A Superpixel-wise Fully Convolutional Neural Network Approach for Diabetic Foot Ulcer Tissue Classification

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Abstract. Accurate assessment of diabetic foot ulcers (DFU) is primordial to provide an efficient treatment and to prevent amputation. Traditional DFU assessment methods used by clinicians are based on visual examination of the ulcer by estimating the surface and analyzing tissue conditions. These manual methods are subjective and make direct contact with the wound, resulting in high variability and risk of infection. In this research work, we propose a novel smartphone-based skin telemonitoring system to support medical diagnoses and decisions during DFU tissues examination. The database contains 219 images, for effective tissue identification and annotation of the ground truth, a graphical interface based on superpixel segmentation method has been used. Our method performs DFU assessment in an end-to-end style comprising automatic ulcer segmentation and tissue classification. The classification task is performed at a patch-level, superpixels extracted with SLIC are used as input for the training of the deep neural network. State-of-the-art deep learning models for semantic segmentation have been used to perform tissue differentiation within the ulcer area into three classes (Necrosis, Granulation and Slough) and have been compared to the proposed method. The proposed superpixel-based method outperforms classic fully convolutional network models while improving significantly the performance on all the metrics. Accuracy and DICE index are improved from 84.55 % to 92.68 % and from 54.31% to 75.74% respectively for FCN-32. The results reveal robust tissue classification effectiveness and the potential of our system to monitor DFU healing over time.

Keywords: Deep Learning · Fully Convolutional Networks · Superpixel Segmentation· Diabetic Foot Ulcer· Tissue Classification· SLIC.

1 Introduction

Diabetes is a chronic disease characterized by abnormally high levels of glucose in the blood. At present, almost half a billion people worldwide suffers from diabetes. Poorly managed diabetes leads to several complications including cardiovascular disease, kidney disease, eye complications, nephropathy, lower limb ulcers, etc. Diabetic foot ulcers (DFU) are the most chronic and severe complication of diabetes associated with neurological disorders and peripheral vascular disease leading to millions of amputations every year. A lower limb is lost to amputation every 30 seconds somewhere in the world due to diabetes [4]. This diabetes related complication has a significant impact on individuals' life quality and imposes a high social and economic cost. However, if an appropriate management of these ulcers is achieved, lower limbs amputation can be delayed or prevented altogether. Diabetic foot ulcers should be regularly checked by healthcare professionals for clinical care and to evaluate the healing progress. In standard clinical practice, the examination of ulcers is mainly based on physical measurements and visual assessment of the skin tissues [5]. Manual methods rely on the use of a simple ruler to measure ulcer perimeter (length and width), an outline over a transparent sheet to calculate the surface area and physiological serum for volume estimation [13]. Moreover, these methods are invasive and in direct contact with the wound bed which carries high risk of infection. On the other hand, analyzing color and proportion of the tissues help to determine the healing progress of the ulcer and provide quantitative measurement without contact. Within the ulcer boundaries, visual inspection is based on red-yellow-black color evaluation model corresponding respectively to the different tissues: granulation, slough and necrosis [29]. However, determining the exact proportion of each tissue through a visual exam is prone to inter-expert variability. In order to provide an accurate diabetic foot ulcer management, using image analysis became an attractive option to help clinicians for an accurate and objective assessment of the ulcer especially with the spread of smartphones with high resolution cameras and powerful processors. Imaging technologies allow low cost, non-invasive, fast and automatic assessment. The principal objective of this work is to develop an automatic smartphone-based system for ulcer segmentation and tissue identification. This work is part of the STANDUP project [1] which aims to prevent diabetic foot ulceration in an early stage and to monitor in an efficient way the ulcer healing over time. In order to provide a robust tissue classification, we propose a novel superpixel-based approach for automatic tissue analysis using deep learning methods. The final system can serve as effective tool to support medical diagnoses and decisions during DFU examination to ensure an accurate management of lower limb lesions. Moreover, this methodology is applicable to other wound conditions such as pressure injuries, surgical and traumatic wounds,venous ulcers, etc.

2 Related work

In recent years, the use of smartphones and imaging technology in daily clinical practice, especially towards wound and DFU assessment has increased considerably. Clinicians can obtain additional information about the wound characteristics from digital image processing to improve diagnostic accuracy. Several image processing studies have addressed wound segmentation using different approaches. Mainly, these methods are based on supervised traditional machine learning (ML) especially SVM classifiers. ML algorithms require handcrafted features extracted from images using different texture and color descriptors followed by SVM [25, 28]. Nevertheless, descriptors can be influenced by image resolution and require a color correction step using a reference pattern inserted in the field of view. Although their performance, ML methods are not robust enough due to their reliance on the handcrafted features. Recent approaches involve more sophisticated methods such as deep learning. Including convolutional neural networks (CNN) for classification or fully convolutional neural networks (FCN) for semantic segmentation. The training of these networks requires the use of a large labeled dataset. In [24], Wang et al. proposed a new deep learning architecture based on en-coder-decoder to perform wound segmentation using 650 images from NYU database [21]. On a different approach, Goyal et al. [11] developed a new DL model called DFUNet to classify DFU sub-images into normal and abnormal skin using 397 images. The proposed network DFUNet outperforms GoogLeNet in all the evaluation metrics. In a recent work [12], the same authors used a two-tier transfer learning model combining R-CNN with Inception-V2 to localize DFU with a precision of 91.8%.

Regarding tissue classification, most of the methods found in the literature use traditional machine learning algorithms. Mukherjee et al. [15] performed wound tissue classification using five color and ten textural features followed by a 3rd polynomial kernel SVM. In a different approach, Hazem et.al. [27] proposed a multi-view tissue classification using 3D model and SVM. Due to the lack of annotated images in the biomedical field and especially for chronic wounds (CW), few studies have been conducted using DL methods for wound tissue classification. In [10], the authors used 30 wound images to perform tissue segmentation using the fully convolutional net-work U-net designed for small medical image databases [19]. The network was initialized with a pre-trained VGG-16 [8]. The results show an accuracy of 94% and 96% after a color space reduction. Zahia et al. [30] presented an approach to handle small datasets in DL through patch-level tissue classification. Their approach was based on partitioning 22 images into small 5x5 patches that have been used to train the proposed convolutional network. The achieved performance was relatively high with an accuracy of 92.01%. Similarly, Nejati et al. [16] performed tissue classification on a patch-level but with combining ML and DL methods. The dataset contains 350 images partitioned into 20x20 patches. AlexNet has been used for feature extraction and SVM to classify each patch into the corresponding tissue class.

Unlike existing approaches using square patches, we used homogeneous superpixels instead. Superpixels have more perceptual meaning since pixels belonging to a given superpixel share similar tissue properties. In a recent work [7], Blanco et al. proposed a superpixel-driven method called QTDU using the CNN ResNet for dermatological wounds tissue classification. The method, outperformed different machine learning approaches. In contrast, our premise is to perform superpixel-based diabetic foot ulcer tissue classification at pixel-level

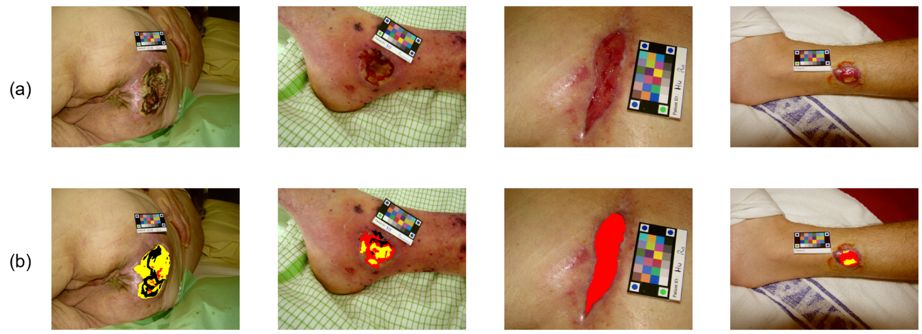

Fig. 1. Some images from ESCALE database (a) and corresponding ground-truth (b).

using fully convolutional neural networks for a more accurate and precise tissue identification.

3 Proposed Method

Our approach is divided into two steps: first, the automatic extraction of the ulcer area eliminates all background elements that may threaten the classification. This ulcer segmentation is useful for perimeter and surface assessment based on a pattern included in the field of view for fixing the image scale factor. Secondly, tissue classification is performed to identify the different tissues within the ulcer area after superpixel extraction.

3.1 Image Acquisition and Data Annotation

A database of diabetic foot ulcer images has been constituted in two hospital centers, Hospital Nacional Dos de Mayo (Lima, Peru) and CHRO Hospital (Orleans, France). The acquisition protocol consists on capturing free-handedly a set of images using a smartphone camera while framing the ulcer area from a point of view as frontal as possible. Chronic wound images from ESCALE database [26] were also added to the training set. The images are with different resolutions, acquired using different cameras and under different illumination conditions. The whole database comprises 219 images with variety of types of chronic wounds including leg ulcers, diabetic ulcers, bed sores, etc. The database has been labeled by medical experts into three main types of tissues using the graphical interface proposed in [17] based on the red-yellow-black usual model. Fig. 1 shows some examples of wound images multi-class annotation.

3.2 Ulcer Segmentation and Superpixels Extraction

The first stage of our method is ROI extraction. This step is meant to extract the ulcer area from healthy skin and to eliminate background elements. The

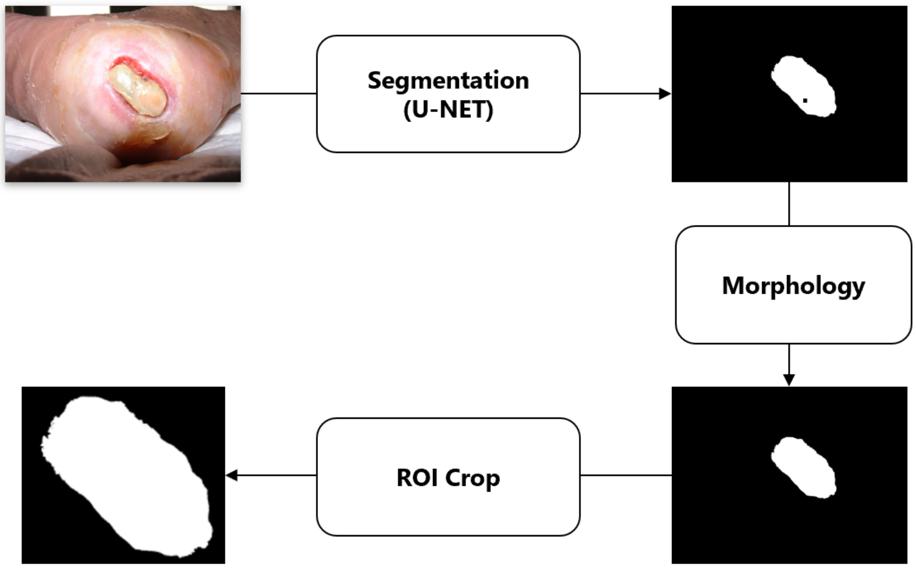

Fig. 2. Diabetic foot ulcer segmentation framework

background removal aims to highlight the tissues features inside the wound bed in order to simplify the classification task. The segmentation was performed using U-net, which achieved an accuracy of 94.96% and a Dice score of 97.25% [18]. To refine the segmentation results, we combined different morphological operations (i.e., erosion, dilation, opening, and closing) [23]. Then, the non-ulcer region has been represented by a white background in the original images and corresponding ground-truth. Mainly, the wound area especially for DFUs represents less than 30% in most images. Hence, using the entire image as input for the training of the network is unnecessary. Therefore, we cropped the ROI in all images and their annotations to focus the training on the wound area only (see Fig. 2).

To extract superpixels from the segmented wound, we adopted simple linear iterative clustering (SLIC) [2] which relies on k-means method to generate an efficient image partition into homogeneous clusters by combining (R,G,B,X,Y) five-dimensional color and image plane space. Superpixel extraction from the ROI was provided using the zero-parameter version of the SLIC algorithm called SLICO. Instead of using the same compactness parameter initialized by the user for all superpixels in the image, this method adaptively changes the compactness parameter for each superpixel depending on its texture [3]. The result is regularly shaped superpixels regardless of the texture while conserving a high computational efficiency. The obtained superpixel segmentation map is then applied to the ground truth image in order to generate the annotation label of each sub-image. After superpixels split, only the ones corresponding to a single tissue and their corresponding label were conserved and all totally white superpixels

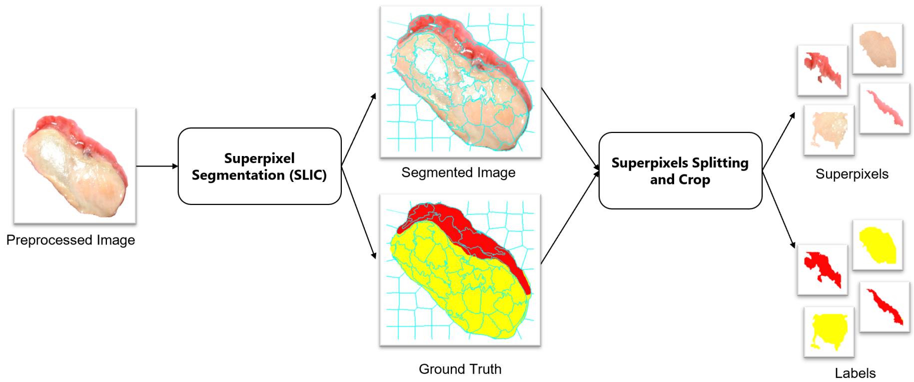

Fig. 3. Superpixel extraction from the segmented DFU image using SLIC

were removed for an efficient training. Finally, the superpixels were cropped and resized to 224x224 resolution (see Fig. 3).

3.3 Superpixel-based Tissue Classification

Our objective is to classify DFU tissue at a pixel level into three main classes combining deep neural networks and superpixels. The segmentation was performed using the state-of-the-art deep neural networks for semantic segmentation called as Fully Convolutional Neural Networks. These networks replace the fully connected layers in the classification models with convolutional layers which allow a pixel-wise prediction. A class label is assigned to each pixel of the image. The typical architecture for semantic segmentation is encoder-decoder and it consists of an encoder network followed by the corresponding decoder. U-Net [19], SegNet [6] and FCN-Net [14] are the most used algorithms for semantic segmentation in the field of medical images. U-Net proposed by Ronneberger et al. is specially designed for small databases segmentation and produces precise segmentation using few images for training. SegNet is an encoder-decoder network identical to the convolutional layers in VGG16 [22] adapted for semantic segmentation, the encoder network is considerably reduced which make it computationally efficient. FCN-32, FCN-16, and FCN-8 are the three main variants of FCN-Net based on a pre-trained VGG16 network as encoder. FCN-32 is same as VGG16 in which fully connected layer of VGG16 is replaced by a 1x1 convolution. FCN-16 and FCN-8 additionally work on low-level features by adding decoder layers to the network in order to produce more precise segmentation.

The generated superpixels with SLIC were used as input to feed these fully convolutional neural network models. (Fig. 4) illustrates the proposed framework based on an FCN-32 architecture. In the model training, we adopted a large-scale dataset with over 5000 wound superpixel and corresponding ground truth without any data augmentation. The output of the proposed method is a semantic segmentation of each superpixel. The model evaluation for DFU tissue

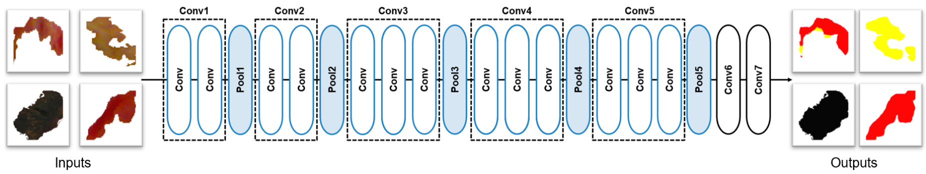

Fig. 4. Overview of the proposed fully convolutional network architecture based on super-pixels

classification of an entire image is done into three steps. Initially, the ulcer is segmented and split into superpixels similarly as presented in the previous section. Then, the generated superpixels and their corresponding labels are cropped and resized. Secondly, each superpixel will be given to the trained network for prediction to get the segmentation map. Thirdly, a class label will be assigned to each superpixel depending on its dominant color (red, yellow or black). The non-tissue superpixels such as bones will be classified as unknown and represented by a white color. Finally, an output image will be reconstructed based on the superpixel classification and the final result is a segmentation map of the different tissues inside the wound bed.

4 Results

4.1 Performance metrics

We evaluated the performance of the proposed method using the most common metrics in the field of medical image segmentation. These metrics are accuracy, sensitivity, specificity, precision, and dice similarity coefficient (DICE) [9]. The formulas are defined respectively as the following:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$DICE = \frac{2TP}{2TP + FP + FN} \tag{5}$$

Where TP, FP, TN and FN stand for the number of the true positive, false positive, true negative and false negative classified pixels.

Table 1. Number of superpixels for the training and testing set

	Training	Testing
Granulation	2872	762
Slough	1897	594
Necrosis	463	155
Unknown	24	19

4.2 Experimental Results

The database containing the generated superpixels and their labels was divided into training and testing set. The partition percentage was around 75% for the training, and 25% for the testing as shown in (Table 1). The evaluation aimed at quantifying the improvement of the of state-of-the-art FCNs using the proposed superpixel based approach (Spx) in comparison to their classic version and determining the most suitable network to perform tissue identification of diabetic foot ulcers. Accordingly, The different models have been trained on the same chronic wound database and tested using only DFU images. The methods were implemented in Keras with TensorFlow backend using the stochastic gradient descent (SGD) optimizer [20] and a learning rate of 0.01.

Table 2 lists the segmentation results of all the tested methods regarding the accuracy, sensitivity, specificity, precision and DICE. The proposed superpixel-based approach outperformed all the state-of-the-art methods. It shows a higher performance for all the computed metrics. As we can see, the results were considerably improved by the usage of superpixels instead of the whole image as training set. This demonstrates the effectiveness of combining SLIC superpixels and FCN as it is capable of performing a more precise semantic segmentation of tissues.

To choose the most suitable network, we selected the best performances of Table 2. Spx-FCN16 and Spx-FCN32 achieved the best results for all the computed metrics, SPX-FCN32 was slightly better than Spx-FCN16 regarding Sensitivity, Specificity, precision and DICE and it achieved a higher accuracy. A fusion of superpixels and FCN-32 improved accuracy by 8.13% to reach 92.68% and led to a high DICE score of 75.74% instead of 54.31%. Fig. 5 shows some examples of DFU tissue segmentation output for both approaches. We also investigated how the method performed on each tissue type. Detailed classification results for necrotic, granulation, and slough tissues using the superpixel-based FCN-32 variant can be seen on Table 3. The results on specific tissue types indicate that necrotic class performance is inferior when compared to slough or granulation tissue. Necrosis appears to be the most difficult to be identified by the network. This could be justified by the number of superpixels per class during the training phase which lead to wrong pixel classification of this tissue. Necrosis represents only 9% of the training set comparing to 54% for granulation and 36% for slough. Therefore, the performance results for non-necrotic classes is reliable and reflect a significant improvement in wound tissue segmentation. Unlike the

Table 2. Tissue segmentation results of FCNs vs. Spx-based FCNs

	Accuracy	Sensitivity	Specificity	Precision	DICE
SegNet	58.6%	36.4%	82.2%	43.7%	33.2%
Spx-SegNet	**79.2%**	**65.9%**	**93.3%**	**72.2%**	**67.1%**
UNet	69.56%	55.1%	87.6%	68.7%	57.5%
Spx-UNet	**80.75%**	**68.3%**	**94%**	**74.8%**	**69.2%**
FCN8	69.37%	61%	90%	63%	60.3%
Spx- FCN8	**81.92%**	**74.5%**	**93.6%**	**78.7%**	**73.7%**
FCN16	72%	57.7%	90.6%	62.9%	56.1%
Spx- FCN16	**83.67%**	**75.4%**	**94.2%**	**76.9%**	**75.5%**
FCN32	84.55%	54.68%	89.32%	62.08%	54.31%
Spx- FCN32	**92.68%**	**74.53%**	**94.39%**	**78.07%**	**75.74%**

existing methods in literature which deal with slough tissue due to the different textures related to it, our method is capable of segment it with the highest DICE score of 77.5%.

Table 3. Classification results for each tissue using the proposed Spx-FCN32 method

	Sensitivity	Specificity	Precision	DICE
Necrosis	51.55 %	99.01 %	70.94 %	59.71 %
Slough	84.63 %	91.89 %	71.48 %	77.50 %
Granulation	69.68 %	95.81 %	76.01 %	72.71 %

Moreover, by observing the qualitative results (see Fig. 5), we can clearly notice that the method based on superpixels produces an accurate segmentation with a very high precision regarding the three classes (Granulation, Necrosis and Slough). The tissue segmentation precision was significantly improved using superpixels instead of the entire image to train the FCN-32 network. In addition, the identification of non-tissue pixels corresponding to bones inside the ulcer area (see Fig. 5, sample 6), is a statement of our method robustness.

Fig. 5. DFU tissue segmentation results: (a) original image, (b) segmented image, (c) output of FCN-32, (d) output of the proposed Spx-FCN32, and (e) Ground truth.

Conclusion

We presented a novel approach for automatic diabetic foot ulcer segmentation and tissue classification. The proposed classification method was performed by a superpixel-based semantic segmentation using fully convolutional networks. The experimental tests show that the proposed image segmentation method exhibits higher performance than the existing state-of-the-art FCN methods regarding all the metrics and demonstrate the robustness of our method especially for slough and granulation tissue. Furthermore, we intend to expand our database by acquiring new high-quality wound images with different tissue types in order to improve tissue identification for all classes especially necrotic one. In addition, our system is embedded into a smartphone with add-on temperature sensor. Assessing the wound temperature can help to localize sign of deep inflammation and infection and to identify the DFU type (neuroischemic or neuropathic) as well. The proposed system could be used by clinicians during diabetic foot examination for an accurate and complete assessment from ulcer delineation, surface and temperature measurements to tissue area identification and analysis. This system can be extended to the assessment of chronic wounds such as burn wounds, pressure injuries, etc.

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