Automated Polyp Segmentation in Colonoscopy using MSRFNet

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ABSTRACT

Colorectal cancer is one of the major cause of cancer-related death around the world. High-quality colonoscopy is considered mandatory for resecting and preventing colorectal cancers. In the recent past, various technological advances have been made towards improving the quality of colonoscopy. Despite the technical advancement, some polyps are frequently missed during colonoscopy examinations. Polyp detection (for example, adenomas) rates are largely influenced by inter-endoscopist variability. Therefore, it is very challenging to standardize a high-quality colonoscopy. A computer-aided detection system could solve the problem with miss-detection. The "MediaEval 2021" challenge entails the chance to study and develop accurate automated polyp segmentation algorithms [6]. In this paper, we propose our approach based on MSRFNet. Our experimental findings show that the model trained on the Kvasir-SEG dataset and evaluated on a competition test dataset obtains a dice coefficient of 0.7055, Jaccard of 0.6176, a recall of 0.7293, and a precision of 0.7769. In addition to the MediaEval 2021 challenge, we evaluated our approach on the Endotect Challenge Dataset and "2020 Medico Automatic Polyp Segmentation Challenge Dataset". The results further demonstrate the efficiency of our approach.

1 INTRODUCTION

Colorectal cancer is the third leading cause of cancer-related death globally [12]. Although colonoscopy has improved the detection of colorectal polyps, computer-aided detection could better indicate the presence and location of polyps in the colon. A CAD system could assist endoscopists by finding out the missed polyps. One of the other significant advantages of the CAD system is that they are not influenced human bias or inter and intraobserver variability. Therefore, such systems could improve clinical performance irrespective of gastroenterologists expertise. In this respect, we propose our approach based on MSRFNet [13], which was specially designed for the segmentation of medical images.

In summary, the main contribution of the paper are as follows:

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(1) The "MediaEval 2021" challenge entails the chance to study polyp segmentation and develop accurate automated polyp segmentation algorithms. Therefore, in this paper, we present our approach based on "MSRFNet" for automatic polyp segmentation.
(2) In addition to the challenge, we evaluated our method on the Endotect Challenge Dataset[1] and 2020 Medico Automatic Polyp Segmentation Challenge Dataset[2] to demonstrate the efficiency of our approach.

2 RELATED WORKS

Automated polyp segmentation is a well-established topic. There has been several works proposed on the automated polyp segmentation [1, 4, 9, 16]. In addition to the individual work, there are several competitions and challenges held in order to solve the polyp segmentation problem [1, 2, 5, 7, 8]. Paudel et al.[10] provided a winning solution for the 2020 "Medico automatic polyp segmentation challenge". They used efficientNet [14] as an encoder and UNet [11] as decoder. Additionally, they also used a channel-spatial attention module and deep supervision to improve the performance of the network. Similarly, Thambawita et al. [15] provided another solution for the segmentation task at the 3rd International Endoscopy Computer Vision Challenge and Workshop (EndoCV2021). The proposed architecture, DivergentNets, combined TriUNet with UNet++, FPN, DeepLabv3, and DeepLabv3+, into a single model to achieve generalizable performance. "Medico: Transparency in Medical Image Segmentation" challenge aims to develop transparent and explainable automated methods. We participate in this challenge to provide our effective solution and benchmark our solutions against other participants on the same test dataset.

3 DATASET

HyperKvasir [3] was provided by the challenge organizers as the development dataset. Kvasir-SEG consists of 1000 images, their corresponding ground truth and the bounding box information. As the test dataset, the organizers provided us with 200 unique images consisting of at least one polyp image. Similarly, we performed further experiments on the Endotect Challenge Dataset and Medico Automatic Polyp Segmentation Challenge Dataset.

[1]https://endotect.com/
[2]https://multimediaeval.github.io/editions/2020/tasks/medico/

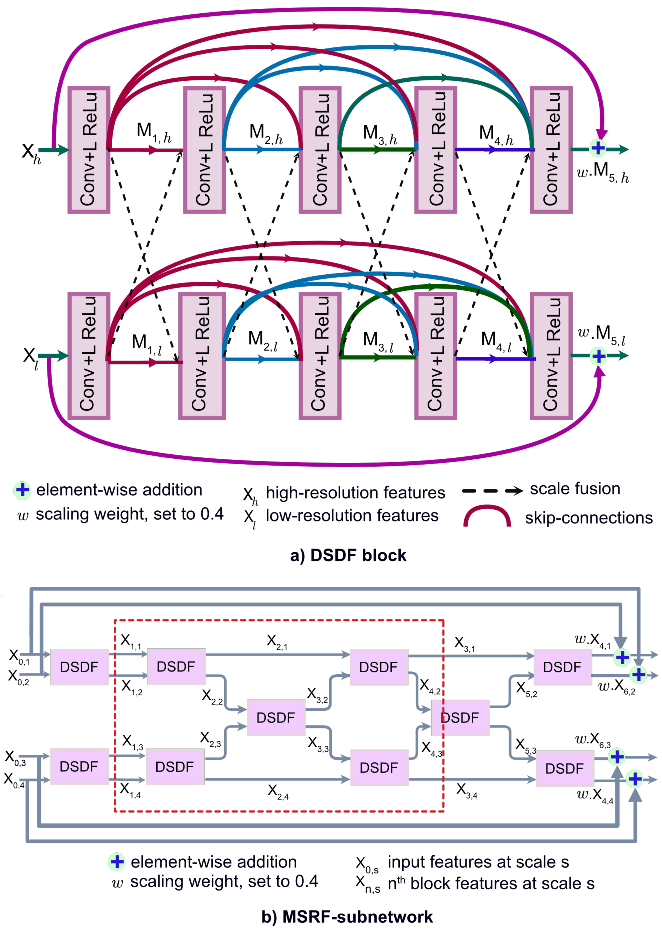

Figure 1: Components of MSRFNet, a) Dual-scale dense fusion(DSDF) block and b) multi-scale residual fusion (MSRF). Dotted rectangle block in (b) represents multi-scale feature exchange in MSRFNet [13].

4 METHODOLOGY

MSRFNet architecture and its components are shown in Figure. 1. MSRFNet has a dual-scale dense fusion (DSDF) block that consists of residual dense connections and is capable of transferring data across different scales. It is a fully convolutional network that computes the multi-scale features and fuses them effectively using a DSDF block. The residual nature of the DSDF block improves gradient flow which improves the training efficiency. Due to page limitations, for more details on the working, components and architecture details of MSRFNet, readers are requested to refer [13].

5 RESULTS AND ANALYSIS

It can be observed from Table 1 that our trained MSRFNet model achieved a dice coefficient of 0.7055, Jaccard index of 0.6167, and a precision of 0.7769 on the MediaEval organiser's test dataset, manifesting MSRFNet generalization capabilities. Similarly, the qualitative results are demonstrated in Figure2. The qualitative results show both obvious polyps and difficult polyps. From the

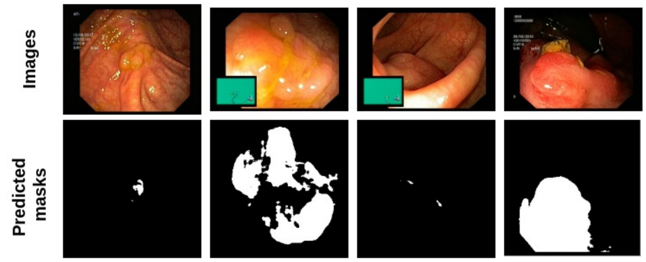

Figure 2: Qualitative results of the proposed solution

Table 1: Results of our polyp segmentation method on the test set provided by MediaEval 2021 challenge

Dataset	Dice	Jaccard	Recall	Prec.
Development	0.9217	0.8914	0.9198	0.9666
Test	0.7055	0.6176	0.7293	0.7769

Table 2: Results of our polyp segmentation method on the test set provided by Endotect & 2020 Medico Automatic Polyp Segmentation Challenge

Training Data	Testing data	Dice	Jaccard	Recall	Prec.
Kvasir-SEG	Endotect Challenge	0.8131	0.6967	0.8581	0.7874
Kvasir-SEG	2020 Medico Challenge	0.7575	0.6337	0.7197	0.8414

qualitative results, it can be observed that our approach is able to detect the obvious polyps, including small polyps, however, it fails in challenging cases. Due to the unavailability of the ground truth, we can only present the original images and the predicted masks.

From the Table 2, we can observe that our model obtains descent performance for both datasets that further demonstrates the efficiency of our approach.

6 CONCLUSION & FUTURE WORK

We competed on the organizer's dataset using MSRFNet architecture and achieved a dice coefficient of 0.7055, Jaccard index of 0.6176, a recall of 0.7293, and a precision of 0.7769. In the polyp segmentation challenge task, the MSRFNet performed well, as depicted by different performance metrics. We further evaluated our results on the Endotect Challenge Dataset and 2020 Medico Automatic Polyp Segmentation Challenge Dataset that demonstrated the efficiency of our approach.

In the future, we want to enhance the MSRFNet performance design by assessing the best hyperparameter settings for the automatic polyp segmentation.

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