Skin Lesion Segmentation by using Deep Learning Techniques

Sohaib Najat Hasan
Institute of Graduate Studies In Sciences, Istanbul University
Istanbul, Turkey
suhaibnajat@gmail.com

Murat GEZER
Department of Informatics
Istanbul University
Istanbul, Turkey
murat.gezer@istanbul.edu.tr

Raghad Abdulaali Azeez
College of education (Ibn-rushed)
University of Baghdad
Baghdad, Iraq
raghad.azeez@ircoedu.uobaghdad.edu.iq

Sevinç GÜLSEÇEN
Department of Informatics
Istanbul University
Istanbul, Turkey
gulsecen@istanbul.edu.tr

***Abstract*—Skin cancer is a common disease among middle-aged and elderly white-skinned people. It is divided into many types in terms of medical criteria. Malign melanoma is one of the most dangerous and fatal cancer types, it can be treated if detected early.**

The main focus of this paper is to provide a precise, effective, robust and automated way to segment the lesion in order to facilitate the classification of the lesion with high accuracy during the early diagnosis of skin cancer. This process consists of two stages. In the first stage, image processing techniques (Image Enhancement, Linear Filtering, and Image Restoration) are used to obtain images free of artifacts such as hair and ruler marks. The second stage which is the important part of this paper is to modify a U-Net architecture and propose a 46-layered structure of U-Net to obtain a successful lesion segmentation rate. In this study, experiments were performed on two different U-Net architectures (U-Net 32, and U-Net 46).

***Index Terms*—Dermoscopy Images, Skin lesion, Deep Learning, U-Net Convolutional Neural Network, Dice-coefficient, Jaccard.**

I. Introduction

Cancer (or malignant tumor) is an abnormal growth of cells, which cells reproduce in an uncontrolled way with the potential to spread to other tissues [1]. There are more than 100 types of cancer. The most common cancer type of malignancy for both men and women among all types of cancer is skin cancer. Which can be categorized into melanoma and non-melanoma [2].

According to SEER's report [4] malignant melanoma is the most mutual and fatal form of human skin cancers and the foremost cause of death, especially among the middle-aged and elderly white-skinned people more than other racial group who are exposed to the sun over long periods of time. Dermoscopy is a noninvasive technique used for examining and diagnosing features in skin lesions. It is supportive for the diagnosis of pigmented skin cancer, particularly melanoma, thus it is commonly used by dermatologists due to its significance in detecting melanoma in its early stages [26, 6, 3].

Digital image is a two dimensional array of pixels used as a way of transmitting information. The important field of application in digital image technology is understanding the digital image and extracting information, and the image segmentation is the first step of understanding the image. In practice, Image segmentation is based on certain standards for isolating an image into two regions foreground and background in order to extract the region which it enters as an input lesion area into the classifier. It aims to simplify the image representation for analysis and to facilitate understanding the medical image features and recognize it. The output of image segmentation is a group of pixels that cover the whole image information [13, 25, 28].

II. Related Work

Image preprocessing is a significant part and challenging task of analysis and effective identification of Dermoscopic images. The Dermoscopic images frequently hold artifacts such as hairs, air bubbles, and ruler marks that probably affect lesion borders detection. These artifacts confuse the border detection process that causes decreasing precision as well as expansion in the computational time.

Abbas et al [7] proposed four steps for repairing information of occluded hair. The first step is transforming input image into gray scale to get accurate detection of hair pixels, the second step is hair detection, in this step the rough hairs are detected by using Matched Filtering with the First-Order Derivative of Gaussian method, then reducing the sensitivity of non-hair pixels in the generated mask by thresholding method, the third step is to refine these detected wisps a morphological edge-based method utilized, and the fourth step used a fast marching algorithm to repair textures from hairs, which is developed by Bornemann et al [8], the proposed method has capability to preserve the skin lesion feature such as texture and color and able to segment both light and dark hairs simultaneously. The Diagnostic Accuracy (DA) and Texture Quality Measure (TQM) metrics are utilized to compare the performance of proposed method with three other methods. The Proposed method achieved highest rate of DA and TQM which is 90.3%, 90.0% respectively.

An automated segmentation of lesion area has a significant im-

978-1-7281-2420-9/19/$31.00 ©2019 IEEE

pact in skin cancer. Many methods are used in the purpose of detecting lesion border, some of these methods are presented below:

Celebi et al [9] used fusion of four thresholding method for building automated lesion border detection which was proposed by Melgani [20]. They applied ((1) Huang and Wang [15] algorithm. (2) Kapur et al [17] algorithm. (3) Kittler and Illingworth [18] algorithm. (5) Otsu's [21] algorithm) to the image blue channel.

Fully Convolutional Neural Network (FCNN) was proposed by Qi's et al [22] to do segmentation process for dermatoscopic images. The authors in this method focused on FCNN with end to end learning, transfer learning, and pixel by pixel prediction.

Cui et al [12] utilized a multi-scale ensemble framework based a modified of U-Net for tackling the challenge of lesion segmentation. After pre-processing step, the original version of U-Net has been modified by down-sampling network 5 times rather than 4 times to make the network deeper for getting more features. Then pre-trained network has been used during model training. The process of enhancement inspired from Chen et al [10] "atrous spatial pyramid pooing" method, by applying multi-scale feature extraction, then concatenating them before softmax layer.

III. Methodology

Accurate segmentation of the lesion area in dermoscopy images is essential to increase the performance of subsequent phases, such as extracting features and classifying the lesion because it substantially affects their results. Consequently, it plays a vital role in identifying melanoma disease in its early stages. The segmentation phase is such a challenging task for two main reasons: First, the existence of noise artifacts such as ruler marks, light reflection, air bubbles, and hairs. Second, the presence of different skin types and the color, texture, and shape of the lesion. Which, both two aforementioned reasons negatively influence the accuracy of the system. This paper presents a method which consists of two main phases: 1. Dermoscopy image pre-processing, 2. Skin lesion segmentation.

1) Image pre-processing: Most of the dermoscopy images are covered by artifacts such as hair, ruler marks, and light reflections. Consequently, those noises could hide the border of the lesion during the segmentation process and make it invisible, which make lesion border detection a challenge. In addition, the improper detection of the lesion border could lead to incorrect classification later. For that reason, the process of artifacts detection and removing became necessary for getting effective segmentation results.

- Image Enhancement. Firstly, the dermoscopy image has been converted to gray scale color space. The image enhanced by utilizing Gaussian Blur for reducing the noises in the dermoscopy images.
- Edge detection. Edge detection is done to achieve a specific border of the artifacts such as hair, ruler marks and air bubble. Sobel filter with X and Y-orientation and canny filter employed to detect the boundaries of the artifacts. And then subtracting the result of sobel filter from the result of canny filter applied to get more accurate results of artifact edges. Then finally adjusting the brightness and the contrast of the artifact edges.
- Generate Mask. The image is thresholded to generate a binary image by using binary threshold then apply morphological dilate to fill the outlines of edges.
- Image Restoration. The inpainting technique works as follows. First, the region of the artifacts is chosen by matching the dermoscopy image with artifacts with the generated mask. Then, the surround image data is utilized to fill in the missing regions.
- Create new dataset, for generating a new dataset without artifacts. The images after getting restoration have converted to gray scale then resized to 448 x 448 pixel.

Figure 2 displays the output of image preprocessing phase step by step.

2) Lesion area segmentation: The proposed system of skin lesion segmentation consists of the output of pre-processing data then shuffle it in order to reduce variance and making sure that proposed model remain general and over-fit less. To ensure good generalization and avoid over-fitting problem, a splitting dataset into two subsets have been used. The first subset was used for training which contains 70% of whole data while the other subset 30% of the entire dataset was used to evaluate a given model. After the data is normalized, it is feed it as an input to the learning algorithm to produce a predicted mask then compare it with the Benchmark data to evaluate the proposed model.

- Improvement of U-Net technique

  The proposed architecture presented in Figure 1, consists of 46 layers separated into two steps: Contraction path and Expansion path, which repeatedly apply convolutions, activation functions, down-sampling, and up-sampling operator. Contraction path consists of 6 blocks: each block contains 3 layers, two non-padded 3×3 convolution layers each pursued by elu activation function then a 2×2 max pooling layer is utilized for down-sampling. While each expansion path consist of 6 blocks as well but each block contain 4 layers, 2×2 up-sampling layer is added halves the number of feature channels then concatenate it with the corresponding encoding layer which, called concatenate layer. In the last two layers, a non-padded 3×3 convolution layers are added. Each convolution layer is followed by "elu" activation function. At the end, a 1×1 convolution layer is utilized to predict the value of which an appointed pixel belongs to the skin lesion.

IV. Experimental Results

A. Dataset

Our data was extracted from the "ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection" grand challenge datasets [11, 24]. This dataset consist of 2594 training images

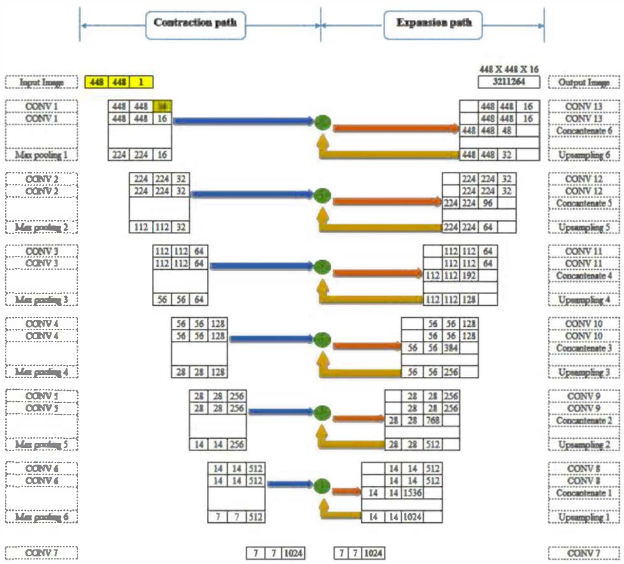

Fig. 1: Proposed Modified U-Net Architecture

with 2594 validation images used for initial self-evaluation online and 1000 testing images used for final performance rank of various research sets [5]. The method has been implemented by using keras 2.2.4 framework.

B. Preprocessing

In the first part of this study, we proposed a preprocessing algorithm for eliminating the artifacts and noises from the dermoscopy images. Figure 2 illustrate the output of each element in the pre-processing algorithm.

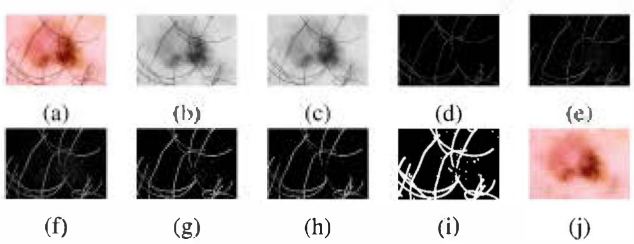

Fig. 2: (a) Original Image. (b) Gray scale. (c) Gaussian Blur. (d) Canny. (e) Sobel. (f) Sobel - Canny. (g) Edge Brightness & Contrast. (h) Global image thresholding. (i) Dilation (the mask). (j) Image Restoration.

C. Comparison of U-Net Models

Our work has been compared with the best 5 results of ISIC 2018 lession segmentation shown in table I. In the second part of this study, two different U-Net layer structures were designed by varying parameters. The goal of utilizing different U-Net structure is to identify good structures which extract an accurate border from dermoscopic images as much as possible. Two U-Net layer structures utilized in this study comprises 32, and 46 layers. In each U-Net architecture, layers are divided in an equal way on both side of encoding and decoding paths. The experimental results are shown in the table I.

TABLE I: Comparison of the top 5 results from the ISIC 2018 segmentation competition with the results of our study

Resource	*Approach*	*Jaccard*	*Specificity*
[23]	MaskRcnn2 + segmentation	0.838	0.963
[14]	Ensemble with CRF v3	0.837	0.952
[16]	feature aggregation convolutional neural network.	0.834	0.964
[27]	Skin Lesion Segmentation with Adversarial Learning.	0.837	0.942
[19]	Leveraging Transfer Learning for Segmenting Lesions and their Attributes in Dermoscopoy Images.	0.837	0.942
Our work	**U-net 32 layers**	**0.8936**	**0.9783**
	U-net 46 layers	**0.9336**	**0.9780**

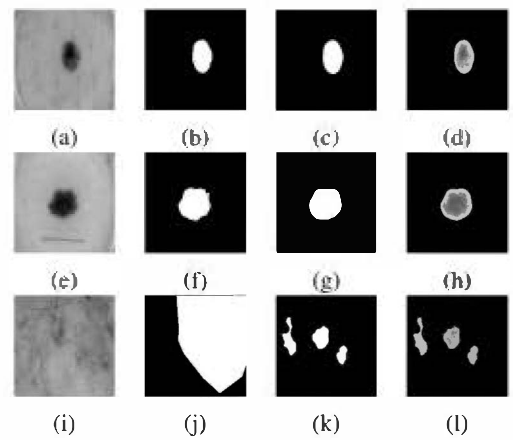

Fig. 3: The first two rows are (The samples of satisfactory segmentation results), the last row is (the sample of unsatisfactory segmentation results). (a), (e) and (i) are the original gray images. (b), (f) and (j)are the original groundtruth images. (c), (g) and (k) are our predicted masks. (d), (h) and (l) are bitewise images

The improved U-Net structure (U-Net 46) presented the lowest loss (-1 for the training set and -0.9 for validation set) and greater accuracy (93%) in comparison to the other approaches. The Sensitivity, Specificity and segmentation accuracy by using both the Dice coefficient and Jaccard Index of the proposed model were (91%, 97% and 85% and 93%) respectively.

Figure 3 shows three samples of what are considered satisfactory results versus not so satisfactory results. For each sample, the original dermoscopy image mask (second column) is compared to the segmentation proposed approach (third column). In the first status (the first two rows), it can be seen how the proposed model is accurate, that is because of the high contrast of the lesion area is so clear. While in the second status (the last row), displays how low lesion contrast negatively influenced on the segmentation process.

V. Conclusion

In this paper, automatic segmentation of dermoscopic images of the skin lesion area has been performed by using two main steps: preprocessing and image segmentation. In the first step, preprocessing techniques have applied on the dermoscopic images to detect and eliminate different artifacts by fusing 6 different image processing approaches. The second step, which is the crucial part in this paper, is to present 2 different U-Net architectures such as (U-Net 32, and U-Net 46). The architecture U-Net 46 achieved 93% accuracy, 91% sensitivity, and 97% specificity by using ISIC2018 dataset of 1815 training images and evaluate it on 779 validation dataset.

ACKNOWLEDGMENTS

This study was compiled from Sohaib Najat Hasan's master thesis which was submitted in Institute of Graduate Studies In Sciences, istanbul university in July 2019.

REFERENCES

[1] What is cancer?, December 2014.

[2] Cancer, November 2018. Page Version ID: 869500515.

[3] Dermoscopy: Overview, Technical Procedures and Equipment, Color. March 2018.

[4] Melanoma of the Skin - Cancer Stat Facts, November 2018.

[5] Task 1: Lesion Boundary Segmentation | ISIC 2018, November 2018.

[6] What is dermoscopy?, November 2018.

[7] Qaisar Abbas, Irene Fondón Garcia, M. Emre Celebi, and Waqar Ahmad. A Feature-Preserving Hair Removal Algorithm for Dermoscopy Images. *Skin Research and Technology*, 19(1):e27–e36, February 2013.

[8] Folkmar Bornemann and Tom März. Fast Image Inpainting Based on Coherence Transport. *Journal of Mathematical Imaging and Vision*, 28(3):259–278, July 2007.

[9] M. E. Celebi, S. Hwang, H. Iyatomi, and G. Schaefer. Robust border detection in dermoscopy images using threshold fusion. In *2010 IEEE International Conference on Image Processing*, pages 2541–2544, September 2010.

[10] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. *arXiv:1802.02611 [cs]*, February 2018. arXiv: 1802.02611.

[11] Noel C. F. Codella, David Gutman, M. Emre Celebi, Brian Helba, Michael A. Marchetti, Stephen W. Dusza, Aadi Kalloo, Konstantinos Liopyris, Nabin Mishra, Harald Kittler, and Allan Halpern. Skin Lesion Analysis Toward Melanoma Detection: A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC). *arXiv:1710.05006 [cs]*, October 2017. arXiv: 1710.05006.

[12] Zhiying Cui, Feifei Xue, Nan Liu, JiaFeng Xie, Gongfa Jiang, Roy Wang, JianGuo Zhang, and MIA Group. Automatic Skin Lesion Segmentation Based on Ensemble of Fully Convolutional Neural Networks. page 4.

[13] R Deklerck, J Cornelis, and M Bister. Segmentation of medical images. *Image and Vision Computing*, 11(8):486–503, October 1993.

[14] Hao Du, Jeon Young Seok, Dianwen Ng, and Ngiam Kee Yuan. Team HolidayBurned at ISIC CHALLENGE 2018. page 7.

[15] Liang-Kai Huang and Mao-Jiun J. Wang. Image thresholding by minimizing the measures of fuzziness. *Pattern Recognition*, 28(1):41–51, January 1995.

[16] Yuanfeng Ji, Xiaomeng Li, Gong Zhang, Di Lin, and Hao Chen. Automatic Skin Lesion Segmentation by Feature Aggregation Convolutional Neural Network. page 4.

[17] J. N. Kapur, P. K. Sahoo, and A. K. C. Wong. A new method for gray-level picture thresholding using the entropy of the histogram. *Computer Vision, Graphics, and Image Processing*, 29(3):273–285, March 1985.

[18] J. Kittler and J. Illingworth. Minimum error thresholding. *Pattern Recognition*, 19(1):41–47, January 1986.

[19] Navid Alemi Koohbanani, Mostafa Jahanifar, Neda Zamani Tajeddin, and Ali Gooya. Leveraging Transfer Learning for Segmenting Lesions and their Attributes in Dermoscopoy Images. page 8.

[20] Farid Melgani. Robust image binarization with ensembles of thresholding algorithms. *Journal of Electronic Imaging*, 15(2):023010, April 2006.

[21] Nobuyuki Otsu. A threshold selection method from gray-level histograms. *IEEE transactions on systems, man, and cybernetics*, 9(1):62–66, 1979.

[22] Jin Qi, Miao Le, Chunming Li, and Ping Zhou. Global and Local Information Based Deep Network for Skin Lesion Segmentation. *arXiv:1703.05467 [cs]*, March 2017. arXiv: 1703.05467.

[23] Chengyao Qian, Hao Jiang, and Ting Liu. ISIC 2018 – Skin Lesion Analysis. page 5.

[24] Philipp Tschandl, Cliff Rosendahl, and Harald Kittler. The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. *Scientific Data*, 5(1):180161, December 2018.

[25] G. Subha Vennila, L. Padma Suresh, and K.L. Shunmuganathan. Dermoscopic image segmentation and classification using machine learning algorithms. In *2012 International Conference on Computing, Electronics and Electrical Technologies (ICCEET)*, pages 1122–1127, Nagercoil, Tamil Nadu, India, March 2012. IEEE.

[26] M. E. Vestergaard, P. Macaskill, P. E. Holt, and S. W. Menzies. Dermoscopy compared with naked eye examination for the diagnosis of primary melanoma: a meta-analysis of studies performed in a clinical setting. *The British Journal of Dermatology*, 159(3):669–676, September 2008.

[27] Yuan Xue, Lijun Gong, Wei Peng, Xiaolei Huang, and Yefeng Zheng. Automatic Skin Lesion Analysis with Deep Networks. page 5.

[28] Song Yuheng and Yan Hao. Image Segmentation Algorithms Overview. page 6.