Tissue segmentation for automatic chronic wound assessment

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Abstract. Chronic ulcers are usually the result of prolonged pressure on the skin and underlying tissues. The assessment and treatment of wounds require an accurate analysis of their physical characteristics. This is due to the fact that the evolution of the healing allows to evaluate the effectiveness of the treatment. In addition, in most cases, the methods of analysis used nowadays are rudimentary, which leads to errors and the use of invasive and uncomfortable techniques for patients. Important point to determine infection signs and healing process. To do this is important know the quantity of necrotic, sloughy and granulating tissue in wound and their evolution. In this paper we will discuss about Computer Vision and Artificial Intelligence techniques that provide an improvement on tissue segmentation and tissue detection. A mobile application has been developed to acquire the data, enable label assignment before training, and finally display the result of the segmentation. This article discusses about the results of a convolutional neural network as a method of segmentation and how this can improve the clinical practice as a part of wound assessment in a real environment.

Keywords. Wound assessment, Pressure ulcers, wound tissue segmentation, necrosis detection, CNN

1. Introduction

Diagnosis and treatment of wounds require an accurate analysis of their physical characteristics, especially in the case of chronic ulcers since the evolution of the wound healing enables the evaluation of the treatment efficiency [1,2,3]. Many methods for analysis currently in use are rudimentary, what leads to errors and the use of invasive techniques that are uncomfortable for patients [2]. Because of that, it is extremely difficult to monitor the evolution [7] of the wound based on the treatment and the healing process as no data is stored and classified efficiently. Literature covering the elaboration of different algorithms focused on the detection and characterization of wounds is limited and mainly based on the capture of size and depth, among others [4]. In order to develop new algorithms, some sections of the standard scale Resvech 2.0 [4] will be used as reference. The main goal is to determine the tissue assessment section, in order to detect the three main tissues (necrotic, sloughy, and granulating) present in wounds. The method proposed will undoubtedly have a greater efficiency on the professional side, in the task of qualifying and following the evolution of the wounds, as well as improving

the attention to the patient and a reduction of costs to the sanitary system preventing infection situations. This article discusses about the results of a convolutional neural network as a method of segmentation and how this can improve the clinical practice as a part of wound assessment in a real environment.

2. Methods

With the aim of ensuring and accrediting the performance of Convolutional Neural Network to determine different tissues on wounds, an application has been implemented to acquire data, label it and prepare the corresponding dataset.

2.1. Participants

In the framework of this project, 100 patients with age of (mean + - std) 75 years +- 5 years of which 75% women and 25% men were enrolled at Hospital de la Santa Creu de Vic. In 15% of cases, patients are hospitalized and 85% have been seen in an outpatient clinic or at home. All participants signed an informed consent form that has been approved by the local ethics committee.

2.2. Dataset

Data have been collected by means of a mobile app. All data have been managed and normalized according the process specification.

2.3. Pretraining process

The professional takes a photograph of the wound and, by means of an application on a digital tablet, will draw three contours manually corresponding to the three tissues to classify. All images had a region of interest (ROI) delimited to discard extra background information. ROI regions were cropped into small matrices of dimension 5 by 5 by 3 to fit the input of the CNN architecture designed. Once the data was loaded into the network, the support given to each class was adjusted to balance the data being represented.

2.4. Training process

To explore all the available algorithms and features, several datasets were used to fully train a Convolutional Neural Network based on Alexnet. Other CNN [5] have been tested but this is the one that has given better results. Convolutional neural networks (CNN) are the most popular artificial neural networks used to analyze images for classification problems. The architecture used in both frameworks was a design based on reference [6]. It is composed of three convolutional layers, two dropout and two dense layers [5]. After trying several times with multiple values, we conclude that the architecture of the network proposed can be seen in the following table:

Table 1. Network architecture

Layer (type)	Output Shape	Param #
conv2d_43 (Conv2D)	(None, 5, 5, 10)	760
conv2d_44 (Conv2D)	(None, 5, 5, 20)	1820
conv2d_45 (Conv2D)	(None, 3, 3, 30)	5430
dropout_29 (Dropout)	(None, 3, 3, 30)	0
flatten_15 (Flatten)	(None, 270)	0
dense_29 (Dense)	(None, 540)	146340
dropout_30 (Dropout)	(None, 540)	0
dense_30 (Dense)	(None, 5)	2705

The evaluation of the network was performed analyzing the precision, recall and F1-score of models. This network should enable automatic wound tissue segmentation by analyzing the location and quantity of each class within the original image. The precision, also called positive predictive value, is the fraction of relevant instances among the instances retrieved by the model. It is calculated as the ratio of true positives to all the positive instances predicted by the system and can be considered as the ability of the classifier not to label a negative sample as positive. The recall, also known as sensibility, is the ability of the classifier to find all positive samples and it is calculated as the ratio of the positives predicted by all positive instances. The third measure considered is the F1-score, which is the harmonic mean of precision and recall, and reaches its best values at one. In our code, this measure weights equally precision and recall. The ROC curve represents probability, while the AUC is a measure of reparability.

3. Results

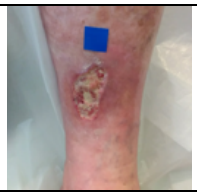
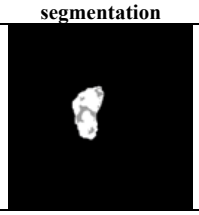
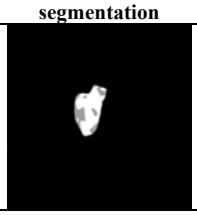
In the following section the results obtained with dataset specified in table 1 will be presented.

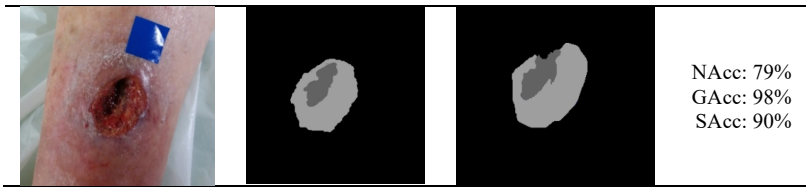
Table 2. Model results using accuracy calculation by precision, recall, f1-score and support.

	precision	recall	f1-score	Support
Necrotic	0,81	0,75	0,78	125553
Granulating	0,60	0,75	0,66	125553
Sloughy	0,73	0,60	0,66	125553
avg / total	0,71	0,70	0,70	376659

The most significant results have been obtained comparing the manually segmented image by a professional and the network result segmentation.

Table 3. Most characteristic results: original image, manual segmentation, automatic segmentation and accuracy results (Necrotic accuracy NAcc, Granulated accuracy GAcc and Sloughing Accuracy SAcc). Area comparation using % of pixels.

Original image	Manual segmentation	Automatic segmentation	Accuracy Results
			NAcc: 99% GAcc: 81% SAcc: 76%
			NAcc: 88% GAcc: 67% SAcc: 90%



4. Conclusions

Tissue identification within a wound is of essential importance for the proper assessment of chronic ulcers as well as for the determination of the best treatment option. The approach presented in this article developed a CNN that aimed to enable automatic tissue segmentation for pressure ulcers assessment. Regarding the application in which the CNN would be used, the CNN model selected was found to give overall best results, specifically with the class necrotic tissue in terms of precision. The reference scale Resvech [4] used defines necrotic tissue as the most significative tissue within a wound, necrotic is death tissue that can extend and be harmful. The precision of the network is of special importance, especially with this tissue, since it determines the treatment that should be chosen as well as the overall expectations regarding the ulcer development. Lastly, considering the class granulating tissue, it should be remarked that as it corresponds to healthy tissue it is of least importance for classification with respect to the other two classes being considered. That is why the main objective of the network in a clinical healing environment is the detection of necrotic tissue.

Finally, we are talking about improve the wound assessment, is important include this method in the clinical practice without being invasive. Using a specific mobile application, the health professional can use the mobile to collect data and analyze them in real time.

5. Conclusions

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6. References

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