Intelligent Localization of Wound Region from 2D Images

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OBJECTIVES

❑ Developing a wound localizer that can detect the wound and its surrounding tissues and isolate the localized wound portion for future processing.

❑ Reducing wound segmentation and classification difficulties and improving their performance.

❑ Developing a mobile application for providing remote service to underprivileged people.

❑ Getting the best use of computer resource (memory).

❑ Keeping the privacy of confidential medical data.

APPROACH

➢ After image acquisition it passes through the wound localizer and gives the localized wound for future wound segmentation and classification. Figure 1 shows the complete wound system, where the green box shows the workflow of this research.

➢ Two convolutional neural network (CNN) based deep learning architectures named YOLOv3 and SSD models have been used for building the automated wound localizer.

➢ Keeping the runtime and memory limitations in mind, for detecting wounds from real-time mobile video feed another version of YOLOv3 (Tiny-YOLOv3) has been used.
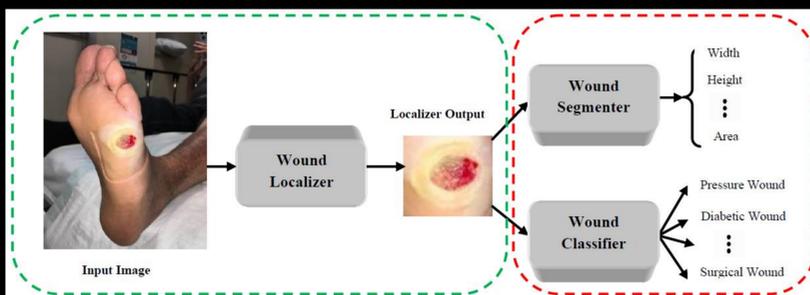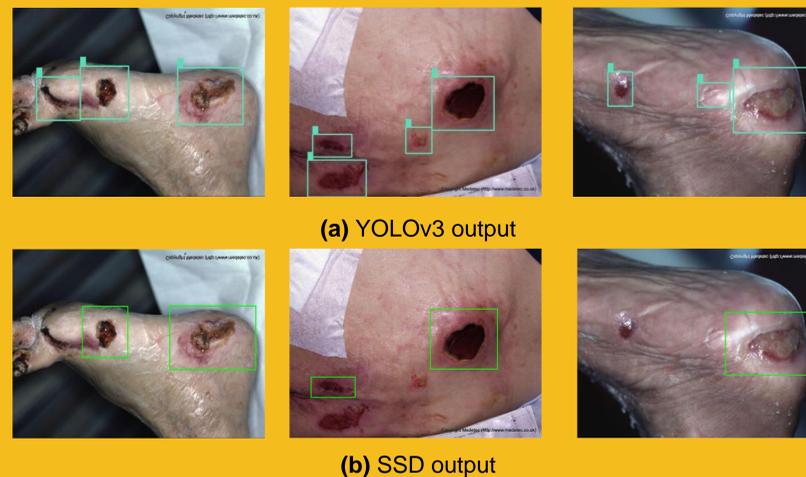

Figure 1: Automated Wound System Overview

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(a) YOLOv3 output

(b) SSD output

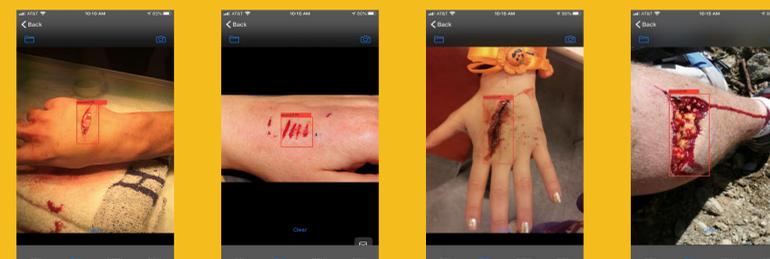**Figure 2:** Robustness and Reliability testing

Figure 3: Mobile Application ROI Detection

METHODOLOGY

⇒ The wound dataset has been collected from AZH Wound and Vascular Center, Milwaukee, WI. This dataset contains a total of 1010 images of Diabetic foot ulcer (DFU), Pressure Ulcer (PU), and Venous Ulcer (VU). For testing the robustness and reliability of our models, 56 images have been collected from Medetec Wound Database [1].

⇒ To increase the number of images for our dataset, we have applied rotation, flipping (up and right), and blurring augmentations. After augmentation we have a total of 4050 images with 3645 images as training and 405 images as test dataset. All the images have been labeled manually with a MIT licensed free graphical image annotation tool: *labelImg* [2].

⇒ In YOLOv3 [3] model, we have used the YOLO annotations. This model is trained for 273 epochs with 8 batch size. This model is trained with a 0.001 learning rate, and stochastic gradient descent (SGD) optimizer. We have used YOLOv3-416 as our model.

⇒ In SSD [4], we have used the Pascal VOC annotations. The SSD model is trained for 475 epochs with a batch size of 8. For SSD we have used the SGD optimizer and the learning rate parameter is set to 0.001. We have used the SSD300 model for our detection.

⇒ Both models are written in Python programming language by using the *Pytorch* deep learning framework. The models are trained on an Nvidia GeForce RTX 2080Ti GPU.

⇒ *CoreML* framework has been used to work in iOS platform with neural networks. Darknet weights are loaded and saved in *Keras* format, followed by a direct conversion to *CoreML* format.

⇒ We have three output layers for YOLOv3-416 and two for YOLOv3-tiny in each of which bounding boxes for various objects are predicted. After receiving the coordinates and sizes of bounding boxes and the corresponding probabilities for all found objects in the image, we can start drawing them on top of the image. Non maximum suppression algorithm is used to solve the problem of many boxes with very large probabilities for a single entity or object. Working directly with the results of neural network prediction can then be considered complete.

RESULTS

➢ All models performance is tested on 405 wound images of our dataset and the results are shown in the Result chart.

➢ Setting the IoU to 0.5, we get the highest mean average precision (mAP) with YOLOv3 (0.94) model, followed by Tiny-YOLOv3 (0.93) and SSD (0.86) models.

➢ The precision, recall and f1-score are also high for YOLOv3 model, as shown in the Result chart.

➢ From the chart also we can see that SSD reflects a low recall and high precision, which leads to the decision that SSD is a very picky or fault-finding model.

➢ On 56 images of the Medetec Wound Database we have performed the robustness and reliability test, and it gives a very impressive result as shown in Figure 2. This figure also reflects the pickiness of the SSD model.

➢ Figure 3 shows impressive ROI detection with the mobile application.

➢ Our model also beats the only existing (to the best of our knowledge) automated wound localization work [5] by a margin of 3.3% mAP value.

CONCLUSION

✓ Wound localizer is the first step of building an intelligent wound healing system, as the output of the localizer will be the input of the future wound processing systems, such as wound segmenter and wound classifier.

✓ Most of the previous works have used the localized wound by manually extracting them from the original image. So this system has great importance in future research of wound healing.

✓ This work reduces the memory load by removing unnecessary information (with respect to our research) from the images, such as patient face, tattoo or any identification marks, bed sheet, etc.

✓ This work makes the wound classification and segmentation easier and also allows us to publish the dataset publicly, which may contribute in future research.

✓ We have broadened the scope of our work by building a mobile platform for it, which will help the patients remotely, who do not have access to specialized wound care and will also reduce the treatment cost by a great extent.

✓ Our system performs well with a maximum mAP value of 0.94 that surpasses all the previous works on wound localization.

✓ Our team is currently working on wound segmentation and classification task by using the localized wound patches prepared by this experiment.

Literature cited

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