Recurrent Residual Convolutional Neural Network U-Net (R2U-Net) based Medical Image Segmentation

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ABSTRACT

Deep learning (DL)-based semantic segmentation methods have demonstrated impressive performance over the past few years. In particular, these methods have been successfully applied to medical image classification, segmentation, and detection problems. One deep learning technique, U-Net, has become one of the most popular for these applications. In this paper, we propose a Recurrent Residual Convolutional Neural Network (RRCNN) based on U-Net models, which are named RU-Net and R2U-Net respectively. The proposed model leverages the power of U-Net, Residual Network, and RCNN. There are several advantages of these proposed architectures for segmentation tasks. First, the residual block is useful for training deep architectures. Second, the accumulation of features through recurrent residual convolutional layers improves the feature representation for segmentation tasks. Third, it allows us to design a better U-Net architecture with the same number of network parameters and improved performance on medical image segmentation. The proposed model is tested on three benchmark datasets, including retinal image blood vessel segmentation, skin cancer segmentation, and lung lesion segmentation. Experimental results show superior performance in segmentation tasks compared to comparable models such as U-Net and Residual U-Net (ResU-Net)..

Keywords: Medical Imaging, Segmentation, Watershed Transform (WT), Convolutional Neural Networks, U-Net, Residual U-Net, RU-Net,and R2U-Net.

I. INTRODUCTION

Nowadays DL provides industry-leading performance forimage classification [1], segmentation [2], detection and tracking [3] and subtitling [4]. Several models have been available since 2012deep convolutional neural networks (DCNNs) such as AlexNet [1], VGG [5], GoogleNet [6],residual net [7], DenseNet [8], and CapsuleNet [9]. Based on aDL approach (especially CNN) provides state-of-the-art performance for classification and segmentation tasks by several reasons: first, activation functions solve the learning problems in DL approaches. Second, screening helps to organize networks. Third, several efficient optimization techniques are available for training CNN models [1]. However, in most cases, models are explored and evaluated using classification tasks on very large-scale datasets like Image Net [1], where the outputs of the classification tasks are single label or probability values. Alternatively, small model variations of the architecture are used for semantic image segmentation tasks. For example, fully connected convolutional neural networks (FCNs) also provide state-of-the-art results for image segmentation tasks. Computer Vision [2]. Another variant of FCN, called SegNet [10], has also been proposed.

Colorectal cancer (CRC) is one of the type of cancer that occurs in the colon or rectum, which are parts of the digestive system. This is the one of the most common cancers worldwide and a significant cause of cancer-related deaths, especially in developed countries. Understanding colorectal cancer, its risk factors, symptoms, and prevention strategies is crucial for early detection and treatment. Colorectal cancer occurs when abnormal cells in lining of the colon or rectum grow uncontrollably, forming a tumor. As time goes on, these cancer cells maybe invade nearby tissues and organs and spread to other parts of the body via a blood system or lymph system (methaaster).

Notably, colorectal cancer (CRC) is the second most deadly kind of cancer in young women and the deadliest in young men (ages 20 to 49). About 10% of new occurrences of colorectal cancer (CRC) occur in people under 50, reflecting the disease's steady rise in frequency among younger persons. The overall decreasing incidence rates since the mid-1980s, which have been mostly attributed to better screening and lifestyle modifications, are in contrast to this increase, which is occurring at a pace of 1% to 2% year.

The main strategies used to fight colorectal cancer (CRC) centre on early detection and prevention, especially through routine screening, which is essential for identifying the illness in its earlier, more manageable stages.

Table 1.1. For 36 cancers, new cases and deaths, as well as the total number of cancers in 2022.

Cancer site	Incidence			Mortality		
	Rank	New cases	% of all sites	Rank	Deaths	% of all sites
Lung	1	2,480,301	12.4	1	1,817,172	18.7
Female breast	2	2,308,897	11.6	4	665,684	6.9
Colorectum	3	1,926,118	9.6	2	903,859	9.3
Prostate	4	1,466,680	7.3	8	396,792	4.1
Stomach	5	968,350	4.9	5	659,853	6.8
Liver	6	865,269	4.3	3	757,948	7.8
Thyroid	7	821,173	4.1	24	47,485	0.5
Cervix uteri	8	661,021	3.3	9	348,189	3.6
Bladder	9	613,791	3.1	13	220,349	2.3
Non-Hodgkin lymphoma	10	553,010	2.8	11	250,475	2.6

(Source: https://acsjournals.onlinelibrary.wiley.com/doi/10.3322/caac.21834)

The risk of colorectal cancer can be considerably reduced by finding polyps early on. Segmenting colonoscopy images can expedite the diagnosis of polyps, however, due to differences in polyp size, shape, and location, precise segmentation is difficult to achieve. Furthermore, the proficiency of the person executing the task has a direct bearing on the accuracy of polyp image segmentation. Fig. 1.4 shows the large intestine, the lower part of the large intestine is the rectum and the upper part is the colon.

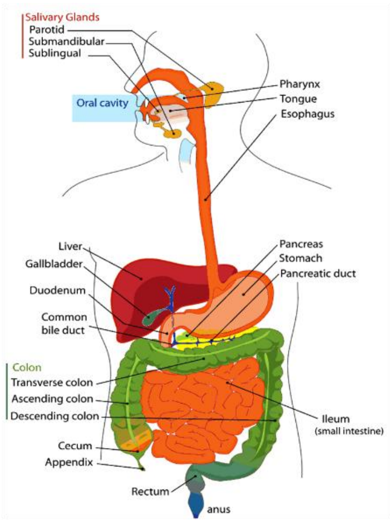
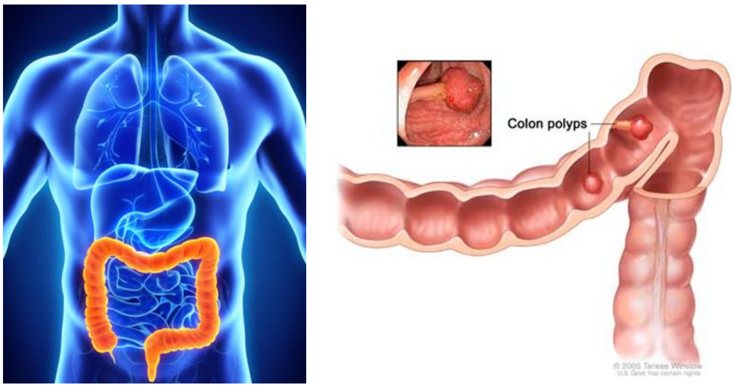


Fig 1: Anatomy of the Gastro Intestinal System

Based on their shape, polyps are classified into two types: (1) sessile (flat) and (2) pedunculated (stalk-bearing). Sessile polyps lie flat on the surface of the inner wall of the colon or rectum and are therefore difficult to detect. Pendulum polyps resemble mushrooms and are attached to the lining of the colon by a long, thin stalk. Based on pathological characteristics, polyps are classified into five categories: adenomatous, hyperplastic, serrated, inflammatory, and villous. Adenomatous polyps have a tubular structure and are the most common form of polyp. Over time, benign adenomatous polyps can turn into malignant polyps. Therefore, identifying and removing benign adenoma tumors can halt the development of colorectal cancer.

Hyperplastic polyps are small in size and have a low risk of developing into cancer. Serrated polyps can develop into cancer depending on their size and location. Small, jagged polyps are called hyperplasia. Larger, serrated polyps in the upper part of the colon are usually flat (sessile), harder to detect, and precancerous. Inflammatory polyps are also called pseudopolyps because they are not true polyps but are formed due to chronic inflammation of the colon or rectum. Inflammatory polyps are often benign and do not pose a risk of developing colorectal cancer.



(a) Large intestine **(b) Colon polyps**

Figure 2. Visualization of the colon and polyps

Inflammatory polyps are also called pseudopolyps because they are not true polyps but are formed due to chronic inflammation of the colon or rectum. Inflammatory polyps are often benign and do not pose a risk of developing colorectal cancer. The chorus glioma, also known as urinary tube glioma, has a serious risk of cancer. They usually stick, making it more difficult to detect and delete. Doctors offer regular screening to detect and eliminate polyps as soon as possible. Discan and mild polyps are probably removed by surgery for new forecasts. There are three types of exclusion selection. The most common type is withdrawal using pliers or wire cycle. This process is called polypectomy. If a polyp is too large to eliminate with this method, a liquid can be injected under it to lift and isolate the polyp of the surrounding tissues so that it can be removed. The second option is minimally invasive surgery. Polyps that are too large or cannot be safely removed during screening are usually removed surgically, which is often done by inserting an instrument called a laparoscope into the abdomen to remove the diseased part of the intestine. The last option is a total proctocolectomy, in which the colon and rectum are permanently removed to prevent the development of potentially fatal colorectal cancer.

CT Colonography

CT (Computerised Tomography) Colonoscopy, also known as virtual colonoscopy, is a procedure in which radiation is used to produce images of the whole colon that are then presented to a gastroenterologist for analysis on a computer screen.

Colonoscopy is a medical procedure used to examine the inside of the large intestine (colon) and rectum, which are important parts of the digestive system. The procedure is widely considered one of the most effective tools for detecting and preventing colorectal cancer, as well as diagnosing other digestive diseases. Coloscopy includes the use of a long flexible tube called Coloscope, in which there is a small video camera attached to its tip. The coloscope is inserted through the rectum and carefully goes all the length of the colon. The camera transmits real-time images to a monitor, allowing your doctor to carefully examine the lining of the colon and rectum for abnormalities such as polyps, tumors or areas of inflammation.

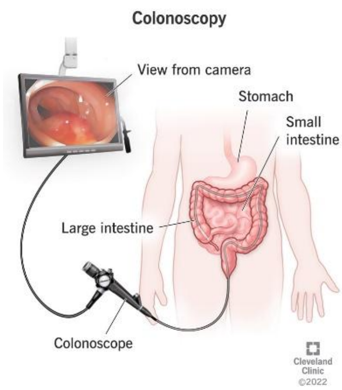


Fig 3. Colonoscopy Screening Test

2. LITERATURE REVIEW

Polyps are an essential sign of early colon cancer, so the main purpose of the examination is to detect them as early as possible to improve patient survival rates. Automatic detection and localization of polyps in video frames of gastrointestinal endoscopy can help reduce missed and false detections in manual manipulation, improve detection quality and efficiency, and have positive implications for early detection of pre-cancerous lesions. Within the realm of medical image analysis, directional radiotherapy, image-guided interventional diagnosis and treatment, and other procedures can all benefit from the application of medical image segmentation.Presently, the most effective means of polyp detection and colorectal cancer prevention is optical colonoscopy. However, colon screening demands considerable time and relies heavily on the operator's skill. Hence, there's a need to create a computer-aided diagnosis (CAD) technique to autonomously segment polyps in colonoscopy images.Within image analysis, the extensive adoption of deep learning techniques has outperformed traditional methods significantly. Extracting polyp features from training datasets involves fitting a non-convex network with non-linear neuron objectives. The deep architecture inherent in neural networks can streamline these chosen features for future classification. CNNs, owing to their impressive achievements, have garnered substantial popularity and widespread utilization in medical image analysis.

Yan Wang et. al proposes a DL based method for multiclassification of endoscopic colonoscopy images into four categories: polyps, inflammation, tumor, and normal. Due to relatively small dataset size, authors used transfer learning by first training on the ImageNet dataset. This allowed applying the prior knowledge learned from the source domain to the target task of classifying intestinal diseases. They then fine-tuned the pre-trained model using their own colonoscopy image dataset to make it more suitable for the specific classification task.M. Akbari et al aimed to improve the classification of informativeframes in colonoscopy videos, which is crucial for effective diagnosis and treatment planning in colorectal cancer. The authors utilize CNNs with the binarized weights to reduce the computational complexity and memory usage while maintaining classification accuracy. Binarized weights allow for faster processing, which is essential given the large volume of video data generated during colonoscopy procedures. The research employs a dataset of colonoscopy videos, which includes frames that are labeled as informative or non-informative. The dataset is critical for training and evaluating the performance of the proposed model.In the research study of J. N. Kather et al., the authors aims to determine whether deep CNNs can extract prognostic information directly from hematoxylin-eosin (HE) stained histology slides, which are routinely available for CRC patients. The researchers conducted a retrospective multicenter study involving tissue samples from patients with resected colorectal cancer across multiple institutions in Australia, Germany, and the USA. They trained a deep learning model to analyze the histological images and predict survival outcomes. he model demonstrated the ability to assess the tumor microenvironment and predict overall survival (OS) and disease-specific survival (DSS) based on the histological features. The study revealed that the deep learning model could stratify patients into high-risk and low-risk groups, with a hazard ratio (HR) of 4.50 for overall survival and 8.35 for disease-specific survival in the high-risk group. The findings suggest that deep learning can effectively utilize histological images to predict survival in CRC patients, potentially serving as a valuable tool for personalized treatment planning and improving clinical decision-making.M. M. Hasan, N. Islam, and M. M. Rahman has proposed a method for detecting gastrointestinal polyps in endoscopic images using a fusion of contourlet transform and deep learning features. Contourlet transform is used to extract directional and multiscale features from the images, which helps capture the complex structures of polyps. Deep learning features are obtained by fine-tuning pre-trained VGG19 model on 224x224 patches extracted from the endoscopic images. Different dimensionality reduction techniques like Principal Component Analysis (PCA) and Minimum Redundancy Maximum Relevance (MRMR) are evaluated to select the most relevant features. Support Vector Machine (SVM) is used as the classifier, with PCA performing better than MRMR in their experiments.S. Graham et al. [2019] developed an method for gland instance segmentation in colon histology images, which is crucial for diagnosing colorectal diseases. The authors introduce MILD-Net, a dilated convolutional neural network designed to minimize information loss during the segmentation process. This architecture allows for better contextual information capture while maintaining high-resolution details in the images. The network employs dilated convolutions to expand the receptive field without losing resolution, enabling the model to capture more contextual information. The architecture is specifically tailored to address the challenges posed by the complex structures of glands in histological images. The model was evaluated on a dataset of colon histology images, and the performance was compared against existing segmentation methods. The results demonstrated that MILD-Net significantly outperformed traditional approaches in terms of accuracy and robustness. The findings in their article highlight the potential of using advanced deep learning techniques for improving histopathological image analysis, which can aid pathologists in diagnosing and understanding colorectal diseases more effectively.Q. Nguyen and S.-W. Lee [2018] has proposed

Colorectal Segmentation Using Multiple Encoder-Decoder Network in Colonoscopy Images. The authors tried to improve the segmentation accuracy of colorectal structures in colonoscopy images, which is critical for the detection and diagnosis of colorectal diseases. For this the authors proposed a multiple encoder-decoder network that leverages the strengths of deep learning architectures to effectively segment complex anatomical structures. This architecture enables the model to capture both local and global features, enhancing segmentation performance.The model is trained and evaluated using a dataset of colonoscopy images, which includes various types of colorectal structures. The authors emphasize the importance of high-quality annotated data for training deep learning models effectively.Z. Zhou, et. al., [2018] proposed a A Nested U-Net Architecture for Medical Image Segmentation. The authors addresses the limitations of existing U-Net architectures in medical image segmentation by proposing UNet++, which incorporates a nested structure to enhance feature extraction and improve segmentation accuracy. UNet++ features a series of nested skip pathways that connect the encoder and decoder sub-networks. This design reduces the semantic gap between the feature maps generated by the encoder and decoder, facilitating better learning and feature representation.D. Jha et al., [2021] proposed NanoNet, a novel deep learning architecture for real-time segmentation of polyps in video capsule endoscopy and colonoscopy images. NanoNet follows an encoder-decoder approach, using a pre-trained MobileNetV2 model as the encoder to capture contextual information from the input images. The decoder consists of modified residual blocks to generate the final segmentation output using the features extracted by the encoder. The authors used the KvasirCapsule-SEG dataset for training and evaluating NanoNet. The dataset contains images from both video capsule endoscopy and colonoscopy. This NanoNet represents a significant advancement in real-time polyp segmentation for endoscopic imaging, combining an efficient encoder-decoder architecture with pre-trained models to achieve better accuracy and speed.

3. Datasets

Knowing the importance of supervised learning techniques for automated disease detection, different group of researchers and organizations have developed various datasets by collecting medical images from radiology centers, hospitals, and cancer research institutes. Many datasets in the reviewed papers have been kept private due to privacy concerns, and reproducing their results is hence not possible. and their descriptions, including the main reference, imaging technique, number of images, and the URL. It can be seen that there are no large scale datasets available to date in the medical imaging field like ImageNet, which often poses challenges in designing effective CNN models.

In addition to the publicly available dataset, we colleborated with Aichi Medical University, Nagakute, Japan and generated a database under the supervision of Kunio Kasugai at the Department of Gastroenterology. The dataset consists of colonoscopy videos recorded with Narrowband Imaging (NBI) and White Light (WL). The expert has selected the frames which contain visible polyps. For stage 1 classification, 900 WLimagesareavailablewhere400images contain polyps, and the rest of the images does not contain any polyps. For stage 2 classification, 400 NBIimageswith275non-neoplastic images and 190 WL images, where 125 are neoplastic, and 107 are non-neoplastic, are available

Furthermore, keep the concern of reproducibility and verification, we use public dataset as well in our work. The details of each of the public dataset used in this work are,

Colon-DB

Colon-DB is a dataset designed for research in colonoscopy image analysis, specifically targeting tasks such as polyp detection, segmentation, and classification. Colon-DB was developed to support research in computer-aided detection (CAD) and diagnosis systems for colonoscopy. It focuses on providing a rich dataset for training and evaluating algorithms aimed at detecting and segmenting polyps, which are critical for the early detection of colorectal cancer. The dataset consists of 380 colonoscopy images, each annotated with detailed information regarding polyp presence. The images vary in terms of polyp size, shape, and appearance, capturing a wide range of scenarios encountered during real-life colonoscopy procedures. Colon-DB includes challenging images with different lighting conditions, contrast levels, and image noise, reflecting the variability seen in clinical practice. The data set can be downloaded from https://www.colon-db.org/

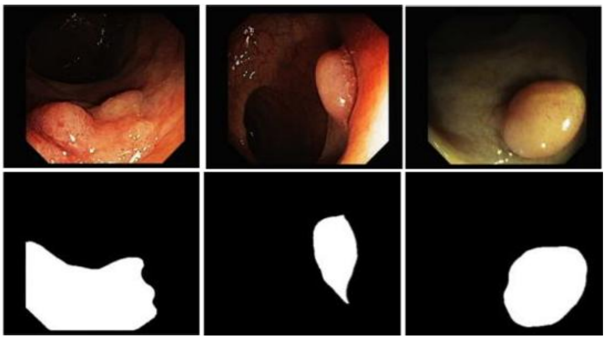


Fig 4. Examples of content of CVC-ColonDB database. First row shows original images whereas second row shows corresponding ground truth

4. R2U-Net Architectures

For segmentation tasks, we present an R2U-Net model, which is inspired by the deep residual model, RCNN, and U-Net. The advantages of all three recently created deep learning models can be leveraged by this method. Using various benchmarks, RCNN and its variations have already demonstrated better performance on object identification tasks. The improved-residual networks provide for a mathematical demonstration of the recurrent residual convolutional procedures. Regarding the discrete time steps that are stated in accordance with the RCNN, the Recurrent Convolutional Layers (RCL) operate. The pixel situated at (*i,j*) in an input sample on the kth feature map in the RCL and the x_l input sample in the lth layer of the residual RCNN (RRCNN) block will be examined. Furthermore, let us assume that the network O_{ijk}^l(t) output is at time step t. The result can be written like this:

$$O_{ijk}^{l}(t) = \left(w_k^{f}\right)^T * x_l^{f(i,j)}(t) + (w_k^{r})^T * x_l^{r(i,j)}(t-1) + b_k \qquad (1)$$

Here $x_l^{f(i,j)}(t)$ and $x_l^{r(i,j)}(t-1)$e the inputs for the lt™ RCL and the standard convolution layers, respectively. The numbers represent the bias, bk is the standard convolutional layer weight, and the RCL of the kth feature map weight. The conventional ReLU activation function f receives the RCL outputs, which are stated as follows:

$$\mathcal{F}(x_l, w_l) = f(O_{ijk}^{l}(t)) = \max(0, O_{ijk}^{l}(t)) \qquad (2)$$

The outputs from the lth layer of the RCNN unit are represented by $\mathcal{F}$(lth, lth). The RU-Net model's convolutional encoding and decoding units employ the output of $\mathcal{F}(xl,\ wl)$ for their down- and up-sampling layers, respectively. Regarding R2U-Net, the residual unit depicted in Fig. 4(d) receives the final outputs of the RCNN unit. Let's assume that the RRCNN-block's output, xl+1, may be computed as follows:

$$x_{l+1} = x_l + \mathcal{F}(x_l, w_l) \qquad (3)$$

In this case, RRCNN-block input samples are represented by xl. The input for the immediately following sub-sampling or up-sampling layers in the R2U-Net encoding and decoding convolutional units is the xl+1 sample. Nonetheless, the quantity and size of feature maps for the residual units are identical to those of the RRCNN-block depicted in Fig. 4 (d).

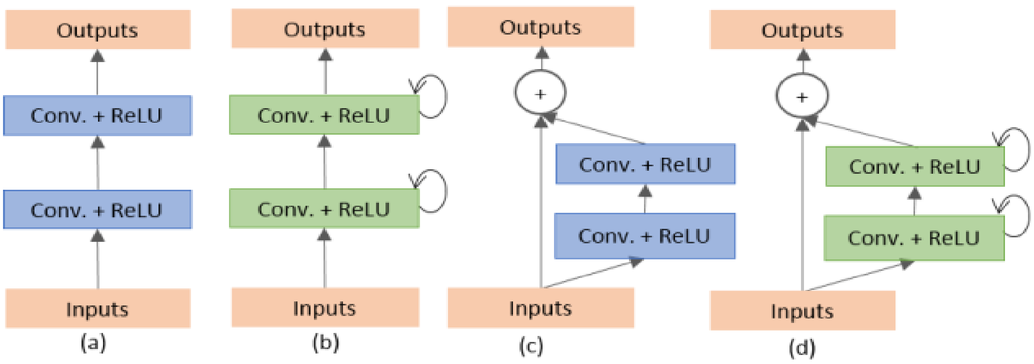


Fig. 5. Convolutional and recurrent convolutional units come in several varieties: (a) forward convolutional units; (b) recurrent convolutional blocks; (c) residual convolutional units; and (d) R2U net units

5. SIMULATION RESULTS

To demonstrate the performance of the R2U-Net model, we have tested on different medical images from different datasets such as Kvasir-SEG, CVC-ClinicDB, EndoScene, Colon-DB. These particularly focused on the segmentation of polyps in colonoscopy images. The network was evaluated using various parameters, such as global accuracy (GA), dice coefficient (DC), intersection over union (IoU), recall (R), and precision (P). The DDR2UPolySeg model was trained using different hyper parameters.Here, the global accuracy represents the proportion of correct predictions. The global accuracy is calculated using Equation (5.1). The intersection over union, also known as the Jaccard index, shows the proportion of overlap between the predicted value and the ground truth mask (represented in Equation (5.2)). The dice coefficient is quite similar to the IoU, but it double counts the intersection, as shown in Equation (5.3). Precision signifies the purity of a positive detection compared with the ground truth, whereas recall signifies the completeness of a positive detection compared with ground truth. Precision and recall can be evaluated using Equation (5.4) and Equation (5.5), respectively. Each of the parameters was evaluated by taking into account the true-positive (T_p), true-negative (T_n), false-positive (F_p), and false-negative (F_n) rates.

$$GA = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \tag{5.1}$$

$$IoU = \frac{T_p}{T_p+F_p+F_n} \tag{5.2}$$

$$DC = \frac{2.T_p}{2.T_p+F_p+F_n} \tag{5.3}$$

$$P = \frac{T_p}{T_p+F_p} \tag{5.4}$$

$$R = \frac{T_p}{T_p+F_n} \tag{5.5}$$

The proposed DDR2UPolySeg model was trained on a system with Intel Core 2.60 GHz i7 CPU running Windows 10 with 16 GB RAM, NVIDIA GeForce GTX 1650 GPU. All of the experiments were performed using Jupyter Notebook.

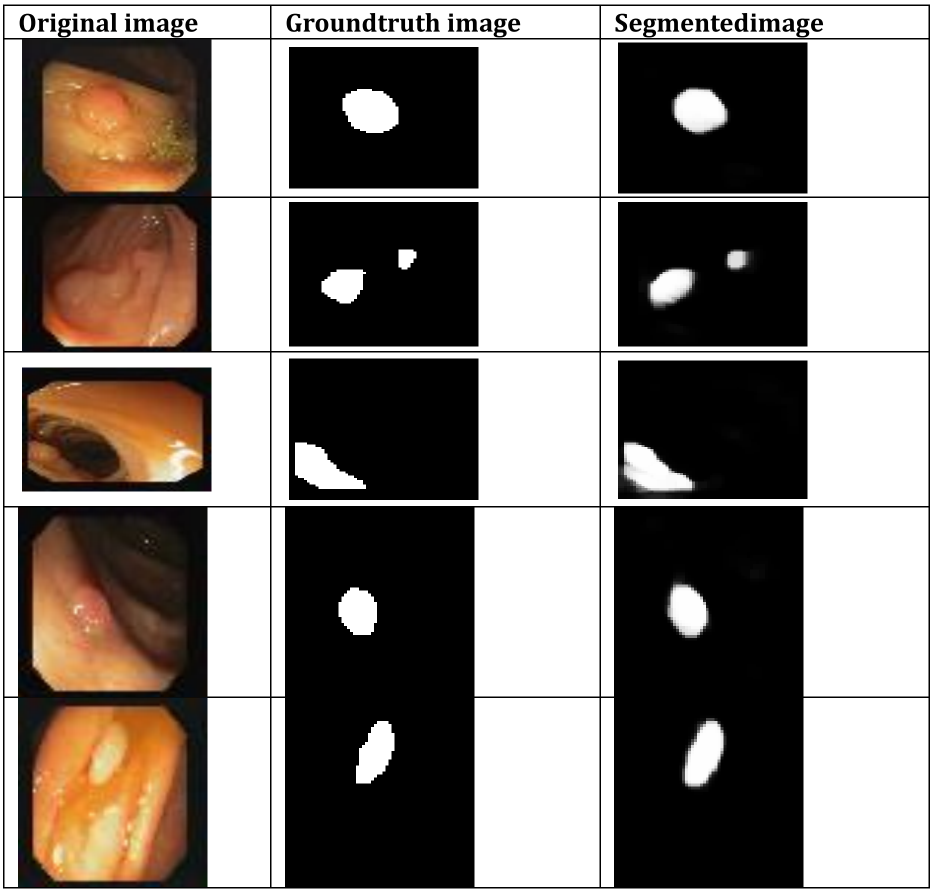


Figure 6. The final segmented image along with the ground truth image for CVC-Colon DB dataset. (a) Original image, (b) ground truth image, (c) segmented image for CVC-Colon DB dataset

Table 5.1. Performance evaluation of DDR2UPolySeg with ColonSegNet and UPolySeg for CVC-Colon DB dataset

Model	Accuracy	Recall	Precision Score	IoU	Dice
ColonSegNet	0.9493	0.8597	0.8497	0.7239	0.8206
UPolySeg	0.9677	0.9477	0.9157	0.8791	0.9566
R2UPolySeg	0.9778	0.9497	0.9189	0.8815	0. 9569

CONCLUSION

Even though colonoscopy can help obtain a detailed visual of an internal portion of the colon and is better at determining the presence of a polyp, the adenoma miss rate is still high. This can be reduced by considering deep learning and finding polyps by segmenting colonoscopy images. This could help professionals even determine the severity of the disease by observing the size of the polyp that is segmented out. In the literature, various state-of-the-art work has been carried out on the segmentation of polyps but few challenges have yet to be handled. The proposed framework was designed by keeping in mind unresolved challenges in UPolySeg and ColonSegNet. R2UPolySeg has a pre-processing module for enhancing the image contrast and for removing specularity in coloscopy images. Additionally, some advanced options are selected and designed in the network based on the R2U-Net architecture. The pre-processing unit along with R2UPolySeg increased the performance compared with other work, but there is still room for improvement. Detecting different categories of polyps using deep learning techniques can be very helpful for experts to determine the level of risk for colorectal cancer. Other segmentation networks can also be implemented to evaluate the segmentation task on different datasets such as,CVC-Colon DB dataset, CVC-Clinic DB dataset, Kvasir-SEG dataset and EndoScenedataset or a different dataset. Fine-tuning of the network can be performed using various optimization techniques, which gives a scope for future research.

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