ConU-net: An Ensemble based deep learning approach for Polyp image segmentation

Md. Toufiqur Rahman
dept. of EEE,ID:0422062518

***Abstract*—Colorectal cancer is one of the leading causes of cancer death. Polyps are a primary cause of colorectal cancer, and early diagnosis by colonoscopy may result in successful therapy. Polyp identification in colonoscopy recordings is problematic due to polyp size and shape heterogeneity. Colorectal cancer, caused by the formation of polyps that can be benign or malignant, is one of the most lethal illnesses in the world. Colonoscopy, which is a particularly efficient procedure in this scenario, is used to locate these polyps in patients. Clinically, finding and segmenting these polyps to establish their existence or absence is a challenging process that necessitates a significant amount of time and skill from doctors. As a result, it is becoming increasingly vital to have an autonomous, effective, and dependable technique of identifying and segmenting these polyps, allowing for faster and more accurate diagnosis. In this report, we developed a convolutional neural network-based polyp segmentation approach. We propose to use fully convolutional neural networks (FCN) to locate and separate polyps in colonoscopy images. Our proposed Ensamble approach(ConU-net) significantly outperforms U-Net and ResUNet, two key state-of-the-art deep learning architectures, by achieving high evaluation scores with a dice coefficient of 68.20%, and a mean Intersection over Union (mIoU) of 66.21% for the Kvasir-SEG dataset and a dice coefficient of 65.90%, and a mIoU of 62.52% with CVC-612 dataset.**

I. BACKGROUND

Colorectal Cancer is one of the top causes of cancer-related deaths globally.CRC patients have a 5-year survival rate of less than 7%, however, with early diagnosis, it improves to more than 90% with professional therapy. However, many adenomatous polyps are missed during endoscopic tests,as a result, it creates problems in the proper detection of poly [1]. As a second observer, Computer-Aided Detection (CAD) system, having pixel-wise segmentation capability can highlight polyps in the video stream from the endoscope in real-time making the reliability for detection and segmentation of poly properly [2].

Developing a CAD system for poly detection and segmentation is a challenging task. However, various semantic segmentation-based methodologies for medical image analysis and segmentation have been proposed in recent years [3], [4], [5], [6]. U-Net [7] is a renowned deep-learning network in the field of semantic segmentation for biomedical applications, having demonstrated state-of-the-art performance at the 2015 ISBI cell tracking competition.

II. CURRENT RESULTS

We analyze colonoscopy image segmentation using two datasets, Kvasir- SEG and CVC-ClinicDB . Kvasir-SEG dataset has 1000 images with a size of (256,256,3) while CVC-ClinicDB has 612 images.Each dataset includes colonoscopy pictures with corresponding masks.For our analysis at first we resize the image into (128,128,3).Fig 2 represents the resized images and corresponding masks .Then we perform data augmentation according to Fig.1 .Finally we train our model with 5600 Kvasir-SEG images. We perform different state-of-the-earth deep learning Models like Unet,ResUnet,ResUnet++ [8].We train the Model and analysis the test result .Table-1 indicates the result of different deep learning algorithm for our augmented data.We also regenerate a model [9] 'Double-Unet' and train with our dataset.

Finally we proposed a new architecture (Fig.4).The model(ConU-net) perform best than any other model in terms of Mean Intersection-over-union score(66.21%,62.52%) also dice loss is minimum for our proposed Model.The nobility of our model is that we use multi-step encoding and decoding for generating mask .Each decoding block is connected with previous encoding block.Fig.6 represents the new generated mask regards to out proposed architecture.

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A. Figures and Tables

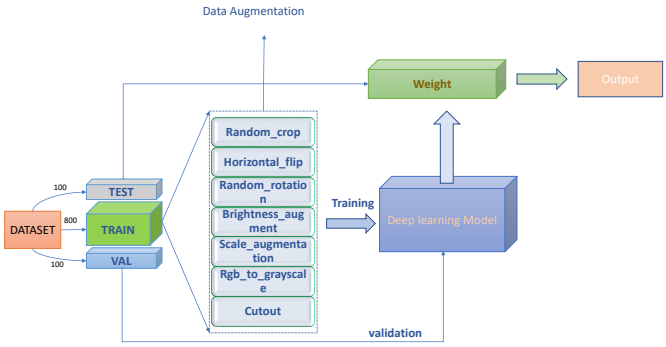

Fig. 1. Overall Algorithm.

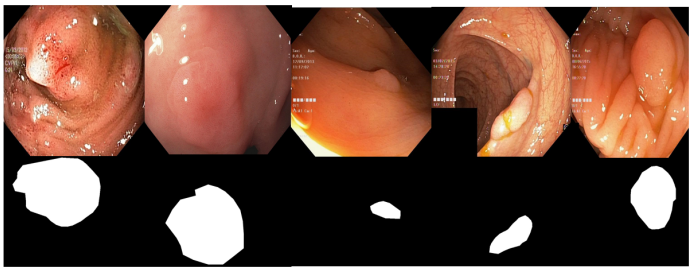

Fig. 2. Data visualization.

TABLE I
PERFORMANCE OF DIFFERENT DEEP LEARNING MODELS FOR POLYP-IMAGE SEGMENTATION

Models	Epoch	Dice-loss	Precision	Recall	Dice-Coeff	M-Io
Unet	50	0.4236	0.7144	0.8162	0.5764	0.4246
ResUnet	30	0.5579	0.5360	0.6826	0.4421	0.4246
ResUnet++	25	0.3927	0.5171	0.8343	0.6073	0.6379
VGG16-U-net	25	0.4912	0.5256	0.7612	0.4810	0.4864
VGG19-U-net	25	0.5156	0.6075	0.6115	0.4851	0.5567
Resnet50-U-net	25	0.5287	0.6198	0.6571	0.4071	0.5691
Inceptionv3-U-net	25	0.4750	0.6418	0.6751	0.5561	0.5861
DoubleU-net	25	0.3027	0.7451	0.7864	0.6209	0.6519
Proposed-Ensamble-approach(Kvisar)	19	0.3527	0.6854	.7129	.6820	.6621
(CVC-ClinicDB)	19	0.3874	0.6752	.6891	.6590	.6252

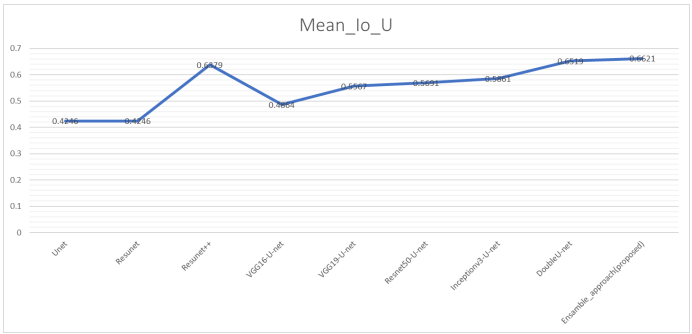

Fig. 3. Performance of Different Model.

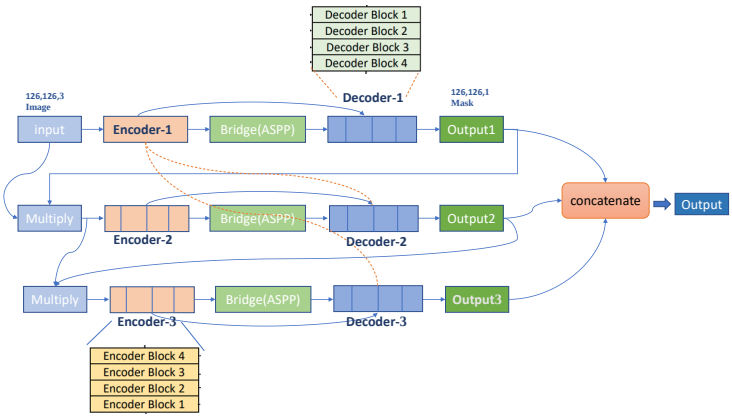

Fig. 4. Proposed Architecture .

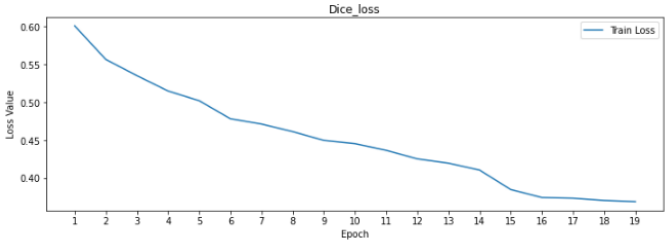

Fig. 5. Training loss for our Model.

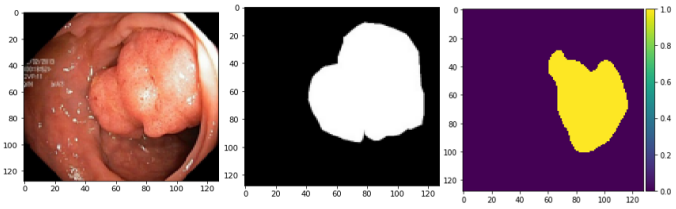

Fig. 6. Output segment for our model (Kavisr-Seg).