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Deep Learning based Skin LesionSegmentation in Dermoscopy Images

R.D Seeja[#1], Dr. A. Suresh[*2]

[#]CSE, Periyar University- Siri PSG College of Arts and Science for Women

sheejarufus.r.d@gmail.com

Abstract

The segmentation of skin lesions plays a crucial role in the early and correct detection of skin cancer by computerized systems. However, automatic segmentation of skin lesion region in dermoscopic images is a challenging task due to visual similarities of melanoma and benign lesions, unclear boundaries, low contrast, sizes, and shapes. The main objective of this paper is to identify the exact spot of the normally indistinguishable lesions and ultimately increase the diagnosing accuracy. This paper presents a scheme for automatic skin lesion segmentation with U-Net and SegNet algorithms which is based on convolutional neural networks. The effectiveness of this framework is evaluated on public challenge dataset ISBI 2016 Skin Lesion Analysis toward Melanoma Detection Challenge dataset. Accuracy, precision, recall, and F1-score are used to evaluate the performance of the proposed work. The results are found from both U-Net and SegNet separately. The U-Net algorithm achieves 94.15% of accuracy and the SegNet method attains 90.2%. By comparing the values of these two methods, U-Net outperforms SegNet and is found to be the suitable method for skin lesion segmentation in dermoscopic images.

Keywords: Melanoma, Segmentation, Convolutional Neural Network, U-Net, SegNet.

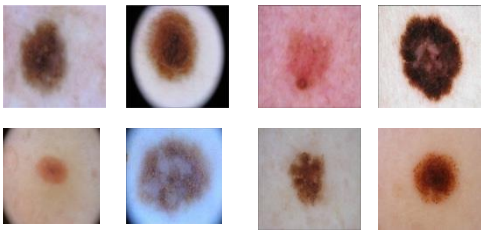
1. Introduction

Melanoma, also called malignant melanoma that starts from melanocytes, is one of the more lethal types of skin cancer for the reason that it spread to other organs more quickly. Excess exposure of ultraviolet (UV) radiation from sun [1], skin cells are damaged and activate melanocytes to produce more melanin. Diagnosis melanoma in early stage and give proper treatment can result in a very high chance of survival rate.

Nevertheless, the accurate diagnosis is very important because melanoma can be confused with normal skin makes it hard to classify melanoma or benign lesions.

Dermoscopy images are important role to increase the survival rate of patients by assisting early detection of melanoma. Dermoscopy is a non-invasive diagnosis technique which is used to increase the clarity of correct spots on the skin surf ace and gives more details of skin lesions. Even for expert dermatologist hard to differentiate melanoma and benign lesions under manual observation due to the visual similarities. Fig.1 shows visual similarities of some sample dermoscopy images of melanoma and benign. Computerized segmentation of melanoma from the nearby skin is a necessary step in computerized analysis of dermoscopic images [2].

Recently, deep feature learning capability has led to breakthroughs in many medical image analysis tasks, including segmentation, classification, and detection. Hence in this paper, convolutional neural network based U-Net and SegNet algorithms are applied to achieve better results.



a) Melanoma b) Non-Melanoma

Fig1: Visual similarities of Melanoma and Non-Melanoma lesions

2. Related Work

Segmentation is the most challenging and important process in the area of image processing. Some of the research works on segmentation are as follows. A combination of Genetic Algorithm and Fuzzy c-means (FCM) method was introduced for segmenting medical images [3]. Segment the skin lesion usingDermoNet

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with densely linked neural network was applied by [4]. The thresholding technique is used for many applications in image segmentation. 2D Otsu's thresholding method with Histogram analysis for image segmentation has proposed [5].

Recently, Convolutional Neural Networks have become one of the most powerful tools for medical image analysis. Several methods for semantic segmentation are based on CNN in which each pixel is labeled with the class of its enclosing objects. Some research work has presented here by using numerous Deep Learning methods for segment the skin lesions. Distinguish melanocytic naeves, seborrheic keratosis and melanoma using Fully convolutional method for multi class segmentation by [6]. Full resolution convolutional networks (FrCN) have used for segmentation and compare the results with various deep learning algorithm by [7]. Self-Generated Neural Networks (SGNN) are used to segment skin lesions by[8]. From the analysis of the above mentioned research, the deep learning methods produced favorable results for skin lesion segmentation. All segmentation methods are not possible and efficient enough for segmenting dermoscopic images. Deep learning based U-Net algorithm is specially designed to solve the segmentation problem. Therefore U-Net algorithm has been adopted to solve it.

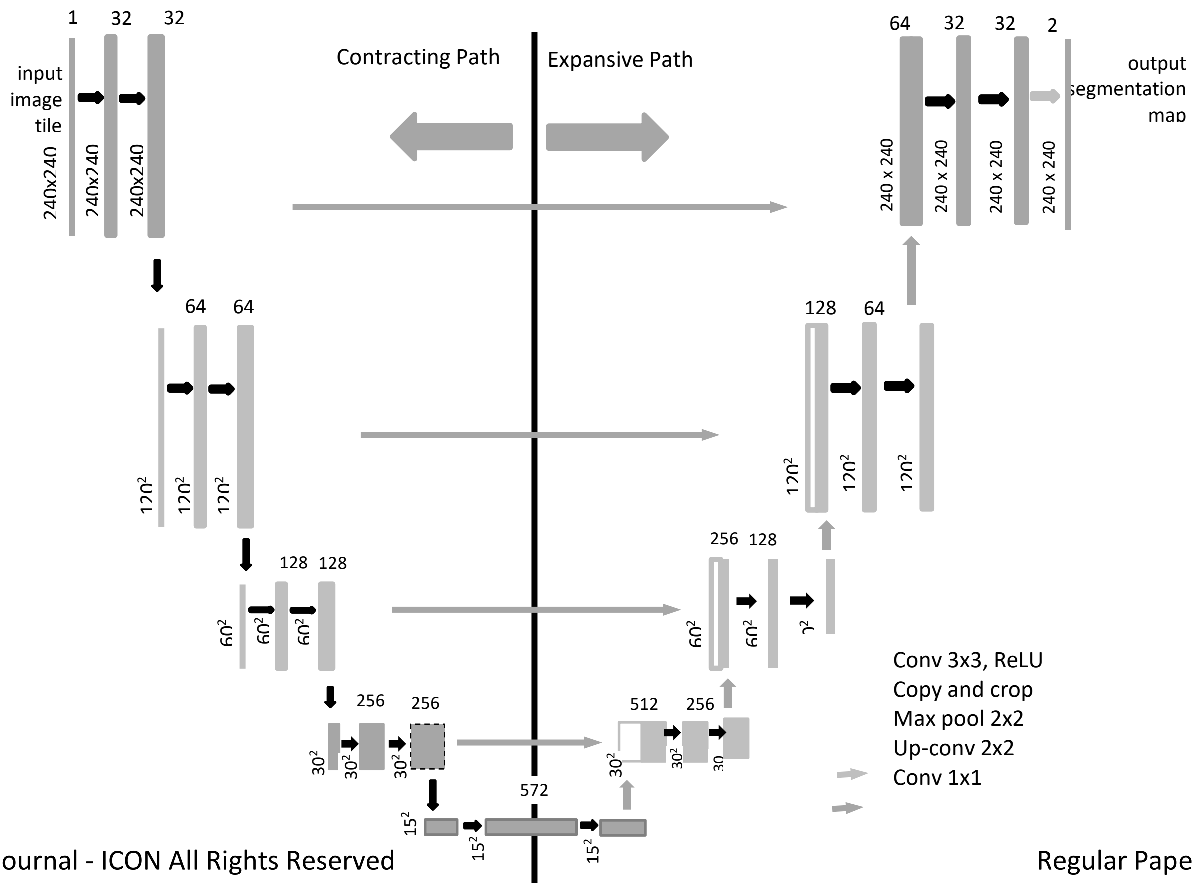

Fig.3: U-Net Architecture

3. Methodology

In this section, the proposed approach for skin lesion segmentation is described. A brief conceptual diagram is illustrated in fig.2. No preprocessing has done in this proposed method for the reason that the convolutional neural networks directly learns the complete features of every pixels of input image without the need of any preprocessing such as image enhancement, artifact removal and low contrast adjustment.

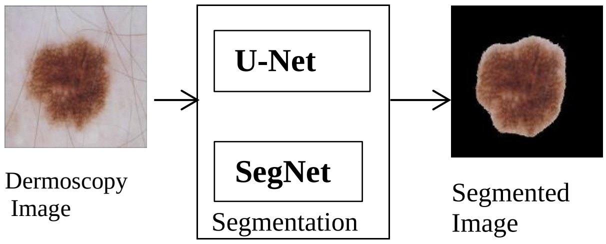

Fig. 2. Block Diagram

First, Segment the skin lesions from the healthy skin by using U-Net algorithm which is especially designed for image segmentation [9]. And then segmentation has done using SegNet algorithm with same dataset and testing images.

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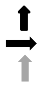

Compare both of the values obtained from these two methods and found that U-Net was produced better results than the other method based on accuracy, dice coefficient, jaccard index, sensitivity, and specificity.

Segmentation:

Segmentation is the process of partitioning an image into multiple segments according to similar features and properties. The main goal of segmentation is to make simpler the representation of an image into a more meaningful image, which helps to analyze the image [10].

Lesion segmentation with U-Net:

U-Net, a kind of deep Convolutional Neural Networks (CNN) model is considered one of the powerful methods for segmentation due to architecture and pixel-based segmentation. Fig.3 shows the architecture of U-Net.

It involves contracting path and expanding path. The contracting path has many convolutional blocks followed by Rectified Linear unit (ReLu) and max-pooling layer. U-Net design can learn the complex images effectively by doubles the number of feature maps after each block. The bottom-most layer intermediates contraction and expansion layers.

The expanding path is a special phase in U-Net architecture. No max-pooling layer, only convolutional layers are used in this phase. Featuresfrom the contacting path are combined with the corresponding upsampling layer, which is used to locate the pixels exactly.

Lesion segmentation with SegNet:

The SegNet architecture was developed by Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla, from the University of Cambridge [11]. The SegNet network is a convolutional neural network which is used for pixel wise semantic segmentation. SegNet has encoder and decoder network and followed by a final softmax layer. The encoder network contains 13 convolutional layers which is same as the first 13 convolutional layers of the VGG16 network. It performs convolution with filters to produce feature maps and then non-linear ReLU is applied. Following that the max pooling with no overlapping operation is performed. Decoders are similar to the encoders and hence decoder network has 13 convolutional layers. After the final decoder output is fed to a softmax classifier to classify each pixel independently. Figure4 shows the SgNet architecture.

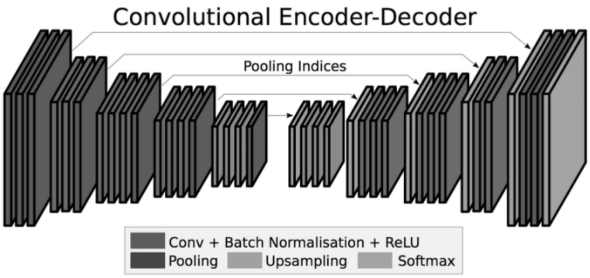

Fig.4: SegNet architecture graphical representation presented by Badrinarayanan[11].

4. Experimental Results

Dataset:

The experimental results are evaluated for segmentation is made on a public challenge dataset ISBI 2016 [12] of skin lesion analysis towards Melanoma detection which is released by the International Skin Imaging Collaboration (ISIC). The challenge has three parts namely part1, part2, part3 and further divided into sub challenges for each task involved in image analysis including segmentation, feature extraction and classification.

This research is carried out with 900 dermoscopic images taken from part1 as a training image for segmentation with ground truth. An additional 900 images from part3 is held out as test dataset for segmentation. Here 90% of the images are used as training data and the remaining 10% images are used as test data to predict the result.

Performance Metrics:

The performance of the proposed segmentation work was evaluated by Accuracy (AC), Dice Coefficient (DI), Jaccard Index (JA), Sensitivity (SE) and Specificity (SP). These measures are defined by the following equations.

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

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$$DI = \frac{2 \cdot TP}{2 \cdot TP + FN + FP} \quad (2)$$

$$JA = \frac{TP}{TP + FN + FP} \quad (3)$$

$$SE = \frac{TP}{TP + FN} \quad (4)$$

$$SP = \frac{TN}{TN + FP} \quad (5)$$

Results and Analysis:

In this section, experimental results and analysis work out with the proposed methods are presented. The segmentation performance of the proposed scheme is measured by U-Net and SegNet algorithms. Two experiments are employed to achieve the segmentation results with same dataset of ISBI 2016.

Table 1 shows the segmentation values obtained from the proposed methods. By analyzing the segmentation values mentioned in this table, it is observed that segmentation with U-Net algorithm yielded better results for all measures compared to SegNet method. U-Net method achieves accuracy of 94.15%, Dice coefficient of 88.02%, Jaccard Index of 79.7%, Sensitivity of 89.1% and Specificity of 97.9%.

Table1: Results of Segmentation for the proposed methods.

Networks	AC	JA	DI	SE	SP
U-Net	**94.15**	**79.7**	**88.02**	**89.1**	**97.9**
SegNet	90.2	73	84	84	92

The Accuracy, Dice Coefficient, Jaccard Index, Sensitivity and Specificity of the proposed segmentation methods evaluations carried out are presented in Figure5. It shows that the U-Net method predicts better results for all the measures than SegNet method.

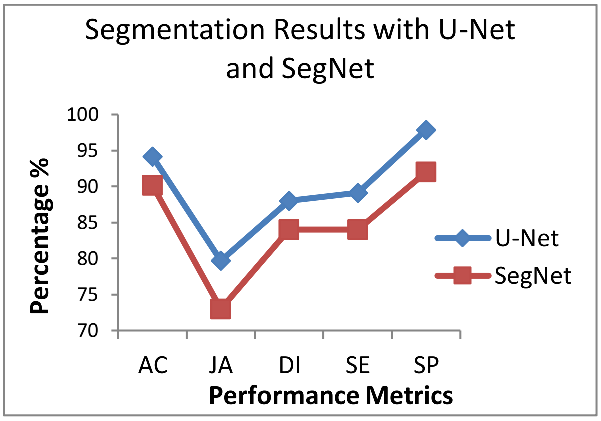

Fig.5.Performance analysis of U-Net and SegNet methods

5. Conclusions

This paper presents a scheme for automatic skin lesion semantic segmentation with U-Net and SegNet methods, which are based on convolutional neural networks. This experiment is evaluated on a public challenge dataset of skin lesion analysis towards melanoma detection on ISBI 2016. The results showed that the U-Net method achieves better segmentation accuracy compared to SegNet algorithm. It is believed that, U-Net method assists researches to achieving highest Dice coefficient and accuracy. In future, developing automatic diagnosing system using segmented lesions can also appliedU-Net to improve classification performance.

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