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Segmentation of Acne Vulgaris Images Techniques: A Comparative and Technical Study

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Abstract: Background: Acne vulgaris is the most common dermatological pathology worldwide. The currently used methodologies for the evaluation and monitoring of acne have been analyzed in several studies, highlighting important limitations that can be concretely addressed using image processing methods by performing segmentation on different acne vulgaris image modalities. These techniques reduce the costs of treatment and acne severity grading, since they improve objectivity and are less time-consuming. That is why, in the last decade, several studies that propose segmentation methodologies on acne patients' images have been published. The aim of this work is to analyze the segmentation methods developed for acne vulgaris images until now, including an analysis of the processing techniques and image modalities used, as well as the results. Results: Following the PRISMA statement and PICO model, 27 studies were included in the systematic review, and subsequently, they were divided into two groups: those that discuss methods based on classical image processing techniques, such as contrast adjustment and conversion of RGB images to other color spaces, and those discussing methods based on machine learning algorithms. Conclusions: Currently, there is no preference between one group of segmentation methods or the other. Moreover, the lack of uniformity in the evaluation of results for each study makes the comparison of methods difficult. The preferred image modality for segmentation is conventional photography, which shows a research gap in the application of segmentation algorithms to other acne vulgaris image modalities that could be useful, such as fluorescence imaging.

Keywords: bioinformatics; acne; image segmentation; image processing; dermatology

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1. Introduction

Acne vulgaris is an inflammatory chronic disease of pilosebaceous units. A pilosebaceous unit is formed by all the hair follicles related to the same sebaceous gland. The main affected regions are face, neck, chest, and back. Clinical manifestations are seborrhea or overproduction of sebum, the presence of non-inflammatory and inflammatory lesions on skin (open and closed comedones, and pustules and papules, respectively), and scars [1]. It is the most common dermatological pathology worldwide [2]. In total, 85% of adolescents suffer from acne [3].

In order to monitor and treat acne properly, a precise and reliable method to establish the severity of the pathology is needed [4]. There is a wide range of systems for acne grading, which shows a lack of a global standard. Nonetheless, all these methods can be classified into two large groups: methodologies based on manual lesion counting by a dermatologist and those based on the comparison of the patient's skin with a model photography [3,4].

Beyond the above-mentioned classical methodologies for the evaluation and monitoring of acne vulgaris, new computer-based techniques (sometimes applied to new image modalities, such as fluorescence images or polarized light photography) have appeared to solve current limitations. These limitations include time spent and human errors, which lead to an increase in economic costs. One of the most common techniques used to solve these problems is image segmentation. To the best of the authors' knowledge, the present work is the first systematic review on the existing segmentation methods for acne vulgaris images.

2. Methods

To conduct a systematic review on segmentation methods for acne images, a systematic literature review was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). This standard is commonly used for reviews on clinical trials. The analysis included all studies published until September 2022. The studies data collection was performed by exploring four different databases: Scopus (https://www.scopus.com, accessed on January 2022), PubMed Central (https://pubmed.ncbi.nlm.nih.gov/, accessed on January 2022), Web of Science (https://www.webofscience.com/wos, accessed on January 2022), and Google Scholar (https://scholar.google.es/, accessed on January 2022).

The searching strategy was defined according to the PICO model, and it was focused on diagnosis question type. A summary is showed in Table 1. The population included in the studies was defined by 'humans,' the main intervention was defined as 'segmentation of face images of acne vulgaris patients,' the comparison was made with 'manual segmentation,' and the outcome or measure of the algorithms utility included 'diverse results.

Search terms were 'acne images segmentation.' Due to the large number of results obtained with Google Scholar, only relevant publications (those that were cited at least once) were considered. This was proven to be a valid criterion, because for the search terms employed, only the first results page included papers related to the topic of interest. Duplicates were removed using Mendeley.

Table 1. Searching strategy according to the PICO model.

Population	Humans
Intervention	Segmentation of face images of acne vulgaris patients
Comparison	Manual segmentation
Outcome	Diverse results

All the studies describing a segmentation method for acne vulgaris images (applied to any image modality) were included. The references of these studies were also analyzed following the PICO model to prevent relevant papers being excluded. The exclusion criteria were the following:

- All the implemented methodologies that use enlarged images, showing only one lesion per image, for example, dermatoscopy.
- Studies not published in English.
- Those publications which are neither open access nor available to the Polytechnic University of Valencia members.
- Studies that are a continuation of a previous one, in which the segmentation methodology is yet described. For instance, publications about acne lesions classification after image segmentation, when the applied segmentation method has been presented in a previous study and has not suffered substantial changes.

3. Results

Figure 1 shows the search results. Most of the publications were excluded because they were not relevant to the topic (no segmentation methods described or segmentation of images of other pathologies). The number of excluded publications can be explained by the search terms used, which were broad to prevent relevant studies from being excluded.

The screening was manually performed by reading the title and abstract of articles. Only six of the one-hundred records excluded after screening by reading the title and abstract met the exclusion criteria. Special attention was paid to these records and also no segmentation method was described in the abstract. If those publications were considered relevant, the Polytechnic University of Valencia has a special service for specific queries to studies with restricted access.

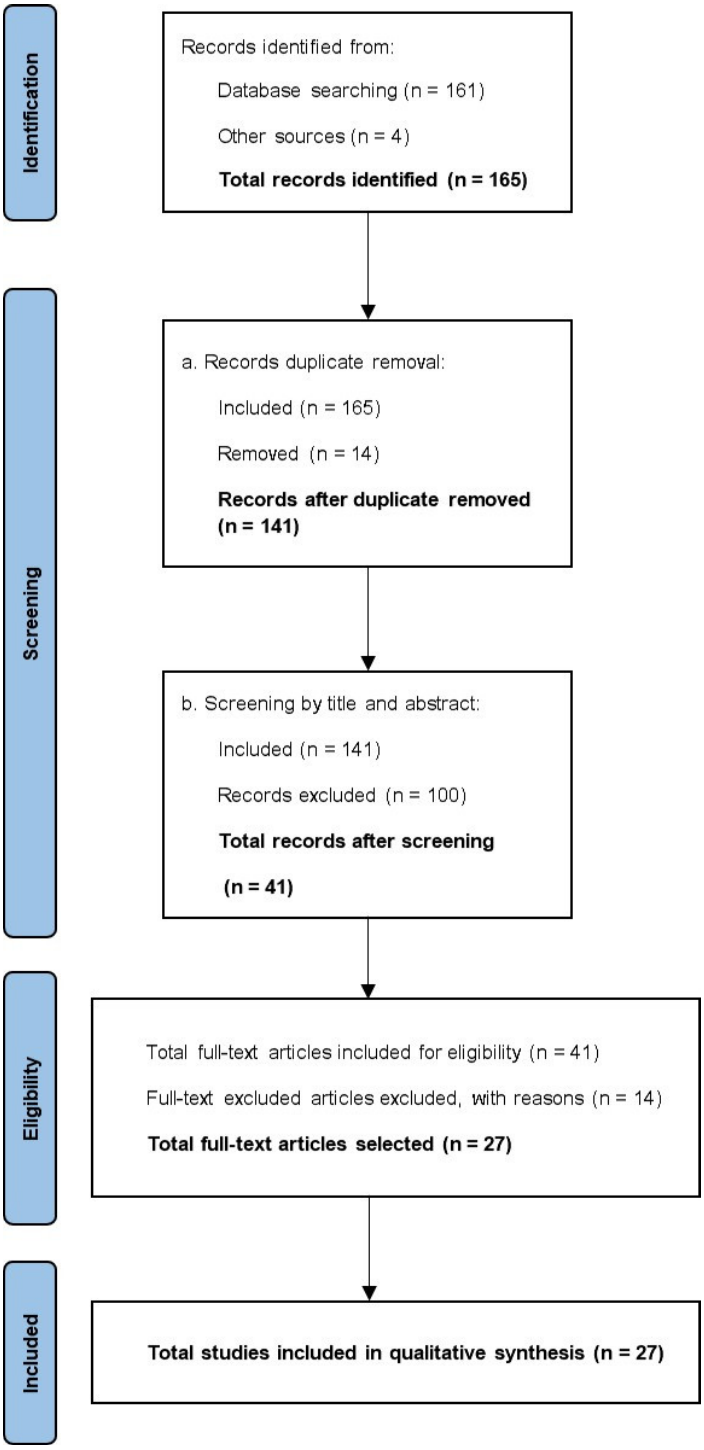

Figure 1. PRISMA flow diagram for the conducted research. Additional records refer to those studies found through the systematic research conducted on the references of the studies found in the databases. Both records and full text articles excluded were done so according to one or more exclusion criteria.

A total of 27 studies were finally included in the systematic review.

In [5], Jena et al., explain that algorithms based on different techniques are used to segment medical images. Globally, these image segmentation techniques studies can be grouped into Classical Image Segmentation Techniques and Machine Learning Segmentation Techniques.

Based on this global classification, the studies were summarized in two different tables. One table includes the studies of segmentation methods based on classical image processing and the other table includes the studies of segmentation methods based on machine learning techniques. Both tables had the following attributes: Study Name, Image Modality, Image database, Proposed Segmentation Method, Ground Truth, Samples for the validation, Relevant limitations, and Outcomes.

As shown in Figure 2, there is a clear definition of Image Segmentation Techniques classification.

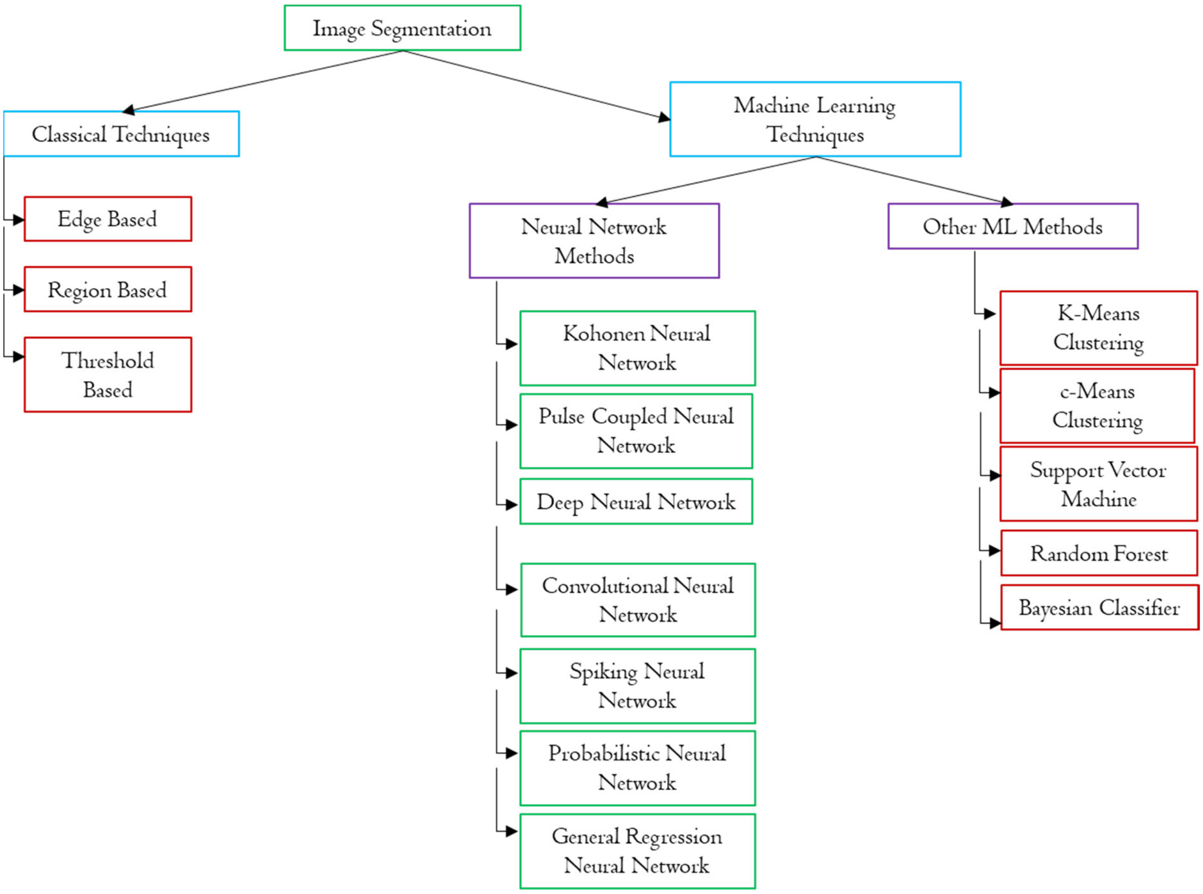

Figure 2. Taxonomy of Image Segmentation Techniques [5].

In general, as mentioned above, the analyzed studies can be divided into two groups: those with segmentation methods based on classical image processing techniques [6–19] and the ones based on machine learning segmentation techniques [20–32]. The first ones consist of a series of steps or operations (such as contrast adjustment, color space conversion, thresholding) that need to be subsequently applied to the image to segment it.

There are also a couple of studies [30,33] that develop three different segmentation methodologies, two of which are based on classical image processing techniques, and the other one uses machine learning algorithms. Some of the publications included in the systematic review not only perform segmentation but also lesion classification with machine learning techniques. In addition, there are studies in which the limit between lesion segmentation and classification is not clearly defined. In those cases, both techniques are mentioned because classification is also relevant. Except for these studies, in the present work, the methods are grouped exclusively according to the segmentation technique.

3.1. Segmentation Methods Based on Classical Image Processing Techniques

It is common for most of the segmentation methods based on classical image processing to convert original RGB color spaces into another one, usually CIELAB or YCbCr. In [7], the authors worked with standard photographs that were converted into gray images (since they were easier to process). To obtain the region of interest (ROI), the authors subtracted the V component of HSV model (obtained from RGB original image) to the normalized gray image. The resulting image enhances the contrast between healthy skin and acne lesions. Afterwards, thresholding with an experimentally obtained threshold value was performed. Later, the authors introduced the use of a Bayes classifier to reduce the errors by training this classifier to distinguish between lesions and noise [34].

HSV color space is also used in [13]. The authors of this study developed a Windows application that detects acne lesions on conventional photographs. To achieve this, the input image needs to be converted to grayscale in order to detect the subject's face and eliminate the image background. Once the ROI is obtained, the application generates a heat map in HSV color space using the G component of the original RGB image. The G (green) channel is chosen because the authors maintain that, with this component, the contrast between acne lesions and healthy skin is maximized. Then, adaptive thresholding on the G component is performed to demarcate lesions using blob detection. Determining the proper threshold value is crucial since it influences the segmentation results. Hence, HSV space is used to create a heat map that shows acne lesions, but this is not necessary to perform the segmentation.

In [6], Ramli et al., uses CIELAB color space. The authors support that this is the most convenient color space to analyze color distribution on the skin. Therefore, the first step of their segmentation method involves the conversion of conventional RGB photographs to CIELAB. Then, Otsu's method is applied to the image to classify pixels into three groups: normal skin, acne lesions, and scars. In another study [15], the authors implemented a method based on the generation of a heat map, on which (after failing to apply global thresholding) adaptive thresholding is applied to distinguish acne and healthy skin. The heat map is created using a* component of CIELAB space (this component emphasizes red areas, enhancing the visualization of inflamed areas above healthy skin). The algorithm offers the possibility to manually choose the threshold value, because adaptive thresholding did not work in every image. Finally, blob detection is performed using the Laplacian of a Gaussian filter. The authors affirm that the algorithm localizes and counts the lesions. However, these results are neither shown in the publication nor quantified.

In the study developed in [8], they opt to increase dynamic range on YCbCr images in order to augment contrast and enhance lesions visualization. This is achieved by modifying the luminance component. Y. Segmentation is performed on RGB modality so that the sequence is as follows: RGB to YCbCr, contrast adjustment, processed YCbCr to RGB. The mapping of RGB image pixels to a visible spectrum is proposed as a way of visualizing little color changes (spectrum 380–720 nm range is obtained with a band separation of 1 nm). This is the only study that suggests RGB to visible spectrum mapping. Finally, the classification of pixels is performed: red, purple, and brown lesions and healthy tissue or specular reflection. Classification is based on Mahalanobis distance—each pixel is assigned to the nearest class (based on spectrum wavelength). This could be considered machine learning, but this study has been included in the classical methods group because the final objective is to obtain a binary mask to demark acne lesions using thresholding. Moreover, in [8], no machine learning algorithm was applied.

YCbCr model is also utilized in the segmentation methodology implemented in [10], where a hardware image capture system for Smartphones and an Android application are developed. This application detects and classifies several dermatological conditions, including the following: spots, wrinkles, and acne. To identify acne, a thresholding using Cb values (which was observed by the authors to be high for acne lesions) is performed. The proportion of acne points in ROI is calculated. It should be noted that the system can acquire fluorescence images, but they are not used in segmentation.

There are some studies that do not use any color space conversion regarding the segmentation of acne vulgaris images. In 2012, the authors of [9] used template matching on acne vulgaris images for the first time. This technique consists of overlapping a template and an image region and calculating their correlation using different statistical parameters (in this case, the chi-squared test was calculated) so that it is possible to locate acne lesions by scanning the image with the template. The template is generated by training an algorithm using acne images (average images). In addition, in [11], a segmentation method with the aim of counting acne points automatically is developed. The authors only use the RGB channels of the image. The first step of the algorithm involves the estimation of the relation between the image pixels and the real length (in mm) they represent. Then, the identification of lesions can be performed as follows:

Detection of papules and nodules is performed by filtering and binarizing B-R and G-R components of the original images. The resulting objects are classified into papules or nodules according to the length of their main axis.

Closed comedones are an elevation on the skin surface, and this results in illumination changes in the images. Hence, templates based on illumination changes are created to detect them. Then, the correlation between these templates and the B component of the images is analyzed. Finally, an artificial neural network (ANN) is used to determine which of the points of the binarized image are true closed comedones.

Open comedones are detected using B-R and G-R components and a series of operations, including the following: contrast increase, image complement, hair elimination, image opening (to eliminate artifacts), contrast adjustment, smoothing, binarization, pruning, and cropping. An ANN is used as in the previous case.

The methodology used for the detection and segmentation of papules and nodules determined the classification of the work in Classical Image Processing Technique.

In [12], Liu proposed a segmentation method for conventional photography based on an iterative algorithm that minimizes energy function. This is color-based segmentation. The morphology of the objects is analyzed to eliminate non-acne formic points. By means of normalized maps of the distribution of skin chromophores, lesions can be classified into inflammation and hyperpigmentation.

There are two segmentation methodologies implemented for fluorescence images. Son et al. [17] used a Wood's lamp in order to obtain fluorescence images and proposed a color-based segmentation method.

In a later study [16], they used fluorescence images to perform automatic acne lesion counting. In this method, images are acquired using VISIA-CR commercial system (Canfield Scientific, Inc.; Parsippany, NJ, USA). Subsequently, images are converted to grayscale, and an increase in contrast via histogram equalization is observed. Then, an extended maxima transform is applied. The authors evaluate the ability of the algorithm to count the lesions, but not the previous image processing.

In [18], they captured images of a small region of skin with a phone LED microscope. The images captured were color images. First, they detected the disease lesions using color image processing techniques and a color gradient segmentation. In a second step, they applied morphological operators to extract the blackheads shape. They concluded that the subjectivity associated with the color umbral provide a poor final result.

In another study [19], Wu et al. used fluorescence images for counting the number of infected points. In this method, the images acquired in RGB space are converted to HSV space, and color threshold is applied.

Table 2 summarizes all the segmentation methods based on classical image processing techniques.

Table 2. Existing segmentation methods for acne vulgaris images that are based on classical image processing techniques.

Study	Image Modality	Images Database	Proposed Method	Ground Truth	Samples for the Validation	Relevant Limitations	Outcomes
[14]	Conventional photography	Not indicated	Region growing	Not indicated	Not indicated	The user must place the seed manually. Each lesion needs a different threshold value.	Authors only report that results are satisfactory, without providing any data.
[15]	Conventional photography	DermNet, DermQuest	Heat map + thresholding	Not indicated	Not indicated	The difficulty of thresholding makes the manual selection of threshold value necessary in some of the images.	No details of segmentation results are provided.
[13]	Conventional photography	Own images	Adaptive thresholding	Method has not been validated yet	Method has not been validated yet	No limitations indicated yet.	Results not evaluated yet.
[7]	Conventional photography	Not indicated	Enhancement of ROI (normalized gray image − V component from HSV space) + thresholding	Manual lesion counting	Ten images were used in the validation	High probability of obtaining false positives because of similarity with the characteristics of acne lesions.	Precision = 80% Sensitivity = 86.37% Accuracy = 70%
[8]	Conventional photography	Own images	Increase in dynamic range + mapping of each pixel to a band of the visible spectrum	Severity of acne estimated by experts	Number of images not indicated	The authors do not indicate any limitations.	Evaluation of the method's ability to grade acne: Specificity > 80% Sensitivity > 60%
[12]	Conventional photography	DermNet NZ	Color-based segmentation using an iterative method based on energy minimization	Human visual inspection	50 images were used in the validation	No limitations indicated.	Quantitative analysis of results has not been performed yet.
[11]	Conventional photography	Own images	Processing techniques vary depending on acne lesion type	Manual lesion counting and lesion type classification	Number of images not indicated	No limitations indicated.	Correlation between manual and automatic counting, for each lesion type: Pearson correlation coefficient > 0.93 (0.54 for open comedos) Detection of each lesion type: Sensitivity > 66% Specificity > 74% except for open comedos (21%).
[10]	Conventional photography	Own images	Thresholding	Skin inspection by experts	99 images were used in the validation	No limitations indicated.	Distinction between acne and healthy skin: Accuracy = 82.82%

[9]	Conventional photography	Kuala Lumpur hospital database	Template matching	Not indicated	Ten images were used in the validation	Optimization of filtering is needed in order to decrease the errors caused by illumination changes and texture of images.	Results are good, but they cannot be considered, since the described method is still under development: it is not robust, there are considerable variations in sensitivity and precision among the images.
[16]	Fluorescence images	Own images	Histogram equalization + extended maxima transform	Manual lesion counting	Ten images were used in the validation	No limitations indicated.	Automatic counting: Accuracy = 83.75% Sensitivity = 98.22% Precision = 85.04%
[21]	Conventional photography	Own images	Thresholding by Otsu's method	Segmentation by experts	185 images were used in the validation	No limitations indicated.	Sensitivity > 80% Specificity > 80%
[17]	Fluorescence images	Own images	Thresholding + color-based segmentation	Not indicated for the calibrated system	29 images were used in the validation	Readjustment of parameters of the color-based segmentation is needed.	Results for the calibrated system are not quantitatively evaluated.
[18]	LED microscopy color images	Own Images	Thresholding by color + morphological operators segmentation	Manual counting	15 images	No limitations indicated	Do not provide good results.
[19]	Fluorescence images	Own Images	Thresholding by color and contour detection	Manual counting	3595 images	No limitations indicated	Accuracy 71% Sensitivity 72% Precision 88%

3.2. Segmentation Methods Based on Machine Learning Techniques Algorithms

K-means is the most common machine learning algorithm used to segment acne vulgaris images. In [21], the authors opt for this algorithm with k = 3.

The methodology proposed by Khan et al., in [23] is based on fuzzy c-means (FCM) segmentation on several color spaces and the intelligent selection of the desired cluster by using a function. Results showed that the optimal number of clusters is three, and the best segmentations results were obtained with I3 and Q components. These results are similar for both channels, because the way they are calculated from RGB space is similar.

The features that can be extracted when implementing machine learning algorithms are diverse. Usually, information is obtained from the images, but there are also studies that analyze the convenience of using other types of features. In [24], Madan et al. use cross-polarized light images to monitor acne lesions considering both spatial and temporal features (the latest ones are their main contribution). In this method, to distinguish acne lesions from healthy skin, a logistic regression classifier is used. In [25], Arifin et al. develop a system that detects different dermatological pathologies, and acne is one of them. They use not only visual information (from conventional images) but also data from the medical record, among other things. The pre-processing and ROI detection phase separates healthy skin from the affected skin. This is performed by processing the color gradient of the image and performing thresholding and k-means. Finally, an ANN is used to classify the lesions.

Chang and Liao in [26] propose a segmentation method to detect both acne points and spots. To detect acne lesions, they use the Cr channel from YCbCr color space. Histogram thresholding is performed to detect potential skin defects on images. These defects are classified into acne, spots, or healthy skin by texture feature extraction and SVM classification.

As previously mentioned, the authors of [33] published a study wherein they describe three different methodologies for the segmentation of acne vulgaris images. The first one involves color-based segmentation using the k-means clustering code from Matlab [35]. They subsequently convert RGB images to CIELAB color spaces and perform clustering twice. The first execution of k-means has to be k = 2. A second k-means is executed on the resulting image but with k = 3. This is performed to reduce error in the first segmentation since second clustering divides pixels in healthy skin, acne points, and healthy skin that is wrongly assigned to the acne cluster in the first segmentation.

The second methodology of Alamdari et al. [33] is based on texture analysis. The authors affirm that the dynamic range of acne pixels is larger than the one of normal skin pixels. They do not provide more information about this method. The last method is their own version of color blob utility with automatic thresholding and tolerance calculations from Matlab [36]. They use HSV color space to perform color-based segmentation. The authors affirm that the segmentation method that provided best results was the one based on k-means clustering. The results for the other methodologies are not provided. It should be noted that Alamdari tried to use watershed segmentation and multi thresholding, but the results were not satisfactory.

In [27], Zhao et al., in collaboration with Microsoft, developed a convolutional neural network algorithm to classify the lesions that appear in selfie images into five classes. They used 4700 images, but ultimately, they only obtained a classification with or without acne skin.

Following the same line as the above study, in [29], Lim et al. used a total of 472 color photographs to apply deep learning techniques and demonstrate the potential for automated clinical image analysis and grading.

Yadav et al. in [30] developed a study comparing three segmentation techniques: k-means, texture analysis, and HSV model-based segmentation. After the segmentation algorithms, they used convolutional neural networks to classify the lesions. The proposed methodology achieved 97.5% accuracy.

In a very recent study, the authors of [32] used an extreme learning machine algorithm for the identification of acne vulgaris type conventional photographs. Hasanah et al. processed 100 images and obtained an accuracy around 80%.

Table 3 summarizes all the segmentation methods based on machine learning algorithms.

Table 3. Existing segmentation methods for acne vulgaris images that are based on machine learning algorithms.

Study	Image Modality	Images Database	Proposed Method	Ground Truth	Samples for the Validation	Relevant Limitations	Outcomes
[33]	Conventional photography	Own images	Nested k-means	Not indicated	35 images were used in the validation	It is necessary to develop a new concept of relative color, in order to prevent differences in segmentation results due to the differences among individuals' skin tone.	Accuracy = 70%
[23]	Conventional photography	Own images	Fuzzy c-means	Not indicated	50 images were used in the validation	No limitations indicated.	With Q component: Sensitivity = 89.67% Specificity = 93.19% Accuracy = 92.63% With I3 component: Sensitivity = 89.54% Specificity = 91.62% Accuracy = 91.05%
[22]	Conventional photography	Own images	K-means + SVM	Segmentation by experts	50 images were used in the validation	No limitations indicated.	After postprocessing: Sensitivity = 90% Specificity = 97.2% Accuracy = 93.6%
[26]	Conventional photography	Own images + database images	Thresholding in YCbCr space + SVM	Not indicated	97 images were used in the validation	No limitations indicated.	Accuracy = 99.40% Sensitivity = 80.91% Specificity = 99.42%
[25]	Conventional photography	Own images	Color gradient + thresholding + k-means	Not indicated	405 samples were used in the validation	No limitations indicated.	In acne detection: Accuracy = 96.66%
[24]	Polarised light photography	Own images	Classifier based on logistic regression	Not indicated	39 images were used in the validation	Big precision needed in images registration.	89.2% of regions correctly classified
[6]	Conventional photography	Own images	K-means	Segmentation by experts	Not indicated	No limitations indicated.	Sensitivity > 81%, specificity > 81%
[20]	Multispectral imaging	Own images	Linear discriminant function	Not indicated	Not indicated	Authors manifest the need of a more complex classifier. Finding spectral features that don not	Results are diverse and details are not reported.

						depend on image conditions is also needed.	
[27]	Conventional selfie images	Own images	Convolutional Neural Networks	230 images selected by dermatologist	4000 images	No limitations indicated.	Good results distinguishing acne and health skin
[28]	Color Images	Own images	Deep Residual Neural Networks	Auto trained validation model	1800 images	No limitations indicated.	94% accuracy classifying 5 acne classes
[29]	Conventional Photographs	Own images	Convolutional Neural Networks	Classification by experts	472 images	No limitations indicated.	Three acne groups with a Pearson correlation accuracy 67%
[30]	Conventional Photographs	Own images	K-means + HSV segmentation + Texture Analysis + CNN classification	Experts Labelling	120 images	No limitations indicated.	K-means + CNN allow detect 70% lesions
[32]	Conventional Photographs	Own images	K-means segmentation + ELMA classification	N/A	100 images	No limitations indicated.	80% effectivity classifying acne lesions in three categories.

4. Discussion

The present systematic review aimed to analyze the existing segmentation methods for acne vulgaris images, with special emphasis on image modalities used and the validation of results. Although there are four studies [16,17,20,24] which perform segmentation on other image modalities, there is a clearly preferred one—conventional RGB photography. This was used in 80% of included studies.

The acquisition of conventional photography is easier than the acquisition of the other image modalities used (polarized light photography, multispectral images, and fluorescence imaging). However, this shows a research gap regarding segmentation for other modalities since they could provide relevant information or make segmentation easier. For instance, polarized light photography helps properly distinguish between inflammatory and non-inflammatory lesions [4]. The properties of polarized light photography and its advantages have been shown in several studies [37,38] and could ease the segmentation process.

With only three spectral bands, RGB cameras have a poor precision in the reproduction of color; hence, detection and distinction of each type of acne lesion is difficult because they present subtle differences in their spectral attributes. Therefore, the use of a multispectral image is a good option to perform segmentation for this pathology [20].

Fluorescence photography clearly shows the location of acne lesions, and hence can be used to implement simple and robust color-based segmentation algorithms. The utility of fluorescence images in the evaluation of acne was proven by Lucchina et al. in [39].

There is a lack of uniformity in the evaluation of the results for each study. In some cases, this validation is not even provided [14,15,17,20]. In works [12] and [13], quantitative evaluation was not performed.

The results provided by Humayun et al. in [9] cannot be considered. Since this technique is still under development, it is not robust and presents considerable variability in sensitivity and precision amongst the images.

The majority of authors [6,7,10,11,16,19,21–23,25,26,28,29,33] validate their results by calculating sensitivity, specificity, precision, and accuracy.

However, the validated aspects of each study differ from the rest because of the different objectives of each work (segmentation itself can be the aim of the publication or one of the necessary steps for achieving automatic lesion counting, for instance). Therefore, there are studies which do not evaluate the segmentation results (the algorithm's ability to detect acne pixels). The authors of [22] thereby evaluated the system's capability to estimate acne severity, whereas in [16], the authors validated automatic acne lesion counting. Detailed information about the evaluation of results for each study can be seen in Tables 2 and 3.

This lack of uniformity makes the comparison of segmentation methods difficult. In most cases, more information about the validation of the segmentation phase is needed. Moreover, it can be noticed that, currently, there is no preference between segmentation methods based on classical image processing techniques and those based on machine learning algorithms because research groups continue to work with both methodologies, as the publication years of the studies show.

Summary of Limitations

Tables 2 and 3 show the limitations for each analyzed study. It should be noted that the main limitation of the algorithms based on classical image processing techniques is the need for human intervention. This lack of automatization makes the algorithms less efficient than those based on machine learning techniques. However, as it has been previously mentioned, it is not possible to affirm that there is a group of methodologies that provides better results than the other one due to a lack of uniformity in the validation of these results.

Related to the design of this study, exclusion criteria number three could be considered its main weakness. As shown in Figure 1, all the records (title and abstract) found were included (Identification step). In the Screening step, we identified those for which we did not have access to the complete work and had to discard them. However, they were not discarded directly—the abstract was analyzed, and since they were not considered relevant, the exclusion criterion was applied. As explained above, if the records were considered relevant, special access to the full text could have been requested.

5. Conclusions

There is a wide range of image processing techniques that have been applied to acne vulgaris images to improve current evaluation and monitoring systems for this pathology.

Although the usefulness of image processing techniques has been demonstrated, there is still a large research gap, and more information is needed on the results obtained in order to compare and improve the techniques.

Segmentation methodologies developed before the cut-off point of September 2022 have been compiled and synthesized in this paper. This synthesis provides a tool on which to base the development of new algorithms and methodologies for dermatologic image segmentation.

As shown in the work, there are developed methods that show good results in the field of segmentation and automatic detection of infected lesions. These methodologies for recording clinical information must be standardized and applied in conventional clinical practice. They are an objective tool for the systematized evaluation of the disease.

In another sense, we find that the results of each work are not evaluated with the same parameters or values, so it is difficult to compare and assess them, which is optimal. It is necessary to standardize the results to be evaluated when applying segmentation algorithms to be able to compare studies.

Finally, it is striking that the most-used image modality is the conventional color image. However, other imaging modalities, such as fluorescence imaging, provide more accurate information about the disease state.

Therefore, further work is needed to develop image segmentation methods that allow the objective assessment of the disease and encourage the application and use of new imaging modalities that provide more accurate information.

The combination of new image segmentation algorithms applied in new imaging modalities, as well as their clinical implementation, should be the future of the diagnostic management of the disease.

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Data Availability Statement: All the data analyzed in the study can be found published in the papers included in the bibliography and references. It is not necessary to consult additional data sources for obtain it.

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