Diabetic Foot Ulcer Segmentation Based on Fully Convolutional Network

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Introduction

In 2017, diabetic foot ulcers (DFU) were estimated to affect 9.1 to 26.1 million individuals. With the rising diabetes population, DFU cases are expected to increase.

DFU can lead to severe complications and higher treatment costs, emphasizing the importance of early detection through patient education and regular check-ups.

Semantic DFU segmentation has the potential to diagnose the condition early and reduce the burden on healthcare providers. It can also help to monitor wound progression or simplify custom insole creation.
Implementing these technologies can help in managing DFU, especially in regions with a shortage of healthcare professionals.

Figure 1: Diabetic foot ulcer and corresponding GT mask.

Results

The model was trained on DFUC2022 dataset consisting of 2000 pairs of images and GT masks. Evaluation was being done online by submitting 2000 masks generated on additional 2000 images from this dataset with unpublished GT masks. The main focus was to maximize the DSC score. Our approach achieved a DSC score of 0.7095. This score put us just 2 percent below the 2022 winner of the Diabetic Foot Ulcer Segmentation challenge, who achieved a DSC score of 0.7287 on the same data.

Algorithm overview

Our proposed method is nnU-Net network enhanced with squeeze and excite blocks, residual connections in the contraction layers, and attention gates in the expansion layers. It also incorporates assymetric mixup augmentation with a threshold of 0.25 and an alpha value of 0.3. We found that mixup augmentation helps network to correctly classify less intense wounds and to distinguish object resembling wounds like blood stain on cloth from the actual wounds. We used Dice loss function to train our model.

Residual connections are applied before the SE (Squeeze-and-Excite) blocks. Intention behind adding residual connections is to improve generalization on new data because they help to preserve important information from previous layers of the network.

The SE blocks are added to emphasize important channels and to suppress unimportant ones. Their output not only sent to lower layers of the contraction path, but also as long skip connections.

In the expansion phase, the increased output is sent to an attention gate along with the skip connection, and the output from the block is then added to the enlarged output. This process is repeated in each layer. The used attention block is a modified version, incorporating batch normalization after each convolution for regularization and training stability. Attention gates differ from SE blocks by applying spatial attention instead of channel attention. Combining spatial and channel attention in our architecture has been proven to be very effective.

We also slightly improved the results by simple postprocessing method which filled masks if they had a background inside.

Figure 3: Comparison of predicted masks (red) with GT masks (green). Overlay of both is displayed as orange.

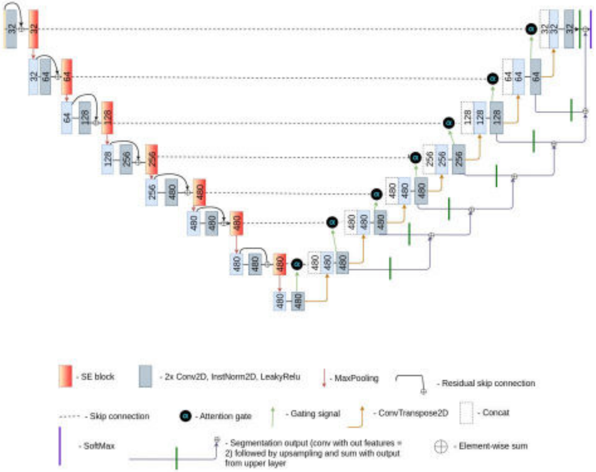

Figure 2: Architecture of the proposed network.

Conclusion

We improved the nnU-Net architecture by proposing enhancements like mixup augmentation, residual connections, and attention mechanisms. These modifications significantly improved DFU segmentation, with achieved (DSC) score of 0.7094.

The research also identified the model's weaknesses, such as early-stage wound recognition problems and confusion between nails or gaps between toes and actual ulcers.

Additionally, our modifications of the nnU-Net architecture have the potential to be effective not only on DFU data, but across various medical imaging datasets.