on intensity change, and segmentation to analyze the wound images.

4. Discussion

This systematic analysis shows the importance of using technology in the health sector. Once again, and in the wake of what we have witnessed, the emergence of new methods, systems, and applications for the health sector has taken advantage of the development of mobile systems exponentially in recent years, as shown in Figure 4.

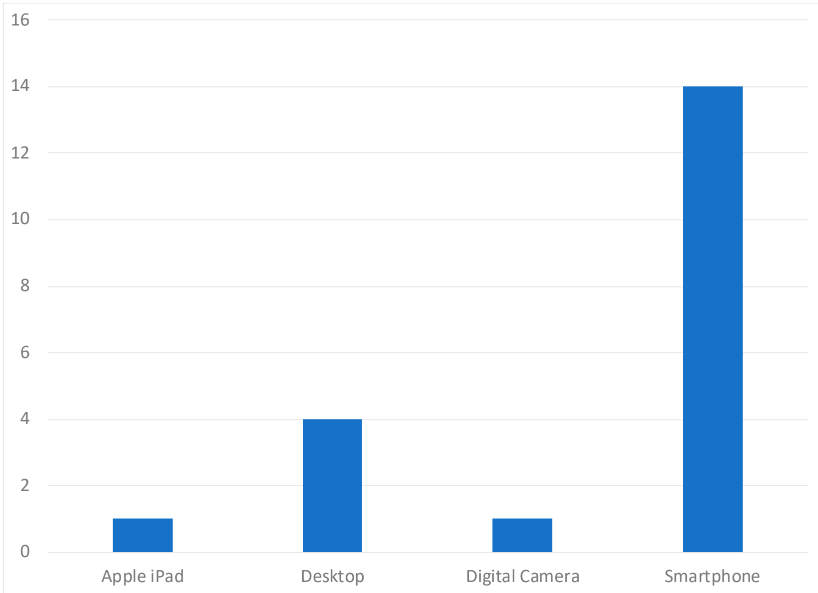

Figure 4. Number of studies per device.

With the improvement of the camera resolution's processing capacity and quality, there is an evident increase in the number of studies and applications related to this integration of health and informatics, especially in recent years, as shown in Figure 5.

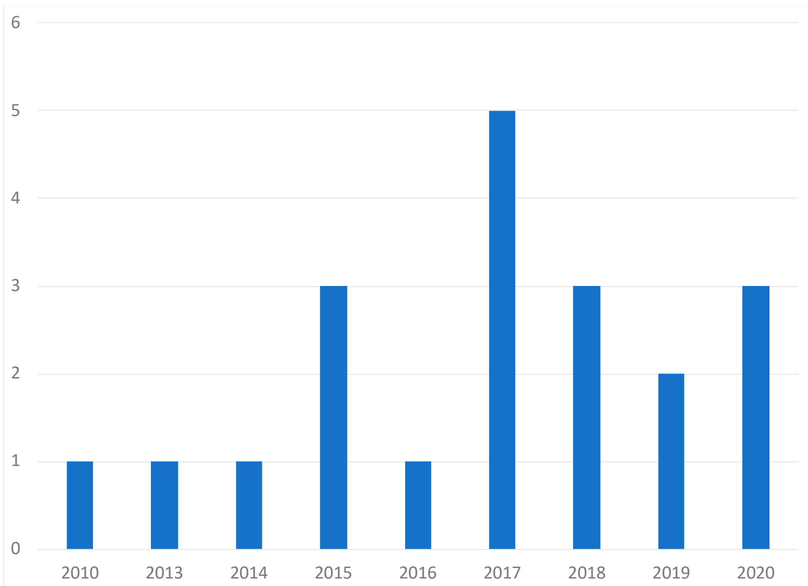

Figure 5. Trend of the selected papers per year.

The analysis of chronic wounds and their calculation and monitoring appear in this context. According to the analysis of this systematic analysis's different studies, they have made firm steps because they present a very high accuracy at 90%. The most-used method in this set of studies was the HSV method, used in 7 of the 20 selected studies, demonstrating its usability and usefulness in these studies. As other recent studies [27,28] in image segmentation show, deep learning has great potential to improve feature extraction. Adaptative learning rates can help speed up the convergence process while achieving better predictive performance [28]. In turn, these approaches might overcome traditional issues in object segmentation related to variable lighting conditions, which might be particularly common when attempting to segment wounds [52].

The number of articles that consider different diseases is shown in Figure 6, and apparently, chronic wounds are in the focus of seven studies.

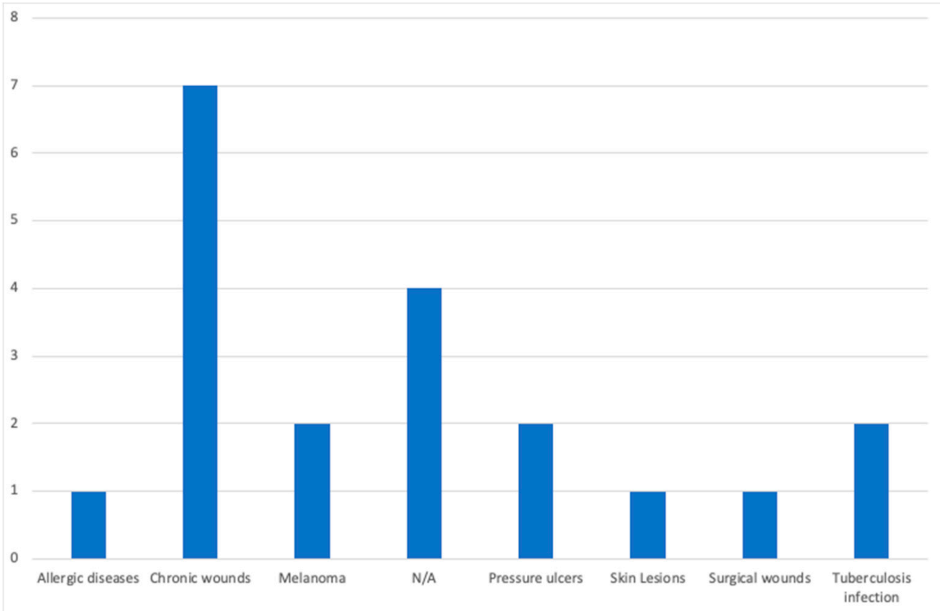

Figure 6. Number of studies per disease.

The use of cameras embedded in mobile devices gives a more commodity-based measurement in different places. However, it may report less accuracy than other measurements performed with more powerful cameras. As this review is more focused on mobile devices, Tables 2 and 3 present the features with more relevance in various studies to measure the wound area and contours with mobile devices and desktop techniques. The use of a desktop computer was not the main focus of this research, and other methods may be applied for the measurement of the wound area, as presented in Table 3. Initially, due to the more high-power processing, we can think that the desktop techniques may allow the more accurate detection of wounds. As presented in Table 2, the mobile devices include other sensors that may increase the accuracy of the wound area's measurement. The mobile devices currently embed more powerful cameras to capture the different wound images with quality to measure the wound area. These devices now include high capabilities for various measurements' performance, and they can perform more accurate measurements. Table 4 complements this analysis with the presentation of the comparison of mobile devices and desktop computers.

Table 2. Implemented methods in mobile devices.

Action	Occurrences
Perform segmentation with threshold	11
Measure the wound area as the number of pixels	5
Convert image to grayscale	4
Perform 3D reconstruction	4
Crop the center of the wound	3
Extract saturation space from color space	3
Perform the histogram equalization	3
Perform threshold to enhance the contrast of the image	3
Adjust the size of the rectangle to the wound	2
Apply snakes model algorithm to define an energy function of the image	2
Apply the level set algorithm to find the boundary of the wound	2
Convert associate degree intensity image to a binary image	2
Extract asymmetry, border irregularity, color, and diameter	2
Extract superpixels which are skin	2
Find contours of the wound	2
Implement support vector machine (SVM) to classify the skin	2
Insert rectangular box in the image	2
Perform dilation operation	2

Table 3. Implemented methods in desktop computers.

Action	Occurrences
Measure the wound area as the number of pixels	4
Perform segmentation with threshold	4
Find contours of the wound	3
Perform threshold to enhance the contrast of the image	3
Convert image to grayscale	2
Detect the wound	2

Table 4. Mobile devices vs. desktop computers.

Mobile Devices	Desktop Computers
Measure the wound area anywhere at anytime	Measure the wound area in a static place
Mobile devices are currently embedding high-quality cameras	The measurement depends on the external cameras that are dispendious
Mobile devices embed other sensors that may allow the calibration of the cameras	The calibration of the cameras depends on other external devices
The resources available are not unlimited	The resources available can be expanded as needed with costs.

Based on the methods applied in the different studies analyzed, the ranking of the most-applied methods is presented in Table 5 to check the most-implemented strategies and further propose of a method to be implemented as future work.

The use of deep learning methods to improve the feature extraction of the different images' image segmentation was used in two of the studies analyzed. This subject is recent and exploiting [27,30]. Other studies in the literature have been about using deep learning techniques for these steps that will improve the results [53,54]. However, using these techniques requires more hardware resources that may not be available in standard mobile devices.

Table 5. Implemented methods.

Action	Occurrences
Perform segmentation with threshold	15
Measure the wound area as the number of pixels	13
Convert image to grayscale	6
Perform threshold to enhance the contrast of the image	6
Find contours of the wound	5
Perform 3D reconstruction	4
Perform the histogram equalization	3
Crop the center of the wound	3
Perform dilation operation	2
Detect the wound	2
Extract saturation space from color space	3
Insert rectangular box in the image	2
Adjust the size of the rectangle to the wound	2
Apply the level set algorithm to find the boundary of the wound	2
Apply snakes model algorithm to define an energy function of the image	2
Convert associate degree intensity image to a binary image	2
Extract asymmetry, border irregularity, color, and diameter	2
Implement support vector machine (SVM) to classify the skin	2
Extract superpixels which are skin	2

From the analysis of the methods for wound area measurement with a mobile device, one important finding is that they need to be more lightweight to have practical applications. Finally, when considering implementing a mobile application for Android devices, the OpenCV library allows the implementation of the different methods locally in the Java programming language. As presented in Figure 7, it must start with the image's capture, and it must be converted to grayscale for further implementation of the threshold. Next, a segmentation method is to be implemented to measure the wound area as the number of pixels for the conversion to metric units.

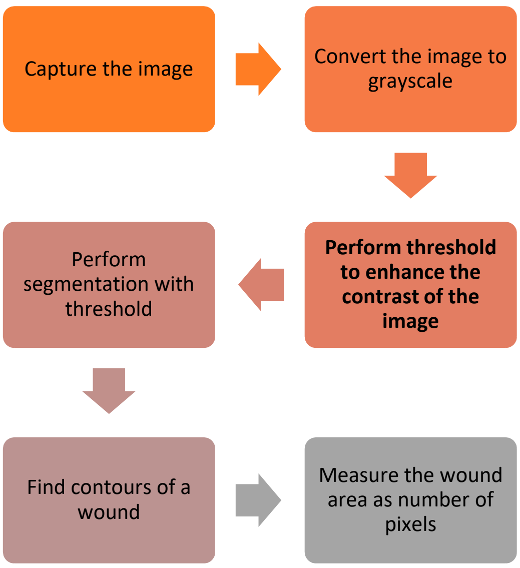

Figure 7. Proposed method to be implemented in a mobile application.

The most critical challenge of this work was the conversion of the measured pixels to metric units. Thus, the mobile devices' proximity sensors can be used to increase the accuracy, measuring the distance to the wound and extrapolating the real area of the injury. The comparative analysis of the studies shown in Table 1 revealed that the smartphone with the operating system was predominant.

No incompatibility was found in the studies analyzed for confidentiality or data protection in the different experiences. We performed a rigorous evaluation of each study to verify the existence of a validation of the study protocol by a human subject research ethics committee, but the information was not conclusive. Thus, we contacted the authors and research groups to obtain more clarification about each study's data protection, but we have not yet received the responses. For the different features in this context, the most common were studies that sought to calculate the wound area, size, and color.

5. Conclusions

In conclusion, this systematic review analyzed, verified, and identified studies that aimed to investigate the size, structure, and area of wounds using open-source systems and most mobile devices. The use of image processing methods for this type of study has grown with the development of smartphones. Still, for the methods to have practical application, the accuracy and robustness of the methods need to be improved. Twenty studies were examined, and the main findings are summarized as follows:

- (RQ1) Which are the techniques that can be applied in a mobile application to measure a wound area? A mobile application can capture different pictures related to different situations, including wounds. The mobile application commonly applies preprocessing techniques, segmentation, threshold, and other methods to measure the wound area;
- (RQ2) What are the most significant features to define a method for the automatic calculation of a wound's size? The most notable feature related to the wound's size is measuring the different pixels and the different points of each wound's contour. The processing techniques and artificial intelligence techniques may be powerful in the measurement of the wound's size;
- (RQ3) What are the benefits that this kind of study can bring to the medical sector? This kind of study's benefits consist of the correct measurement of the evolution of a wound's treatment and the medicine's adaptation according to its changes. It is especially important in patients with diabetes.

For future work, we intend to develop a mobile system to measure the wound size anywhere for a non-specialist. It must have acceptable accuracy for implementing the segmentation, threshold, and identification of the wound size, measuring the distance between the camera and the wound for the accurate measurement of the wound size.

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