Colon Blood Vessel Detection Based on U-net

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***Abstract*— Detection and analysis of colon blood vessels play a significant role in medical diagnosis. This paper proposed the colon blood vessel detection method based on the U-net architecture with a few training images. The proposes method performs better colon blood vessel detection with a few training images from experiments result.**

***Keywords*–Colon Blood Vessel Detection; CNN; U-net; Biomedical Image Processing.**

I. INTRODUCTION

Detection and analysis of colon blood vessels play a significant role in medical diagnosis in a large number of areas like retinopathy, endoscopy, etc. Colon blood vessel lesions are frequently derived from malignant polyps. While some algorithms [1]-[4] are proposed for retina blood vessel extraction, they can not be used in an endoscope environment as well. The algorithms based on convolutional neural network (CNN) [3] [4] perform high precision in retina blood vessel. However, common CNN needs massive datasets. It is difficult to prepare massive datasets with mask images in biomedical image processing. The typical use of convolutional networks is for the classification tasks, where the output of an image is a single class label. However, in many visual tasks, especially in biomedical image processing, the desired output should include localization, i.e., a class label is supposed to be assigned to each pixel. This paper proposes a method based on the U-net architecture [5] for colon blood vessel detection with a few training images. Section Ⅱ explains the proposed method, Section Ⅲ mentions experiments and Section Ⅳ concludes the paper.

II. POPOSED METHOD

The U-net is a network and training strategy that relies on the active use of data augmentation to use the available annotated samples more efficiently, and it is the so-called “ fully convolutional network” [6]. The proposed method based on this architecture works with a few training images to try better colon blood vessel detection.

The network architecture of the proposed method is shown in Fig. 1. The network architecture was constructed with less down sampling layers because the resolution of the targeted endoscope images is not high.

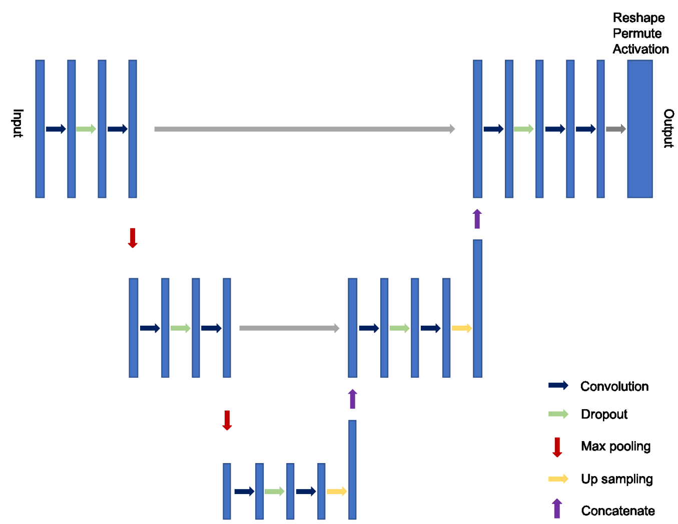

Figure 1. Network Architecture

The network architecture details are as follows. The loss function is the cross-entropy and the neural network employees the stochastic gradient descent for optimization. The activation function after each convolutional layer is the Rectifier Linear Unit (ReLU) and between two consecutive convolutional layers use a dropout of 0.2 empirically set.

The following pre-processing is performed for the training datasets before training.

- Gray-scale conversion
- Normalization
- Contrast-limited adaptive histogram equalization (CLAHE)
- Gamma adjustment

The neural network is trained based on sub-images (patches) of the pre-processed full images. Each patch with dimensions 48x48 is obtained by randomly selecting its center inside the full image. Sample patches are shown in Fig. 2. Also, selected patches partially or entirely outside the Field Of View (FOV), thus the neural network learns how to discriminate the FOV border from the blood vessels.

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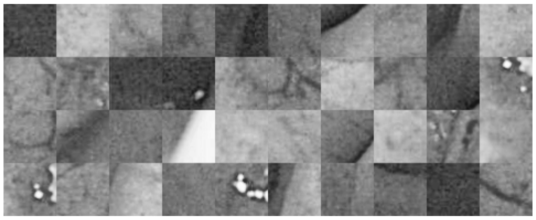

Figure 2. Sample of Patches

III. EXPERIMENTS

An evaluation experiment was conducted to confirm the effectiveness of the proposed method.

A. Training

A set of 142,500 patches was obtained by randomly extracting 71,250 patches in each of 15 training images. Although the patches overlap, i.e., different patches may contain a same part of original images, no further data augmentation was performed. The first 90% of the dataset was used for training (128,250 patches), while the remained 10% was used for validation (14,250 patches). Training was performed for 150 epochs, with a mini-batch size of 32 patches. It took about 4 hours using GeForce GTX 1080 GPU × 4 for the training.

B. Evaluation of the trained model

The vessel probability of each pixel was obtained by averaging multiple predictions to improve the performance. With a stride of 5 pixels in both height and width, multiple consecutive overlapping patches were extracted in each test image. Then, the vessel probability was obtained for each pixel by averaging probabilities over all the predicted patches covering the pixel.

Fig. 3 shows the results of colon blood vessel detection and overall accuracy of the prediction comparison with correct mask image was 0.8432.

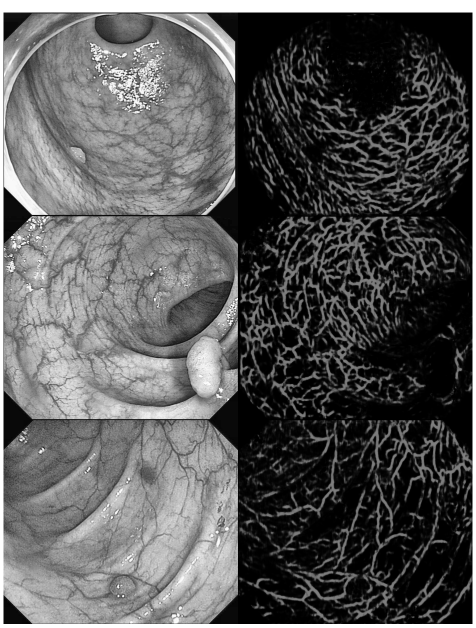

Figure 3. Example of Prediction Results

Fig. 4 shows the Area Under the ROC curve (AUC ROC) of the evaluation, and AUC was 0.9030.

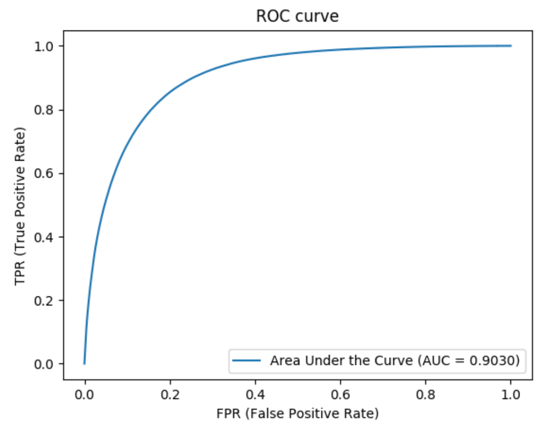

Figure 4. AUC ROC

IV. CONCLUSION

This paper proposed the colon blood vessel detection method based on the U-net architecture with a few training images. It was confirmed that the proposed method performs better colon blood vessel detection with a few training images from experiment results. Applying the proposed method to another kind of endoscope image such as Narrow Band Imaging (NBI) and detecting malignant polyp based on results are future works.

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REFERENCES

[1] Frangi, A. F., Niessen, W. J., Vincken, K. L., & Viergever, M. A. (1998, October). Multiscale vessel enhancement filtering. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 130-137). Springer, Berlin, Heidelberg.

[2] Azzopardi, G., Strisciuglio, N., Vento, M., & Petkov, N. (2015). Trainable COSFIRE filters for vessel delineation with application to retinal images. Medical image analysis, 19(1), 46-57.

[3] Melinščak, M., Prentašić, P., & Lončarić, S. (2015, January). Retinal vessel segmentation using deep neural networks. In VISAPP 2015 (10th International Conference on Computer Vision Theory and Applications).

[4] Liskowski, P., & Krawiec, K. (2016). Segmenting retinal blood vessels with deep neural networks. IEEE transactions on medical imaging, 35(11), 2369-2380.

[5] Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer, Cham.

[6] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).

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