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A System for Wound Evaluation Support Using Depth and Image Sensors

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Abstract— **This paper proposes an evaluation/treatment support system enabling automatic determination of wound evaluation indices from RGB-depth images and fully convolutional networks (FCNs). Segmentation experiments based on wound images and surface area determination experiments based on artificial images showed reduced errors and smaller parameters/higher levels of tissue classification than with previous approaches (proposed: 65.8 %; conventional: 60.2 %), thereby demonstrating the effectiveness of the technique.**

I. INTRODUCTION

Illness and injury often require prompt emergency measures, treatment and medication in line with severity. Nevertheless, in the case of wounds, performing self-diagnosis and self-treatment without a medical background can cause infection and slow down the healing process. On the other hand, visiting a doctor only to check the severity of the wound is impractical considering the cost that has to be paid by the patient and the limited number of doctors. It would be useful if mobile devices could be used to evaluate severity of wounds without the need for a medical visit.

Photographic Wound Assessment Tool (PWAT) is one of the standard metrics that physicians use to estimate wound severity [1]. It determines whether a wound is serious or not by visually inspecting the wound and measuring eight indices related to the wound's size and depth and the state of the cellular tissue. The visual examination, however, is difficult to quantify and may lead to inaccurate results. Besides, obtaining reliable results requires expertise in observing types of wounds and tissue in wound base. Therefore, developing a mobile application that can assess the severity of the wound is necessary.

Previous works have attempted to solve that problem by developing a wound assessment algorithm that can estimate the wound area and classify the tissue types. Kolesnik et al. [2] performed pixel-to-pixel classification to identify wound on an image with color and textures features and Support Vector Machine (SVM). The experimental results suggested that combining both color and texture features yielded a higher performance rate than processing each feature separately. Liu et al. [3] proposed a DNNs model to segment wound areas and investigated the trade-off between the model's parameter and its accuracy. The experimental results demonstrated that the model could achieve high accuracy results, even with a small number of parameters, and could be used in mobile devices. While the segmentation wound algorithm attempted to differentiate wound and not wound pixel, previous studies on the cellular-tissue classification methods classified tissue type on the wound area. Employing AlexNet, Nejati et al. [4] classified seven different tissue types, while Ronneberger et al. [5] proposed U-Net to perform three-type fine-grained tissue classification. In another study, Fliko et al. [6] found that using RGB images and depth information to segment and measured wound area yielded more accurate results.

Despite their promising classification performance, previous studies have not provided a practical assessment method that considers the wound's location, size, and tissue. Also, since the previous method algorithms involve a complex algorithm and require a large number of parameters, implementing them on a mobile device is difficult.

This paper proposes RoleNet (Role-oriented Fully Convolutional Networks) to segment the wound area and classify the tissue type on it. RoleNet comprises wound segmentation and tissue classification models that perform sparse estimation of the wound area and fine-grained classification of the three tissue types (granulation, necrotic, and sloughy). This allows the model to have a high accuracy rate with few parameters, thus making it feasible to be implemented in a mobile device. Moreover, this paper proposes an evaluation system employing the RoleNet to quantitatively assess the wound severity based on PWAT model.

II. WOUND ASSESSMENT WITH PWAT

Fig. 1 depicts the proposed method that estimates the wound area and identifies tissue type using RGB images and depth information from a mobile camera. Employing 3D point group data, the proposed approach automatically calculates the size of the wound and cellular tissues.

A. Noncontact Area Presumption Using 3D Point Group Data

Using a mobile device equipped with an RGB-D sensor such as the iPhone X, point cloud data with RGB and 3D information of each pixel was acquired. Then, a point group area estimation algorithm was applied to measure the wound area in 3D space. The proposed framework grouped data points with a sliding window; each three-point insides the window was grouped with a triangle while two triangles were used to connect four points.

B. RoleNet Architecture

Fig. 2 shows the RoleNet architecture. RoleNet consists of two models that estimate wound area and classify tissue

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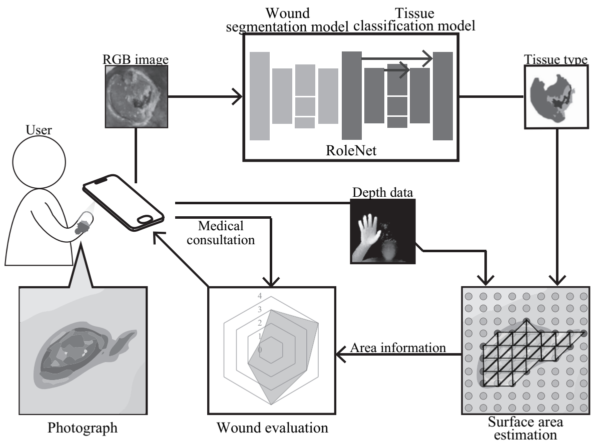


Fig. 1. The framework of the proposed system

types, respectively.

The wound-area estimation model utilizes stacked convolution and pooling layers to extract features from the input image. Then using the extracted features, the model performs upsampling and segment the wound area.

The tissue-type classification model categorizes each pixel of the wound images into three categories: granulation, necrotic, and sloughy. After merging the input image with the probability map of the wound area, an encoder model is employed to extract features for tissue-type classification. In this step, features from shallow layers are combined with the deeper layer features by using a contracting path [5]; this increases the sharpness of the output image and improves the accuracy of the tissue-type classification model. Using stacked convolution and upsampling layers, the model performs pixel-to-pixel tissue-type classification. This architecture enables the model to perform both wound area segmentation and tissue-type classification with a small number of parameters.

To further reduce the number of the proposed model's parameters and increase its accuracy, proposed model employs depthwise separable [7] and atrous convolution [8] networks in CNNs block and perform downsampling using stride [9]. Depthwise separable convolution reduces the number of parameters by splitting the convolution kernel into depthwise and pointwise convolution kernels. Atrous convolution introduces spacing between the values in the kernel, thus allowing the model to understand a wider field of view with smaller parameters. Performing downsampling with stride prevents loss of informative features by varying the number of strides in the classification.

C. Model Training

RoleNet model was trained in two steps. First, the parameters of the wound area and tissue-type classification models were estimated separately. Then, the models were conbined and were jointly retrained.

III. EXPERIMENT

To evaluate the proposed model, four experiments were conducted: wound area segmentation, tissue type classification, the combined tasks, and wound area estimation. Comparison with U-Net was performed on the first, second, and third experiments.

TABLE I
RESULTS OF THE WOUND SEGMENTATION

Model	Accuracy	mIoU	Params
RoleNet	0.883	0.790	2.64 M
U-Net	0.896	0.812	31.4 M

A. Experiment on Wound Area Estimation

We collected 40 wound images from a medical book [10] and made labels based on medical knowledge. The original size of the images was 480×480. The original ones were then resized into 256×256. The wound and nonwound areas were labeled as white and black areas, respectively. Proposed model performance was evaluated on those images and compared its performance with U-Net's (Fig. 3) . The data was split into training (31 images), validation (3 images), and test (6 images) datasets. Data augmentation was performed on the training dataset; it included horizontal flipping, vertical flipping, horizontal translation, vertical translation, shear distortion, scaling, and rotation. The models were trained using multi-class cross-entropy loss and Adam optimizer [11] and evaluated the model's performance with accuracy and mean Intersection-Over-Union (mIoU) metric. The batch size, the number of epochs, and the learning rate were respectively set to 2, 32 and 0.001.

B. Experiment on Tissue Type Classition

Evaluation on tissue classification was performed on 30 wound images with a size of 256×256 pixels. Each image consisted of three labels: granulation (red), necrotic (blue), and sloughy (green) tissues. The training, validation, and test data comprised 21, 3, and 6 images, respectively. The models were trained using the same loss function, optimizer, and metric as the first experiment. The Batch size, the number of epochs, and the learning rate were 2, 48, 0.001, respectively.

C. Experiment for the Integrated Model

This evaluation scheme validated the performance of the proposed model on both wound segmentation and tissue classification. The experimental protocol was the same as in the second experiment. And two-stacked U-Net was utilized as the comparison model.

D. Experiment of the Surface Area Estimation

Fig. 4 shows the A4 paper used to print out circles with different radius demonstrating wounds. The proposed method estimated the area of the circles on the images taken with RGB-D sensors on iPhone X 10 times. The distance between the camera and the object was about 40 cm. Metrics used to evaluate the model were the mean value, standard deviation, and relative error.

IV. RESULTS

A. Identification of Wound Area

In Tab. I, even though the proposed model required 91.05 % fewer parameters, it could achieve comparable performance. The accuracy and the mIoU of the proposed model were 1.3% and 2.2 % lower than U-Net's, respectively.

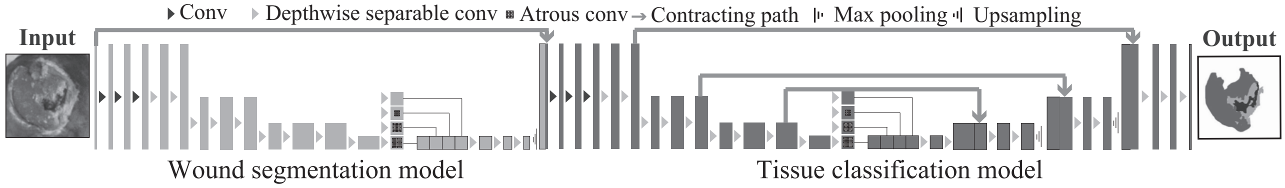


Fig. 2. The structure of RoleNet

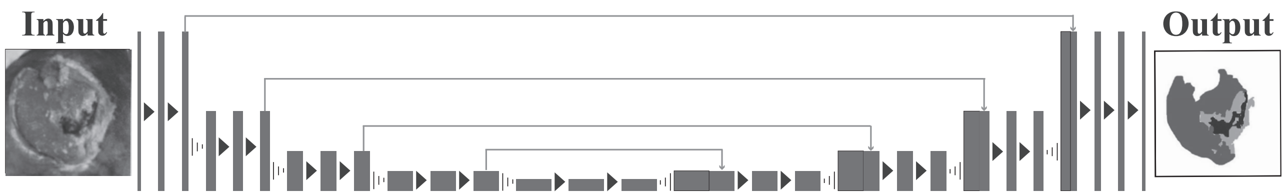


Fig. 3. The structure of U-Net

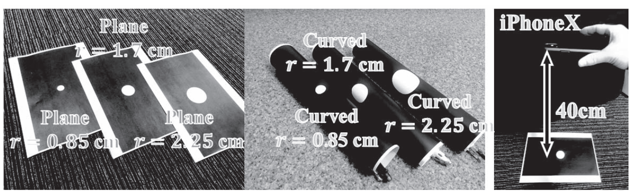


Fig. 4. Condition of the experiment of area estimation evaluation(left: white plane circle to shoot, center: white curved circle to shoot, right: photographing condition)

TABLE II
RESULTS OF THE TISSUE CLASSIFICATION

Model	Accuracy	mIoU	Params
RoleNet	0.955	0.861	3.04 M
U-Net	0.934	0.809	31.4 M

Besides, the comparison of segmentation results (Fig. 5) demonstrated that the proposed model made less false-positive. This result demonstrated that proposed model could classify wound and nonwound areas.

B. Classification of Wound Tissue

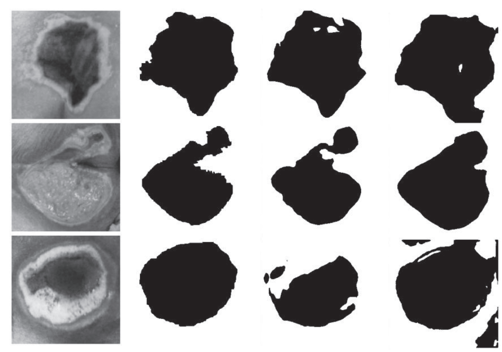
In Tab. II, the proposed model obtained better performances. The accuracy and the mIoU result of our method were 2.1% and 5.2 % higher than U-Net and also RoleNet required 90.3 % fewer parameters than U-Net. Nevertheless, the semantic segmentation results suggested that the proposed model often misclassified necrotic tissue as granulation tissue (the first and the third rows of Fig. 6). This issue might be caused by the small training set used in this experiment and the noisy labels because of mislabeling.

C. Performance on Integrated Tasks

Comparison results (Tab. III) demonstrated that the proposed model outperformed two-stacked U-Net. With 90.1% fewer parameters, the proposed approach obtained 4.7% and 5.6 % higher accuracy and mIoU, respectively. The classification results (Fig. 7) suggested that the proposed DNNs model could differentiate three-type wound tissues and made less false positive (misclassified non-wound as wound region) results than U-Net models.

TABLE III
RESULTS OF THE INTEGRATED MODEL

Model	Accuracy	mIoU	Params
RoleNet	0.827	0.658	5.69 M
two-stacked U-Net	0.780	0.602	62.8 M



(a) Image (b) Ground Truth (c) RoleNet (d) U-Net

Fig. 5. Evaluation by test dataset in wound segmentation

D. Estimation of Circles' Surface Areas

The estimation result (Tab. IV) shows that the proposed method achieved a high accuracy estimation of the surface area of most of the circles with less than 3 % relative error, which is considered accurate enough to be evaluated by PWAT.

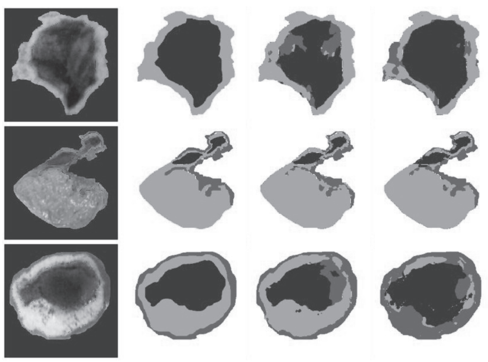
The above results show that the proposed method is effective for estimating PWAT. In future works, we will evaluate PWAT using actual wounds with a prototype application of the proposed system, as shown in Fig. 8.

V. CONCLUSIONS

This paper proposed the image analysis model RoleNet and the simple estimation system for estimating PWAT scores. The proposed method automatically estimates three out of eight items of PWAT. In the experiments, the effectiveness of the proposed method was examined by estimating the surface area of artificial images and classifying wound images. In the surface area estimation for artificial images, it is shown that the proposed method can estimate the real area

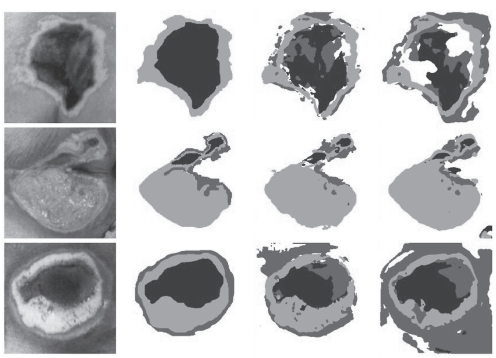
TABLE IV
RESULTS OF THE SURFACE AREA ESTIMATION

	$r = 0.85$ cm	$r = 1.7$ cm	$r = 2.25$ cm
Actual area (cm^2)	2.27	9.08	20.43
Estimated area(plane) (cm^2)	2.34 ± 0.06	9.23 ± 0.12	20.86 ± 0.09
Standard deviation (cm^2)	0.06	0.17	0.09
Relative error (%)	2.99	1.68	2.11
Estimated area(curved) (cm^2)	2.43 ± 0.11	9.31 ± 0.14	20.93 ± 0.18
Standard deviation (cm^2)	0.11	0.14	0.18
Relative error (%)	6.89	2.59	2.42



(a) Image (b) Ground Truth (c) RoleNet (d) U-Net

Fig. 6. Evaluation by test dataset in tissue type classification



(a) Image (b) Ground Truth (c) RoleNet (d) U-Net

Fig. 7. Evaluation by test dataset for integrated models

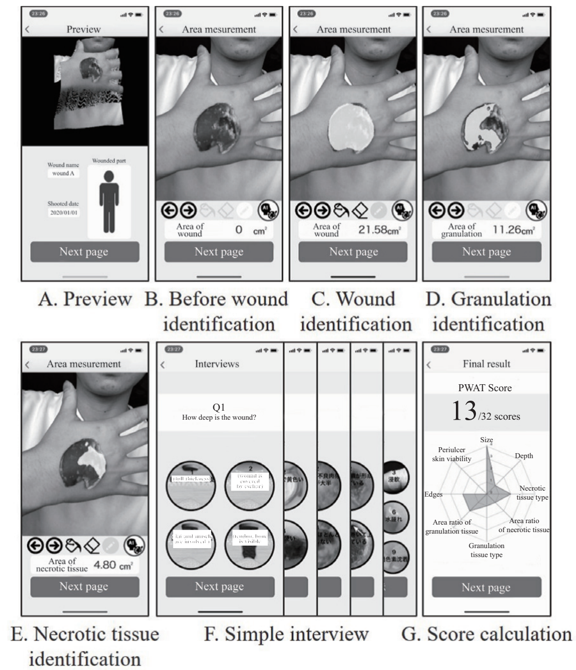


Fig. 8. Proposing method (flow of PWAT calculation)

with small error. In the wound area estimation and tissue type classification experiments, the proposed method achieved lighter models and more accurate classification of wound images than the conventional method. In the future, we will further improve the accuracy by increasing the number of training data and using pre-trained models, and evaluate the effectiveness of the proposed method on actual wounds.

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