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Dermoscopic Lesion Segmentation via Optimal Color Channel Fusion

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***Abstract*—Death caused by various kinds of cancer is on rise and skin cancer is one of the most common one worldwide. Due to the importance of early detection, dermoscopy is adopted for visualizing skin lesions and computer-aided detection benefits from these dermoscopic images for better diagnosis results. One of the most important phase of automated skin lesion detection or classification is segmentation, but it is a very challenging task because of several artifacts existing on these images. In this paper, a new method to improve skin lesion segmentation from the existing deep network architectures is proposed, based on the fusion of various results produced by existing models on different color channels. Experimental validations demonstrate that the proposed method increases the average accuracy, on lesion segmentation in terms of Sorensen-Dice and Jaccard indices, when compared to conventional techniques.**

***Keywords*—Skin cancer, melanoma, dermoscopy, segmentation, color channel fusion**

I. Introduction

According to studies in recent years, cancer incidences cause of death over the world has been increased in a very large scale [1]. Briefly, the term "cancer" describes an abnormal cell proliferation on a specific tissue [2]. Cancer has the possibility to pervade surrounding body parts and spread to the other organs through blood and lymph vessels which is called metastasizing [3]. In worldwide, number of new cancer cases are evaluated over 4.5 millions and number of cancer deaths are more than 2 millions [4]. One of the prevalent lethal cancer, skin cancer is the most common one in the United States and Australia [5]. Melanoma which is an aggressive type of skin cancer has come over as 8th concerning the new cases in all types of cancers [4]. Early detection is imperative for increasing the survival rate from melanoma and it is important to avoid evitable situations which can increase the risk of melanoma, such as having five or more sunburns (that doubles the risk of melanoma). It is estimated that the number of new melanoma cases diagnosed will increase by 7.7% [5].

Melanoma is one of the most invasive type of skin cancer which can spread to other organs in the human body [6]. It develops from the melanin-producing cells (melanocytes) that contains pigment which gives the skin its color. Melanoma occurs when some deteriorations are originated from them. In general, cell reproduction is done regularly and healthy new cells push older cells toward skin's surface, where they die and eventually fall off. However, abnormal cell increase, that is cell growth out of control, may happen and eventually cause a form which is a mass of cancerous cells [7]. This can occur anywhere on the body, but the most commonly affected areas are the back of men and the legs of women [6].

Biopsy is a direct method of excision of the abnormal skin tissue and a small amount of normal tissue around it. A pathologist looks at the tissue under a microscope to check for cancer cells [8]. Alternatively, dermoscopy (dermatoscopy, epiluminescence microscopy) is a painless medical technique which facilitates the early detection of melanoma. It generally uses a handheld magnifying device combined with either the application of a liquid between the transparent plate of the device and the skin, or the use of cross-polarized light. This technique allows the visualization of diagnostic features of pigmented skin lesions that are not seen with the naked eye [9]. Dermatologists can diagnose the pigmented skin lesion using the patterns of size, shape, and pigmentation that comes from dermoscopy [10]. The diagnostic accuracy for melanoma, as expressed by the relative diagnostic odds ratio, is 15.6 times higher for dermoscopy compared with naked eye (clinical) examination [9]. 7-point checklist, ABCD(E) rule and Menzies method have been used for assessing the macroscopic and dermoscopic images of skin lesions with pattern analysis [11].

Computer-aided detection (CADe) or diagnosis (CADx) have been used as computer-based systems those help doctors and experts to make decisions and diagnose the inspected tissue promptly and adequately [12], [13]. Artificial intelligence (AI), machine learning, computer vision, pattern recognition and (medical) image processing techniques are used in CAD systems which include a combination of multiple methods with several stages. Here, automated melanoma detection generally consists of three individual such stages, i.e., segmentation, analysis and classification. In explicit words, in order to analyze and classify a dermoscopic lesion accurately, segmentation is the first step of an automated melanoma diagnosis system. This initial step assists to delineate the boundary of skin lesion, since the boundary provides significant information for a precise diagnosis [14] and the clinical feature extraction stage critically depends on the accuracy of the boundary [15]. However, fuzzy contrast between lesions and skin, different tones inside lesions, irregular borders of lesions, as well as complex and tough artifacts such as skin hairs, air and gel bubbles, marker inks, color charts, ruler marks and dark corners present in dermoscopic images makes the segmentation process difficult and challenging, and generally

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causes commotion in the segmentation results [16].

This study develops a novel algorithm in order to cope with above mentioned problems, to increase the success rate of dermoscopic lesion segmentation from the existing deep network architectures. The proposed method is based on the fusion of various results produced by existing models on different color channels. Extensive validations illustrate the effectiveness of the proposed method in terms of the average accuracy on lesion segmentation –in terms of Sorensen-Dice and Jaccard indices– when compared to traditional techniques in the literature.

The remaining part of this paper is organized as follows. Section II details the background work from the literature. Section III presents the details of the employed architecture and methodology for dermoscopic image segmentation. It also reports experimental results and related discussions over these outcomes. Finally, Sec. IV concludes the paper with a brief conclusion.

II. Background

Benefits of AI has led researchers to adapt new algorithms based on neural networks. Nowadays, most of the architectures adapting neural networks for segmentation prefer convolutional neural networks (CNNs) due to their favorable performance on images. But, of course, as other algorithms which do not adapt neural networks, artifacts explained in the previous section generally lead to inaccuracies in the resulting segmentation outcomes. Some algorithms such as [16], [17], [18], [19], [20], [21], [22], [23] include one more step to their systems to preprocess input images. The approach in [16] employs a median filter to enhance the input image, tries to lessen the impact of artifacts, and a black top-hat transformation accordingly detects thick and dark hairs for hair removal. The algorithm in [23] only reduces the effect of artifacts by smoothing them using a guided filter and feeds the filtered output to their network. That being the case, some researchers like [24], [25], [26], [27], [28], [29] focus on the off-the-shelf networks and try to improve them. For the purpose of improving existing architectures, most of the studies are based on well-known image segmentation networks such as SegNet [30], U-Net [31] and DenseNet [32] due to their demonstrated successful abilities. Some of the works use these architectures as is and achieve better statistical results by integrating preprocessing and/or postprocessing, and some only are inspired from those architectures and change some typical features and parameters they have. The study in [24] mimics the DenseNet architecture to eliminate the necessity of learning the redundant features. They have made their architecture so that each encoding layer can have direct access to the gradients of the loss function of all previous encoding layers and the original input image, using skip connections which are also used to overcome checkerboard artifacts appearing in the segmentation mask, and also sub-sampling limitations (its structure is inspired from U-Net). In this study, depth-wise separable convolution is used to reduce the number of parameters. On the other hand, the work in [25] uses the U-Net architecture with preprocessing and postprocessing to achieve better results, and accordingly, they outperform the winner of the International Symposium on Biomedical Imaging (ISBI) 2016 Challenge with a Jaccard index of 0.9176. In [26], it is shown that it is possible to achieve high accuracy on segmentation results, and they have also proposed a semi-automatic annotation tool which generates mask of the skin tissue, melanoma, nevus and other unknown objects in the input image. Due to the nature of the segmentation problem, some segmentation artifacts may occur on a number of output images. Some researchers such as [17], [18], [20], [21], [33] implement various postprocessing methods to improve their results on those images, e.g., filling up small holes and smoothing the boundary, morphological operations for removing isolated small pixels, connected thresholding.

In this paper, the aim is to adapt an approach capable of increasing the statistical success of the present segmentation networks. Motivated by the works proposed in [34], [35], the proposed method is able to get higher statistical accuracy on the segmentation of lesions by a straight-forward fusion from the results of different color channels.

III. Methodology

A. Dataset

In this work, a public dataset is used which is released by the International Skin Imaging Collaboration (ISIC) for the "Skin Lesion Analysis toward Melanoma Detection" Challenge at the 2017 ISBI [36]. In accordance with this challenge, lesion segmentation data includes $2,000$ dermoscopic images for training, paired with the expert manual tracing of the lesion boundaries in the form of a binary mask as their ground-truths. In addition, official test dataset consists of 600 dermoscopic images.

B. U-Net

In this work, U-Net architecture is employed for experimentation. It consists of two paths as contracting and expansive which are left and right side of the architecture, respectively. Contracting path follows repeated applications of convolutions of 3×3, each followed by a ReLU and a max pooling operation with a 2×2 window and stride 2 for downsampling. Feature channels are doubled at each downsampling. Expansive one follows upsampling of the feature map, followed by a 2×2 convolution, and feature maps are reduced to half again by concatenating the feature map with the corresponding cropped map in the contracting path. After these operations two 3×3 convolutions, which each are followed by a ReLU, are applied and at the final layer a 1×1 convolution is utilized.

In this study, all U-Net architectures are trained on four epochs with batch size of 16.

C. The Proposed Method

The main objective of the proposed approach is to enhance the lesion segmentation statistics of currently available architectures. According to [34] and [35], the segmentation

Input Type	Jaccard index	Dice index
Gray(RGB)	0.4080	0.5301
Min(R,G,B)	0.5266	0.6409
Median(R,G,B)	0.4608	0.5804
Max(R,G,B)	0.4033	0.5217
R	0.4058	0.5221
G	0.4599	0.5798
B	0.5224	0.6400
RG	0.5326	0.6440
RB	0.5394	0.6519
GB	0.5829	0.6870
RGB	0.5344	0.6448
Proposed	**0.5929**	**0.7041**

TABLE I: Test segmentation results using U-Net.

accuracy strongly depends on the characteristics of the input image and is highly related to color channels. To overcome this problem, an approach can be envisaged which fuses the results produced on different color channels via networks trained on various inputs. These inputs are artificially produced from original RGB images and are indeed variations of those originals. Here, RGB color space is preferred because it is the most frequently used color presentation in image processing [37]. Inspired from the work of [37], this study analyses 11 different input images, namely, R (red only), G (green only), B (blue only), RG (red and green), RB (red and blue), GB (green and blue), RGB (red, green, blue), Min (minimum of all channels), Max (maximum of all channels), Median (median of all channels) and Gray (gray-scale version), for the automatic segmentation system.

In detail, 11 different U-Net networks are trained on each 11 inputs (per input image) by means of the corresponding binary ground-truth masks. After training, segmentation results received from each of them are analyzed in terms of the Dice similarity coefficient and the top-six statistically successful input types are determined from the training set (2000 images). For a given test image then, for each pixel, these top-six input segmentation results determine if that specific pixel belongs to a lesion or not. In short, if at least two segmentation outputs label that pixel as lesion, then the final segmentation label marks that pixel as lesion. This process is repeated until all pixels in the image are marked as lesion or not.

D. Results and Comparison

Experiments on 600 test images are conducted using the U-Net architecture and each input-type statistics obtained are compared to the proposed method in terms of Jaccard index and Dice similarity coefficient. As it can be seen obviously from Table I, the proposed algorithm performs the best for skin lesion segmentation compared to the results obtained solely from U-Net. This reflects the advantages of the developed method for increasing the statistical accuracy on dermoscopic lesion segmentation.

IV. Conclusion

In this paper, a novel approach is proposed for improving skin lesion segmentation statistics on dermoscopic images. The method simply consists of fusing different segmentation outputs produced by existing architectures on various color channels. Experimental results demonstrate that the developed method can reach a higher level of accuracy rather than the results obtained on each separate channel.

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