Analysing and Distinguishing Images of Failed Skin Cancer using Modern Swarm Intelligent Techniques (MSITs)

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Abstract: One of the damaging diseases among people in the world is skin cancer. Skin cancer leaves an important scientific, clinical and public task. Swarm intelligence techniques (SITs) are new, improved and modern methods for optimization algorithms. Failure of detection in skin cancer images can be seen in SITs. This work proposes an efficient image and examines for some samples in this disease. The study presents a simple technique for a pre-processing and an automatic detection of SITs to make the needed analysis. This paper estimated all these various models using the PH², Dermis, ISIC (2016, 2017, 2018) segmentation challenge dataset. The input images are improved for better processing than, the lesion sampling is segmented from the improved image by using Otsu thresholding and median filter operations. In the earlier studies, skin cancer is analyzed by means of several optimization algorithms. Now, the outcomes of the above algorithms were compared with the dice coefficient and it was demonstrated that the value of 97.35% which is nearer to manual segmentation. The accuracy the value of 98.58% when used for solving the same problem. To this end, a somewhat comprehensive analysis was showed to compare the effectiveness of many parameters' combinations.

Keywords: lesions, median filter, otsu thresholding, SITs, skin cancer.

1. Introduction

Humanity information from 1930 to 2015 was provided by the National Centre for Health Statistics (NCHS) [1-3]. Humanity data, available through 2015, were composed by the NCHS. In 2018, 1,735,350 new cancer cases and 609,640 cancer demises are expected to arise in the USA. Over the past decade of data, the cancer occurrence rate (2005-2014) was stable in female and decayed by about 2% annually in male, despite the fact the cancer demise rate (2006-2015) degenerated by approximately 1.5% annually in both male and female.

The united cancer death rate dropped continuously from 1991 to 2015 by a total of 26%, interpreting to about 2,378,600 fewer cancer deaths than would have been projected if death rates had continued at their peak [4]. A projected 609,640 Americans will die from skin cancer in 2018, conforming to demises per day [4].

Melanomas is one of the utmost popular cancers in the world. According to the appropriate report of the ACS in the USA in 2018, it is assessed that approximately 99,550 cases were detected as new cases with melanomas, and the predictable deaths from this disease accounted about 13.52% from the new cases. Additionally, melanomas have a mortality rate of 2.21% among all other cancer types [5].

Nevertheless, it has been shown that the survival rate from melanoma could be improved if the disease is early noticed and correctly identified [6]. Dermoscopy is the gold normal imaging...
technology used for melanoma screening [7]. Deeper specifics of the skin lesion assembly can be imagined utilizing the dermoscopy imaging device. The dermoscopy images support dermatologists to enhance the diagnostic accuracy of the melanomas [8]. Automatic segmentation of skin cancer from close skin tissues is a requirement stage toward better skin disease [9,10,11]. Nevertheless, the segmentation is not an informal task because the skin lesions have large variations in the dimensions, figures, colours, and positions in the images. Figure 1 illustrates some challenging samples which pose extra problems to the segmentation task. Recent advances of the artificial swarm intelligent approaches on various medical applications have been getting a lot of attention in the fields of object recognition, segmentation, and acknowledgement [12,13,14].

In 2017, Yuan et al. implemented the deep convolutional-deconvolutional neural network (CDNN) with a loss function of Jaccard distance for skin lesion segmentation [15]. The CDNN was accomplished using augmented data with various colour images utilizing the 2017 database. This technique was classified first in the International Skin Imaging Collaboration (ISIC) 2017 challenge with Jaccard index of 76.5%. In 2017, Yu et al. planned deep residual networks for both segmentation and classification tasks utilizing the ISBI 2016 database [16]. Their network was classified second, with Jaccard index of 82.9%, in the segmentation challenge.

Al-masni, in 2018 utilised ISIC 2018 arrangement challenge for dermoscopy images includes 7 classes for skin lesions, to become the estimation results of the validation database for skin lesions cataloguing [17].

The results in Aljanabi et al [18] were compared to current approaches (ASI) in the literature for skin cancer detection to get assessment performance long-established, which confirms the highly variance power of the recently presented structures. Figure 2 shows several examples of the melanoma lesions superlative-segmentation outcomes found from the 4 databases. This work can get the effectiveness of the planned method when compared to the pictures gotten by the planned method with the pictures of the model ground truth (GT).

![Image](https://example.com/image1.png)

**Figure 1.** Around challenging cases of the melanomas lesions segmentation for example (a) low contrast, (b) asymmetrical boundaries, (c) hair artifact, and (d) colour illumination. Overlaid red lines designate the GT contours of the lesions by proficient dermatologists [17].
2. Materials and Method

2.1 Database of Skin Cancer Lesion Segmentation

The projected method was estimated in five various public databases images, PH2 [19], ISBI 2016 [20], ISBI 2017 [21,30], ISBI 2018 [22,23] challenges and DermIs datasets [24], the dermatological databases are brief in Table 1. From this work information was taking out from the ISIC 2018 grand challenge datasets the dermoscopy images in this challenge comprise eight-bit Red Green Black with various image dimensions and deferent cancer kinds. The training databases contains of 2,594 images with their equivalent GT response masks which were explained by professional dermatologists.

| Databases     | Numbers of Images | Skin Cancer Images | Non-Skin Cancer Images | Ref.    |
|---------------|-------------------|--------------------|------------------------|---------|
| PH2           | 200               | 40                 | 160                    | [19]    |
| ISBI 2016     | 900               | 273                | 627                    | [20]    |
| ISBI 2017     | 2000              | 374                | 1626                   | [21]    |
| ISBI 2018     | 2,594             | 2000               | 594                    | [22,23] |
| Dermis        | 300               | 300                | 0                      | [24]    |

2.2. Segmentation Models

In this study, we present a simple technique for a pre-processing and an automatic detection of the swarm intelligence techniques to make the needed analysis to segment the skin lesions of the PH, Dermis, ISIC (2016, 2017, 2018) segmentation challenge dataset. These methods are a resolution-protective typical which leads to learn high-level features and enhance the segmentation performance. We have utilized stimulation function in the last layer of the proposed segmentation networks to classify each pixel in the dermoscopy image into two classes (skin cancer lesion and non-lesion).

All the segmentation models were trained using a dealt optimization method with a batch size of twenty. Today's acquisition technologies have the disadvantage that they can only process a certain type of image, and their quality can be affected by noise, brightness or various external factors. To minimize or even eliminate these disadvantages and to improve image quality, we have used a wide range of pre-processing methods. The images used in this study come from the medical field, because they allow for more in-depth analysis due to their complexity.
3. Results and Simulations
Demonstrations a comparison samples between the planned technique segmentation outcomes and other approaches that utilized the five databases. We compared a model image from PH2, Dermis, ISBI (2016, 2017) and 2018 databases with the effort of Khan et al. [25] (row 1), Yu et al. [26] (row 2), Guo et al. [27] (row 3), and Dey et al. [28] (row 4) as shown in Figure 3. It can be detected that the projected technique surpassed these approaches. Besides, these techniques are very active in result the finest threshold values as shown in Figure 3. Figure 4 displays pictures which have segmentation failure. The pictures in rows show colour intensity, due to colour comparisons between skin lesion and related and the lesions did not have important colouring.

![Figure 3](image)

**Figure 3.** Comparisons of studies outcome using modern swarm intelligence method for the four databases: Row (1–4) PH2, ISBI 2016, ISBI 2017, and ISBI 2018 databases; Columns (a) original image; (b) guide segmentation image GT; (c) projected technique segmentation image (d) results of modern swarm intelligence method.

![Figure 4](image)

**Figure 4.** Several samples of segmentation failure images: Row (1–4) PH2, ISBI 2016, ISBI 2017, and ISBI 2018 databases; Columns (a) original image; (b) manual segmentation image (GT); (c) projected method segmentation image; and (d) result of projected method (blue) and GT (red).
For the experimentation achieved in this work, ten images are randomly selected from each of the categories of low contrast, thin air, thick air, irregular border, fuzzy border, air bubble and variegated colouring or different colour and shape as shown in Figure 4. One can easily note that the first three non-saliency image segmentation algorithms faced difficulty in segmenting the lesion object from the healthy skin. This is because there is low contrast between the lesion and healthy skin. However, the algorithm produced binary segmentation results with smaller lesion object compared to the GT image.

The failure images be able to fully describe any skin lesions based on: shape, arrangement, colour, distribution and morphology. Early detection and distinguish failure segmentation images are very important because it decreases the death and improved survival.

**Figure 5.** Some samples of segmentation images for different skin lesions

**4. Conclusion and Future work**

This work has presented different segmentation methods on the validation databases using the PH2, Dermis, ISIC (2016, 2017, 2018) segmentation challenge. In future at a time of releasing ground truth masks of the testing dataset, we will include the segmentation performance of different testing of images. An automatic acknowledgement for all five classes of skin lesions could be used to practically assist the dermatologists. After releasing the ground truth responses of the testing database, we will be able to evaluate all classification deep learning models utilizing testing database as well. While artificial swarm intelligent techniques can reach good performance on separable problems by improving each variable self-sufficiently.

In this study, we are existing our energies towards an accessible, Neural networks system that can be used for healthy and non-healthy moles lesion cataloguing, thus important to an enhanced melanoma showing system.

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