Southeast Europe Journal of Soft Computing ISSN 2233 – 1859
Available online: http://scjournal.ius.edu.ba

Vol 9, No. 2, September 2020, pp. 6-10

Deep Learning on Wound Segmentation and Classification: A Short Review and Evaluation of Methods Used

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Article Info

Article history:

Article received on dd mm 20xx

Received in revised form dd mm 20xx

Keywords:

Deep Learning; Wound Segmentation; Classification; Review; wound assessment

ABSTRACT: The abundance of research on wound segmentation suggests that it is significant in order to provide a good analysis and assistance in the medical field. Although there is some relative dearth of wound segmentation on other approaches, this review finds that deep learning is central to the objective of image segmentation. Here, the review informs on the methods that are credible towards wound segmentation, training, classification, validation of datasets, data collection, and evaluation of segmented images. While the literature establishes a clear connection between the segmentation algorithms of the object, therefore this study seeks to find the segmentation algorithm directly applicable to wound assessment.

1. INTRODUCTION

One of the key aspects of Computer Vision is image segmentation. Image segmentation is rather different from its counterpart image recognition. Image recognition is not comparable to image segmentation where image recognition only tends to classify the object that has a specific label to it such as Cat, Ear, and Person. Parallel to that, image segmentation algorithm will segment known or unknown object whether it is a new or known object. Several researchers have been done [1] where image segmentation can be useful to burn prognosis which can help on assessment of early burn depth diagnosis to accurately discriminate burnt skin from the rest, and how many percent of the body is burned. While most literature reviews mentioned the state of the art of wound segmentation using image segmentation techniques, this paper will delve into the best deep learning model approach for wound segmentation.

In all of these applications, the deep learning model is widely used for medical image processing with a large amount of labeled data. Among those common techniques, Convolutional neural networks (CNN), Fully convolutional networks (FCN) and Recurrent neural networks (RNN) and several other architectures have been proposed with AlexNet being the most well-known architecture for classification purposes [2], [3].

In wound segmentation, the manual methods are deemed to be flawed and unhygienic, while most of the studies using wound segmentation are the basis of the automated wound area measurement and analysis to save labor and time. Based on the research, deep learning is popular due to the advantage it gives to the ability of the trained deep neural network to process images. While most of the studies on deep learning to wound segmentation, a few of them found it insufficient due to lack of labeled wound images [4]–[6].

According to the main component of semantic image segmentation, the paper divides it into three categories: Supervised DNN, CNN Based Segmentation and Fully

Convolutional network. With the findings in this paper, there are several approaches to be used as a model for wound segmentation and assessment which will be discussed further in this paper. In the next part, the paper will discuss the methodology found in the literature.

2. METHODS

2.1. Data source

The literature primary data set was compiled from 20 studies with the keywords filtered to wound segmentation, wound assessment, image segmentation, wound evaluation, artificial neural network, deep learning, computer vision, machine learning, and chronic wound. The publications selected were published between 2013-2018 and available in Google Scholar, Elsevier Digital Library, Springer, SPIE Digital library, and IEEE Xplore digital library. While there is a limitation on using the deep learning model on wound segmentation compared to other frameworks, other researchers experimented on a more traditional machine learning [7] and the combination of traditional methods and DNN [2]. Wound segmentation can also be done using wound pus as implemented on the Android platform by Vision-Based Pus Segmentation [8].

2.2. Wound image datasets

The literature shows that the most commonly used wound image datasets are from Igurko -Hospital at Bilbao-Spain [4] the National Pressure Ulcer Advisory Panel (NPUAP) at Santa Clara Valley Medical Center, UMASS – Memorial Health Center Wound Clinic located at Worcester, Massachusetts [9]. Wound images from the Internet such as Medetec image database (http://www .medetec.co.uk/files/medetec-image-databases.html and (http:// www.handsurgery.cn) have also been used. Some work utilizing the AlexNet transfer learning model has also used the ImageNet as a training dataset combined with images from Google search. Most of the datasets are free but validation datasets can be purchased from NPUAP [4]. The wounds in the dataset mostly contain infected and necrotic tissue healing state tissues. There are different types of resolution as the image taken differs from one source to another. Most of the images are manually segmented using expert knowledge from a nurse and medical personnel to obtain the ground-truth datasets. Examples of wound labeling for the purpose of wound classification are shown as follows:

- Black background (gray level 0) = external skin
- Dark grey (gray level 89) = necrosis
- Light grey (gray level 170) = granulation
- White (gray level 255) = slough

3. CLASSIFIERS AND MODELS OF DEEP LEARNING

In the field of computer vision, image segmentation techniques are typically known in attempting to make a classification of the images. Typical of segmentation algorithms, the goal tends to segment the most pronounced edges or similar regions as shown in Figure 2. Most of the common findings on tissue classification were Red Color on granulation tissue, Yellow Color on Slough tissue and Black Color on the Necrotic tissue. However, H. Nejati [6] discovered new findings on tissue classification where he classified 7 wound tissue types with another color. There are several classifiers used during the findings in the literature, some hand-crafted features as seen in Figure 3, and machine learning classifiers such as SoftMax, Support Vector Machine (SVM), Random Forest and Bayesian Classifier.

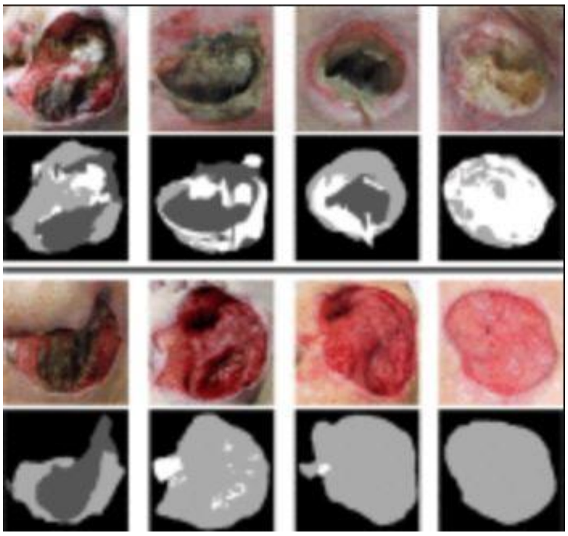

Figure 1. A set of pressure injury images [4] and their corresponding ground truth segmentation used to create the dataset and labels.

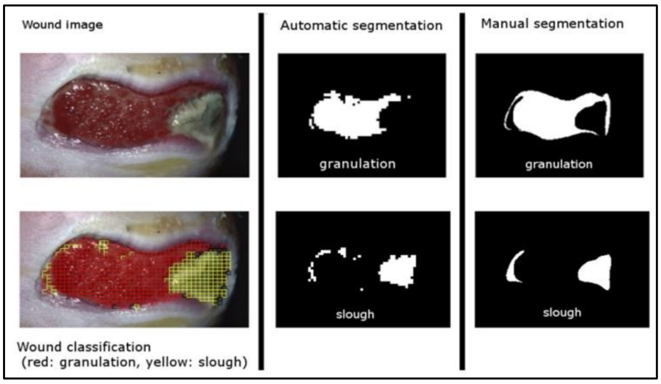

Figure 2. Example of Wound Classification and Automatic segmentation

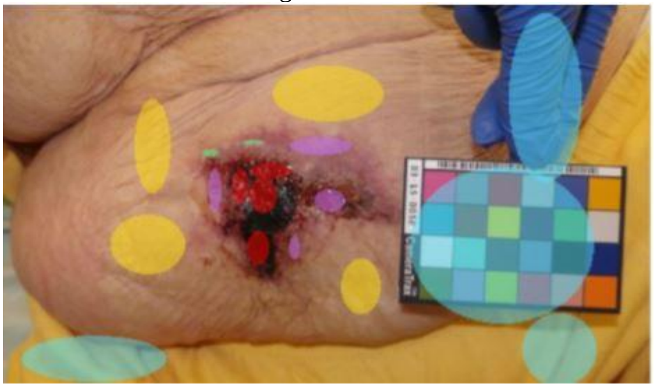

Figure 3. Example of handcrafted colour features that were used on wound segmentation

Some limitations of using machine learning classifiers are identified, thus the uprise of deep learning techniques used in wound segmentation. Some of the limitations that can be concluded in the literature are:

- Problem with verification of wound tissue – False-positive detected by the classifier if red cloth present in the background gets wrongly classified as granular tissue.
- Limitation on the dataset – The result will be too wide/general when compared to the ground truth images.
- Machine learning algorithm – Has high dependency on the statistics of the database.

The use of Deep Learning techniques was often considered when there are large datasets available to be utilized. In general, the most commonly used Deep Learning architecture for wound segmentation based on the scrutiny of this literature is via the Convolutional Neural Network (CNN). Based on the literature, CNN is devoted to performing optimized segmentation by having convolutions inside, which see different tissue types present in pressure **injuries** [4],[10], [11].

4. SUPERVISED DNN CLASSIFICATION (WOUND CLASSIFICATION)

The supervised DNN methods follow the reuse of a "pre-trained DNN as a feature extractor (AlexNet) pipeline, with each image labeled and partitioned into n x n patches, the class of each patch is determined based on the majorities of the included pixels. This method relies on layers of the DNN to extract high-level information of images [6].

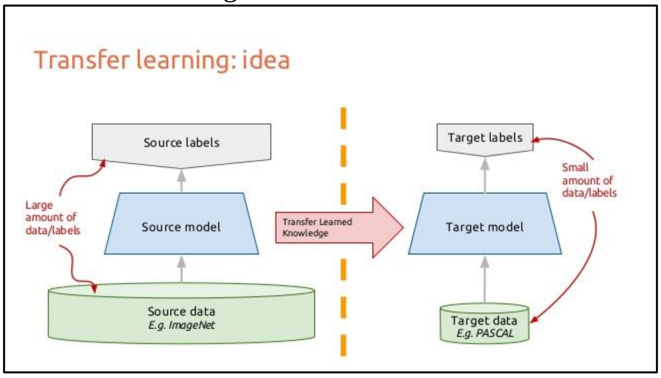

Figure 4. Example of model training via transfer learning

For the image classification task, AlexNet transfer learning is illustrated in Figure. 4. Two main factors were considered:

- The size of the new dataset
- The similarity between the original and the new dataset

The model is trained with 1.2 million images in 1000 categories including general kinds of images and man-made images. From each image patch, the wound image is resized to 277 x 277 to make it a valid AlexNet input with k-fold cross-validation [6]. For the classification step, a support vector machine (SVM) with a linear kernel was used to split the data into disjoint training and testing sets.

5. CNN BASED SEGMENTATION (WOUND SEGMENTATION)

Most of the methods that had been reviewed require a large number of high-resolution wound images. In [4], CNN Based Segmentation approach involves using a limited number of high-resolution images and extracting a larger dataset of small images in order to achieve comparable segmentation. For the wound segmentation task, their system is based on CNN to perform optimized segmentation of the different tissue types into granulation, slough, and necrotic tissue [4],[11].

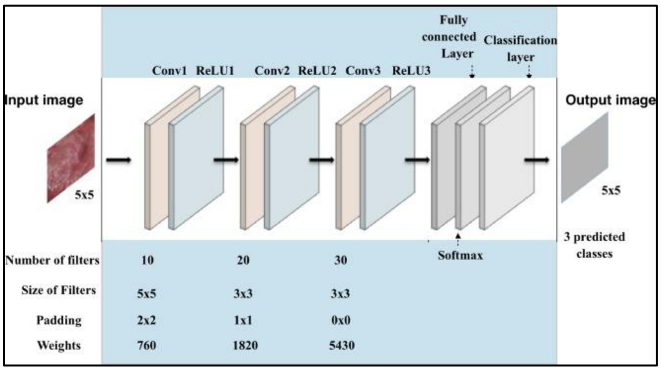

Figure 5. Example of CNN Architecture

In this method as illustrated in Fig. 5, a 5x5 sub-image has been created after they remove the flashlight reflection (noise) which is used as input for CNN network. The core building block of CNN is based on:

- Convolution layer – Learn the features of the input or the output images
- Pooling layer – Reducing the number of computations needed
- Fully connected layer – Combines all features learned to classify the images
- SoftMax layer – For multi-class classification purposes
- Classification layer – Assigns the output results of the SoftMax layer

6. FULLY CONVOLUTIONAL NETWORK (FCN)-BASED SEMANTIC SEGMENTATION

There are two key aspects of FCN model. Firstly, FCN model adapts to the traditional deep convolutional nets. The output segmentation mask will be $Height \times Width \times Class$ [1]. Secondly, semantic segmentation requires simultaneously capturing fine-grained, pixel-level information. Thus, the information is obtained through the up samples back to the original image dimensions and combines predictions at the final layer with prediction at the earlier layers. To make further prediction more consistent, a conditional random field has been formulated and attached as RNN cell onto the FCN. [1]. Fig. 6 shows an example of FCN architecture.

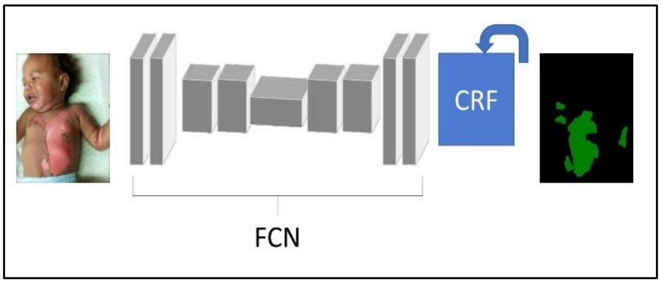

Figure 6. Example of FCN Network architecture from Orion Despo (2017) [ref] with a CRF Layer attached.

7. DISCUSSION

7.1. Strengths and Benefits

The literature findings provide compelling evidence that wound segmentation and classification will be one of the state-of-the-art technologies that will be beneficial to the medical and science industry. As it is different from object recognition, wherein object recognition you have a restricted class of objects (depending on your dataset). Parallel to that, semantic segmentation segments the image and labels each pixel with a class (Wound, Skin, Background). Accuracy can also be improved by removing the background noise. The benefits of wound segmentation are not limited to merely the speed of the process. With minimal training, it can enhance the accuracy of the wound assessment. When medical personnel assesses the wound manually, there will be some difficulty in the assessment preparation and it is time-consuming. [10],[12]. Furthermore, wound classification can give us more insights into the wound tissue composite and database.

Table 1. Pros and Cons of Deep Learning on Wound Segmentation

Pros	Cons
• Deep learning can help enabled physicians and medical staff to assess pressure injuries efficiently by providing them with accurate measurements. • Deep learning can give deep insights into wound assessments by recognizing the stages of the wound (necrotic, granular, slough)	• However, deep learning method can still be improved as can be seen from the misclassification of tissue classes on most of the papers. (adversarial examples) • Many of the approaches from the literature, requires a huge chunk of labeled wound datasets and some find it difficult

• The method can be implemented on a mobile platform to assist the patient in their own wound care and surgical recovery from the comfort of their home.	or impossible to create such sets • Deep learning also requires a high amount of computational resources to achieve the best accuracy.

8. CONCLUSION

Wound segmentation will be more relevant in the near future as more and more studies have been more arise. Recent work suggests that most of the wound segmentation was done on deep learning techniques which have been a good sign. The CNN-Based Segmentation was found to produce compelling evidence that the strategy proposed is more reliable when compared to other research reported, with regards to their method approaches on wound segmentation.

9. ACKNOWLEDGEMENT

Due acknowledgment is accorded to the Ministry of Education and Research Institute of Research, Management and Innovation, Universiti Teknologi MARA for the funding received through the Niche Research Grant Scheme, 600-IRMI/NRGS 5/3 (13/2013)

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