Comparative Study for Melanoma Segmentation in Skin Lesion Images

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ABSTRACT

Melanoma is the leading cause of fatalities among skin cancers and the discovery of the pathology in the early stages is essential to increase the chances of cure. Computational methods through medical imaging are being developed to facilitate the detection of melanoma. To interpret information in these images efficiently, it is necessary to isolate the affected region. In our research, a comparison was made between segmentation techniques, firstly a method based on the Otsu algorithm, secondly the K-means clustering algorithm and finally,the U-net deep learning was developed. The tests performed on the PH2 images base had promising results, especially U-net.

Keywords

Melanoma; Segmentation; Otsu; K-means; U-net.

1. INTRODUCTION

The number of people with cancer is increasing worldwide, the International Cancer Research Agency (IARC) reported that by 2018 the estimated global cancer burden has been increased to 18.1 million new cases and 9.6 million of deaths [5]. This research addresses cancer known as cutaneous melanoma that originates in melanocytes (melanine-producing cells).

Among skin cancers, melanoma is the leading cause of fatalities and has been increasing worldwide. According to the World Health Organization (WHO), around 132,000 new cases of melanoma occur each year [14]. For [6] melanoma may arise from a normal skin or a pigmented lesion. In a normal skin, the manifestation of the disease occurs after the appearance of a dark spot of irregular edges accompanied by itching and peeling.

If detected in the early stages, melanoma is more likely curable and increases patient survival rates. The need to discover the disease in it's early stages, coupled with the increased number of cancer cases has boosted research to produce ways to diagnose pathologies promptly. Thus, with the help of pattern recognition techniques and image processing in medical examinations aiming at obtaining automatic and accurate reports, with lower cost and greater agility, allows the physician a better pre-diagnosis.

According to [10], image processing refers to the transformation of an image successively so that the information contained in it can be extracted more easily. It is possible to interpret visual information during diagnosis by analyzing color, shape, and texture from obtaining a description of a particular region of the image by extracting static features it has.

The segmentation of skin lesions in dermoscopic images has been the subject of much research. For a better classification of the lesion, it must be analyzed in isolation, without the interference of background noise. However, isolating the region of interest is a difficult task, because the images have several elements such as shadows, hair and other types of noise beyond the lesion [13].

Thus, this paper proposes to perform a comparative study for the segmentation of melanoma in images of skin lesion. For this purpose, the traditional Otsu and K-means technique will be used in comparison with the U-net convolutional neural network.

2. RELATED WORKS

This section is focused on approaches of some works of literature developed with segmentation methods to analyze each methodology used.

In [3] a segmentation algorithm that includes two stages was proposed. At the enhancement stage, healthy skin information is extracted and color and brightness bump maps are constructed. By merging the two protrusion maps, the object of the lesion is enhanced. At the segmentation stage, the Otsu threshold is adjusted by an optimization function, finally, points and holes are removed and final segmentation is obtained. In the database PH2 had index Dice of 0.8935.

In the work of [11] a segmentation architecture based on adversarial networks is proposed. The architecture consists of a U-net segmentation network and a discrimination network linked by certain convolutional layers. Both networks are alternately trained for high segmentation accuracy. In database PH2 obtained 0.9000 of coefficient Dice.

In [2], a new method of automated segmentation of skin lesions by Supervised Image Learning (ISL) and Multiple-scale Superpixel-based Cellular Automata (MSCA) was proposed, resulting in a Dice index of 0.8157.

In [1] work, it has been suggested that protrusion detection using reconstruction errors derived from a sparse representation model together with a new background detection can more accurately discriminate injury from surrounding regions. They also proposed a Bayesian structure that better delineates the shape and boundaries of the lesion. The proposed SSLS method resulted in 0.7838 average Dice.

Regarding the works, it is observed the need to improve the results in [2] and [1] because they were more distant from the others. In [11], however, as the opposing network is made up of two networks that learn from each other, it demands greater computational power. The purpose of the methodology in question is to develop a simplified U-net that is faster and achieves similar results with a reduced computational cost. An Otsu-based methodology will also be developed to compare with the U-net.

3. THEORETICAL FOUNDATION

For computer-assisted diagnosis (CAD) of melanoma, it is essential to perform automatic segmentation of skin lesions, since the analysis of the region in isolation increases the chances of correct classification of the disease. According to [13], the segmentation of skin lesions is a challenging task because the lesions present high variations in size, shape, color, and appearance. The confusing and jagged margins of hairy lesions and other background noises make the task even more difficult.

For segmentation can be used the Otsu algorithm, which according to [9] is a non-parametric and unsupervised method of automatic threshold selection for image segmentation. An ideal threshold is selected by the discriminant criterion in order to maximize the separability of the resulting gray level classes. Using otsu, it is possible to generate a new image only with the region of the skin lesion where melanoma manifests.

In order to obtain better segmentation, several clustering algorithms were proposed. Among them, the K-means algorithm is widely used in many applications. According to [7], K-means is an unsupervised learning algorithm that aims at grouping, being able to divide a set of N observations into K categories. In it, each observation will belong to the category closest to the average. For this, the amount of K categories is provided is known as centroids.

Traditional segmentation methods such as Otsu and K-means require extensions to complex problems, instead convolutional neural networks such as [12] U-net can be used. This networking and training strategy is based on the strong use of data augmentation and consists of a contraction path to capture context and symmetrical expansion path that allows precise localization. The network is very fast and can be trained from end to end from a few images yet still get a good result.

4. MATERIALS AND METHODS

The method proposed in this paper aims to segment melanoma in dermatological images and will follow the steps presented in Figure 1, starting with the acquisition of images where the PH2 base was chosen, segmentation with the Otsu algorithm and U-net network, finally validation with the Dice coefficient.

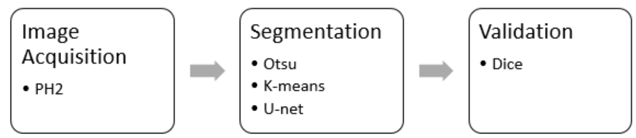
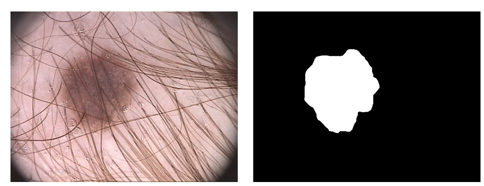


Figure 1: Flowchart of methodology steps.

4.1 Image Acquisition

The image acquisition stage consists of gathering the images with cutaneous lesions and segmentation masks made by doctors to be used in the research. The base chosen was PH2, which has 200 images, 40 melanoma and 160 non-melanoma [8]. In Figure 2, in (a) we have an example of skin lesion and in (b) the doctor's segmentation mask.



(a) (b)

Figure 2: Example of PH2 database lesion and mask. (a) Lesion and (b) Mask.

4.2 Segmentation

This section is aimed at presenting the segmentation techniques used in this work so that we can know the characteristics and stages of each one.

4.2.1 *Otsu*

The segmentation using the Otsu algorithm occurred following the steps in Figure 3. Initially in (a) tests were performed between the red, green and blue channels, in addition to gray levels where the green channel obtained the best results. In (b) the images were blurred using the average filter to smooth out the hair in order to discard them during binarization.

Already in (c), the images were binarized with the Otsu threshold and at the same time, the morphological closure operation (dilation followed by erosion) was performed with the structuring element of circle type 5 to remove loose artifacts without affecting the region of the lesion.

In (d) the intensity range of the input image was inverted so that the maximum type became the minimum and vice versa so that in (e) objects connected to the edges of the image were removed, with the operation of segmentation clean edges.

Finally, in (f) the image regions are identified and a mask is created with the coordinates of the largest area region, eliminating loose regions that are not part of the lesion.

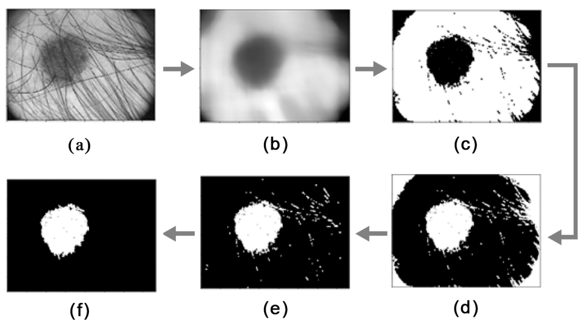


Figure 3: Proposed Otsu Segmentation Methodology. (a) Green Channel, (b) Hair Removal, (c) Otsu threshold, (d) Inversion of Intensity Range, (e) Edge Removal and (f) Mask Creation.

4.2.2 K-means

Segmentation using the K-means algorithm occurred following the steps in Figure 4. In (a) tests were performed between the red, green and blue channels and gray levels, and gray levels were chosen because they obtained the best result. Next, in (b) a gamma correction was performed in the input image to enhance the lesion region, making it darker, using the gamma = 2 value.

To remove the hair in (c), the morphological operation was performed (dilation followed by erosion) with a structuring element of the disc type 6. Due to the image has many heterogeneous areas, in (d) a Gaussian filter was applied of sigma = 30 to blur the image and make it more homogeneous, facilitating the clustering of regions.

To further highlight the lesion, in (e) gamma correction was performed again, with gamma value = 3. Many images had weak intermediate regions between the lesion and the edges, which connected the two regions during clustering. To highlight these intermediate regions we used (f) a Contrast Limited Adaptive Histogram Equalization (CLAHE).

After performing this pre-processing on the input images, the K-means clustering algorithm is used in (g) with three clusters. With the clear edges segmentation operation, objects connected to the edge's in (h) have been removed. In the end, some images still held some loose artifacts to remove them, in (i) the image regions are identified and a mask is created with the coordinates of the largest area region.

4.2.3 U-net

The U-Net-based deep learning model created in this research differs from [12] proposal in it's number of layers and its architecture can be seen in Figure 5. On the left side, there is the contraction path to capture the context. Symmetrically, there is on the right side of the expansion path,

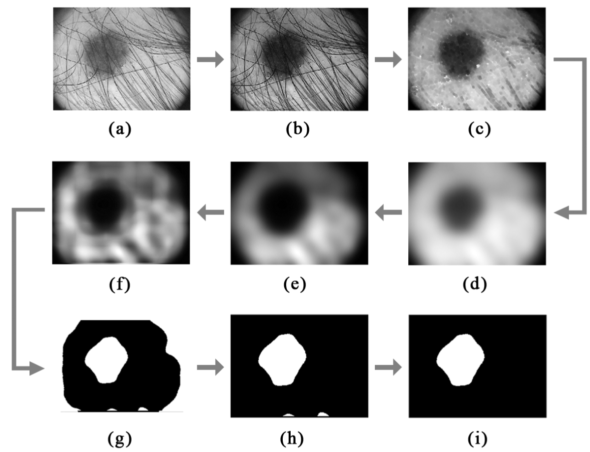


Figure 4: Proposed K-means segmentation methodology. (a) Gray Levels, (b) Gamma Correction, (c) Hair Removal, (d) Gaussian Filter, (e) Gamma Correction, (f) CLAHE, (g) K-means Clustering, (h) Edge Removal and (i) Mask Creation.

which allows a precise location. Network entry is an RGB image of the skin lesion and the doctor's segmentation mask.

The model has four sub-sampling layers that has an average activation function. A convolution transposed on the expansion path is used. The convolutions are followed by a batch normalization layer and a 20 % Dropout layer. In the end, the segmentation is generated by a convolution (1 x 1) with a sigmoid activation function.

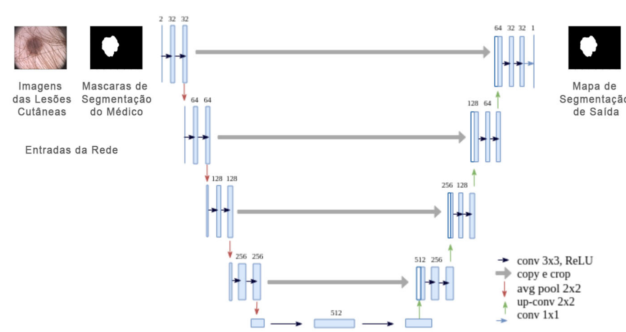


Figure 5: U-net network architecture used.

Finally, network training occurs through a loss function called Dice Loss, which can be represented by Equation 1, where VP means true positive, which is when pixels are correctly classified as melanoma. FP is false positive when pixels are misclassified as melanoma and FN false negative when pixels are misclassified as non-melanoma.

$$DiceLoss = 1 - \frac{2 * VP}{2 * VP + FP + FN}. \tag{1}$$

4.3 Validation

In this research, the Dice Index (DSC) is used for validation, which is widely used as a measure for segmentation performance and indicates the proportion of shared pixels between two samples in relation to the total pixels. Its value ranges from 0% (no match) to 100% (full match) between volumes. The Dice is calculated by Equation 2 [4].

$$DSC = \frac{2 * VP}{2 * VP + FP + FN}. \quad (2)$$

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

After segmenting the entire set of images with the proposed methodologies, the DSC average was calculated. Table 1 presents the results of the developed methods and related work.

The best result of the segmentation technique was obtained using the Otsu algorithm, the mean DSC = 0.8090. For the proposed technique with K-means algorithm, the best result was 0.7398.

It was noticed that the results of traditional techniques are impaired by several factors such as low contrast, presence of hair on top of the lesion, poorly defined boundaries and the existence of other surrounding artifacts, which makes it difficult to create a generalized technique. Because for some images the resulting DSC index is very high, while in other images it is very low, often being zero, and it is necessary to make several modifications and adaptations in the algorithms to try to improve the result in specific images which ends up harming the image result in others that had good results.

To try to get around these problems, a deep learning model based on U-Net was used. The proposed model requires all input images to be the same size, which must be a multiple of 4. However, the base PH2 has images of varying sizes, mostly 765×574. Therefore, a resizing to 32×32 and 128×128 pixels pixels was performed, which consequently also reduces the processing time.

We run the network 10 times by modifying the number of epochs from 50 up to 300 and splitting the dataset. It was found that 150 seasons were sufficient to find the best results and the best division of the dataset was 60% for training, 20% for testing and 20% for validation. For the 32×32 set, the mean DSC = 0.8723. However, the best result was with the 128×128 set which reached DSC = 0.8924. The results indicate that U-net adapted better the adversities of melanoma segmentation than the traditional techniques proposed.

It was found as a plus point of U-net that there is not so much concern in trying to improve the images because the network is able to find the best features to segment melanoma.

Concerning works-related to deep learning, they outperform our tests, but with a subtle difference. Although the technique proposed by [3] is classified by this work as traditional, it was very efficient, with results similar to deep nets, which shows the potential of traditional techniques.

The technique proposed by [11] obtained better results than the one proposed in this paper. However, it is noteworthy that because it is an adversary network, it is composed of two networks that learn from each other, among them a U-net, which makes it slower than the U-net used in this work.

Table 1: Comparison of proposed methodologies with related work.

Method	Technique	Dice
[11]	Adversarial Network with U-net	0.9000
[3]	Otsu	0.8935
[2]	Others	0.8157
[1]	Others	0.7838
[12]	U-net	0.8924
Proposed	Otsu	0.8090
Proposed	K-means	0.7398

6. CONCLUSION

This paper presented a comparison between melanoma segmentation methodologies. For this, two traditional techniques were developed, one using the Otsu algorithm and the other using the K-means clustering algorithm. Also, a technique was developed using deep learning based on U-net.

The tests were performed with the PH2 melanoma database and promising results were obtained, being 0.8090 Dice coefficient for Otsu methodology, 0.7398 for K-means methodology and 0.8924 for U-net.

The results indicate that the U-net was more efficient for melanoma segmentation than conventional techniques. Compared to other recent research, the proposed and used methodologies have obtained very similar results. Although [11] methodology has better results, it differs only by 0.0076% of the U-net used in this work.

For future work, we intend to modify the techniques to improve the results and apply them in other melanoma bases, as well as use other indicators. Pre-processing will also be performed on U-net input images to improve results.

The aim is to test melanoma segmentation using Adverse Generator Networks. In addition to classifying melanoma using conventional feature extraction techniques and Convolutional Neural Networks.

7. REFERENCES

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