Fully Automatic Wound Segmentation with Deep Convolutional Neural Networks

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INTRODUCTION

- Fully automatic segmentation of wound areas in natural images is an important part of the diagnosis and care protocol since it is crucial to measure the area of the wound and provide quantitative parameters in the treatment. Various deep learning models have gained success in image analysis including semantic segmentation. Particularly, MobileNetV2 [1] stands out among others due to its lightweight architecture and uncompromised performance.

- Our group proposes a novel convolutional framework based on MobileNetV2 and connected component labeling to segment wound regions from natural images. We build an annotated wound image dataset consisting of over 1000 foot ulcer images to train and test the deep learning models. The full implementation is available at https://github.com/uwm-bigdata/wound-segmentation.

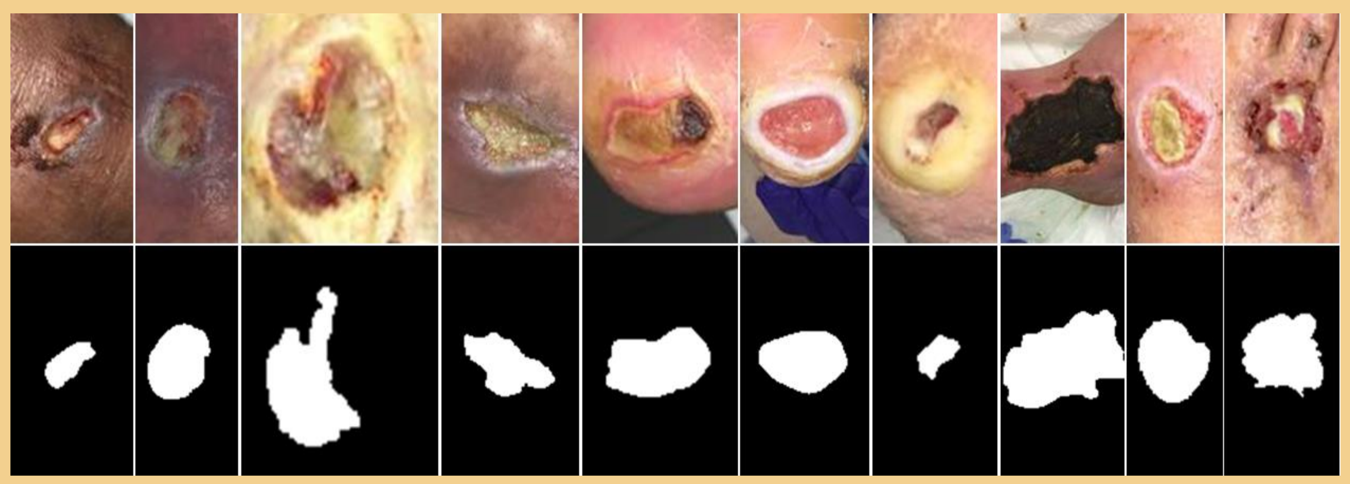

Figure 1. An illustration of our dataset. The first row contains the raw images collected. The second row consists of segmentation mask annotations

DATASET

- To build a chronic wound dataset, we collaborated with the Advancing the Zenith of Healthcare (AZH) Wound and Vascular Center, Milwaukee, WI. The images were collected over 2 years at the center and includes 1,109 foot ulcer images taken from 889 patients during multiple clinical visits.

- Shown in **Figure 1**, the images in our dataset were manually annotated with segmentation masks that were further reviewed and verified by wound care specialists from the collaborating wound clinic.

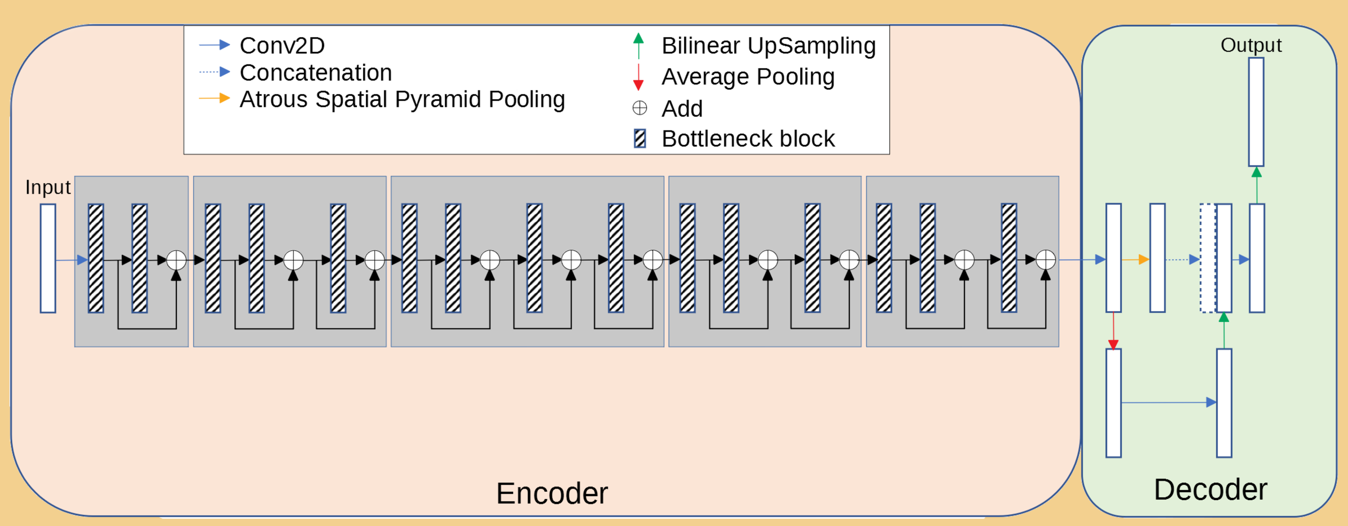

Figure 2. The encoder-decoder architecture of MobilenetV2.

METHODS

- A convolutional neural network, MobileNetV2, is adopted to segment the wound from the images. The model has an encoder-decoder architecture as shown in **Figure 2**. The encoder is built by repeatedly applying the depth-separable convolution block (marked with diagonal lines in Figure 2). Each block consists of six layers: a 3×3 depth-wise convolutional layer followed by batch normalization and Relu activation, and a 1×1 point-wise convolution layer followed again by batch normalization and Relu activation.

- In the decoder, the encoded features are captured in multiscale with a spatial pyramid pooling block, and then concatenated with higher-level features generated from a pooling layer and a bilinear up-sampling layer. After the concatenation, we apply a few 3×3 convolutions to refine the features followed by another simple bilinear up-sampling by a factor of 4 to generate the final output.

- Post Processing, including hole filling and removal of small regions, is performed to improve the segmentation. As shown in **Figure 3**, Small holes (marked by red boxes) are detected by finding small connected components in the segmentation results using connected component labeling (CCL) [2]. The small false-positive noises (marked by yellow boxes) are removed in the same way. We simply remove noises in the segmentation results by removing the connected component small enough based on adaptive thresholds.

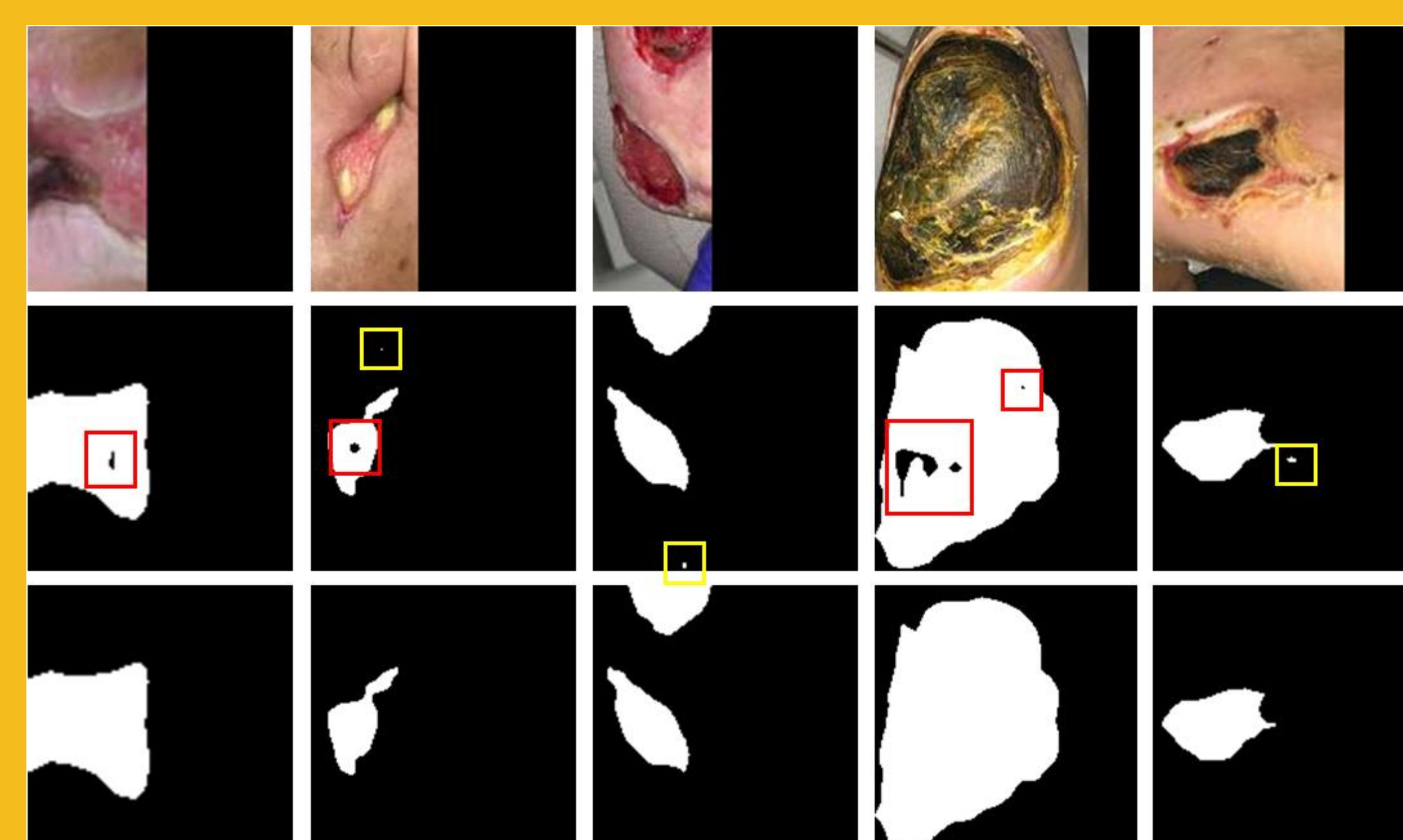

Figure 3. An illustration of the segmentation result and the post processing method. The first row illustrates images in the testing dataset. The second row shows the segmentation results predicted by our model without any post processing. The holes are marked with red boxes and the noises are marked with yellow boxes. The third row shows the final segmentation masks generated by the post processing method.

RESULTS

- An illustration of the testing images and predicted segmentations are shown in **Figure 3** and the Quantitative results are shown in **Table 1.** To evaluate the performance on chronic wound segmentation, Precision, Recall, and the Dice coefficient are adopted as the evaluation metrics. Comprehensive experiments are conducted and analyzed on popular models including SegNet, VGG16 and U-Net, which are further compared with our model based on MobileNetV2 and CCL.

Model Name	FCN-VGG16	SegNet	U-Net	MobileNet V2	MobileNetV2+CCL
Precision	90.77%	87.32%	92.21%	94.61%	94.76%
Recall	95.26%	88.04%	92.54%	92.55%	92.75%
Dice	80.36%	88.04%	88.94%	89.92%	90.09%

Table 1. The highest precision, recall and dice score reached among trainings on our dataset.

- Apart from our dataset, we also conducted experiments on the Medetec Wound Dataset [3] and compared the segmentation performance of these methods. The results are shown in **Table 2**.

Model Name	FCN-VGG16	SegNet	U-Net	MobileNetV2	MobileNet V2+CCL
Precision	94.06%	81.82%	91.80%	85.04%	85.19%
Recall	91.08%	83.56%	91.55%	90.44%	90.65%
Dice	83.36%	74.64%	84.99%	86.78%	86.95%

Table 2. The highest precision, recall and dice score reached among various trainings on the Medetec dataset.

CONCLUSIONS

- We attempted to solve the automated segmentation problem of chronic foot ulcers in a dataset we built on our own using deep learning. We conducted comprehensive experiments and analyses on SegNet, VGG16, U-Net and our model based on MobileNetV2 and CCL to evaluate the performance on chronic wound segmentation.

- In the comparison of various neural networks, our method has demonstrated its superiority and mobility in the field of image segmentation due to its fully convolutional architecture consisting of depth-wise separable convolutional layers. We demonstrated the robustness of our model by testing it on the foot ulcer images in the publicly available Medetec Wound Dataset where our model still achieves the highest Dice score.

- In the future, we plan to improve our work by extracting the shape features separately from the pixel-wise convolution in the deep learning model. Also, we will include more data in the dataset to improve the robustness and prediction accuracy of our method.

Literature cited

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