Data Augmentation for Colon Polyp Detection: A Systematic Study

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Table of Content

Abstract

Colorectal cancer (CRC), which is also known as bowel cancer or colon cancer, is the development of cancer from the colon or rectum called a polyp.
Early colon polyp detection from medical images is still an unsolved problem due to the large variation of polyps in term of shape, texture, size, color, illumination and also due to the lack of publicly annotated datasets.
In this paper, we adapt a recently proposed auto-augmentation method for polyp detection. We also conduct a systematic study on the performance of different data augmentation methods for the colon polyp detection.

Introduction

1. Colorectal cancer (CRC) is the third largest cause of worldwide cancer deaths in men and the second cause in women, with the number of patients died each year up to 700,000 [1].

2. There are several methods for colon screening such as CT colonography or wireless capsule endoscopy but the gold standard is colonoscopy.

3. Automatic polyp detection is a potential approach to assist clinicians in improving the sensitivity of the diagnosis.

4. In this paper, we adapt Faster R-CNN together with AutoAugment to detect polyp from colonoscopy video frames. In addition, we also evaluate traditional data augmentation to see the effectiveness of different augmentation strategies.

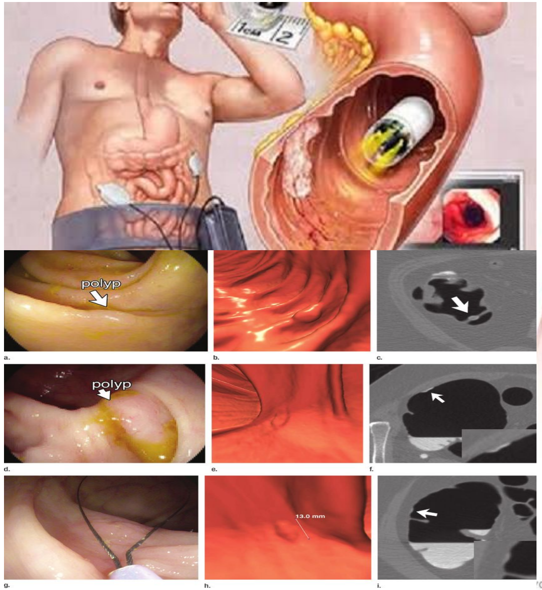
Polyp Screening

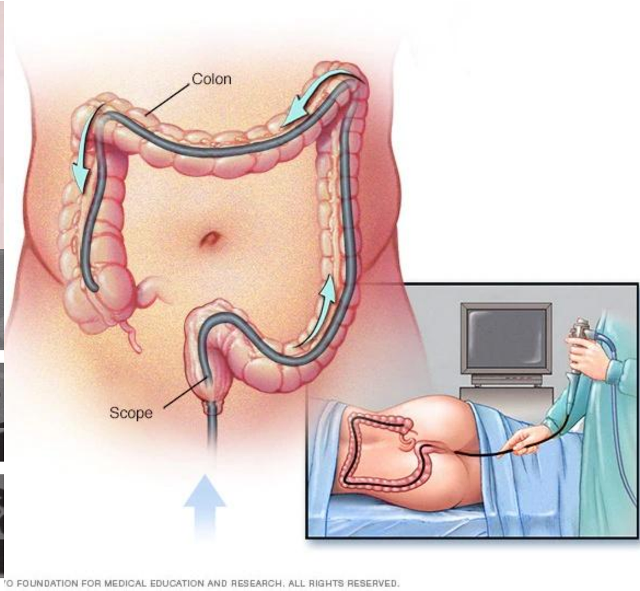
Several methods for colon screening is shown as below

01 | CT Colongraphy

02 | Wireless Capsule Endoscopy

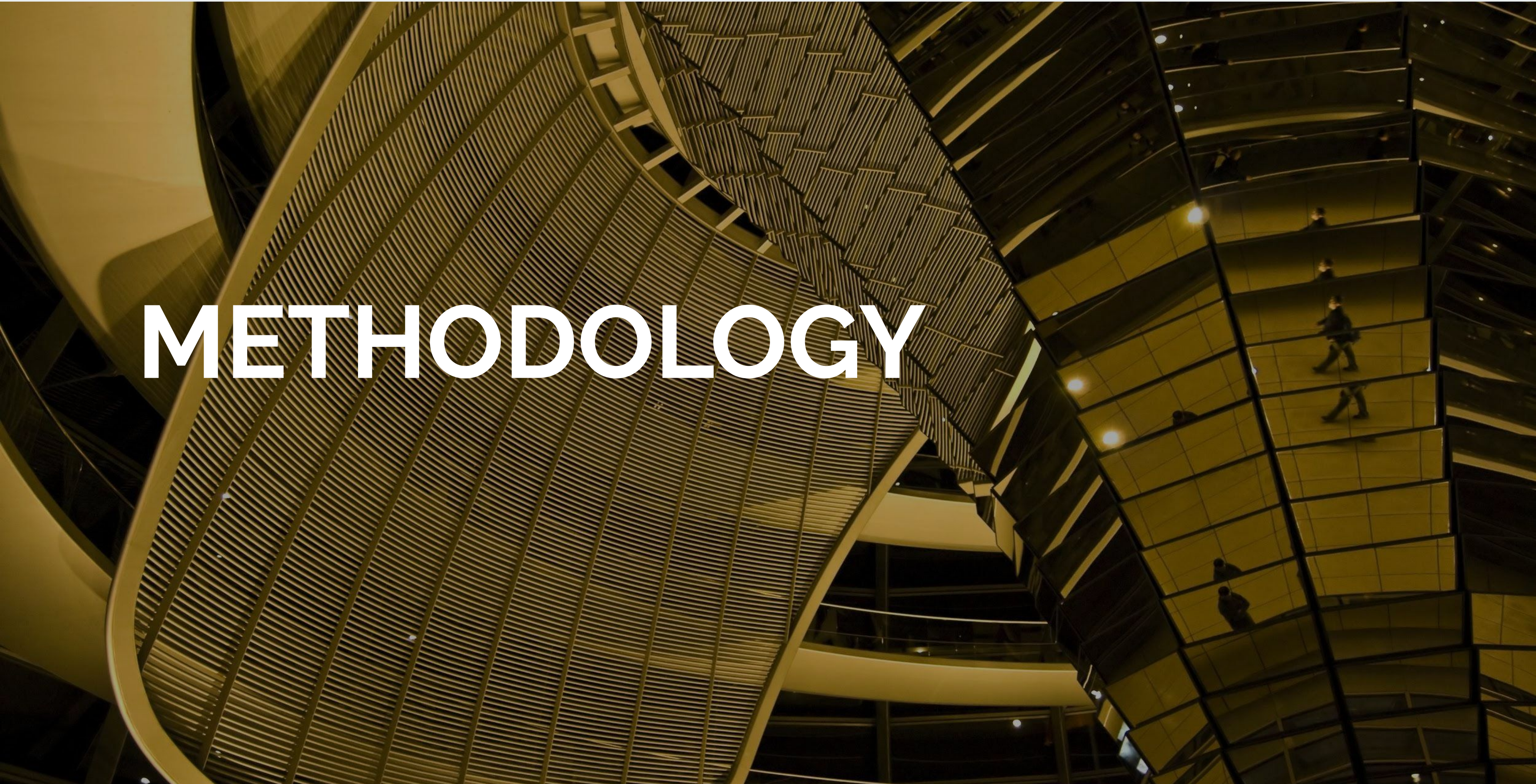
03 | Colonoscopy





Related Work

- MICCAI 2015 Challenge.
- AutoAugment.
- AutoAugment for Object Detection.

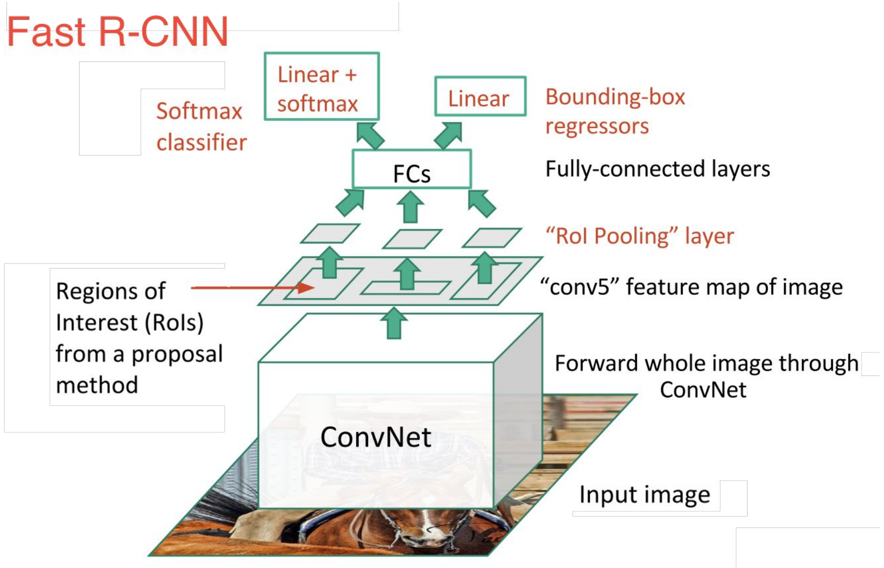


METHODOLOGY

Polyp Detector
Sec3.1

We use Faster RCNN Object Detector with Resnet101 backbone pretrained on COCO dataset.

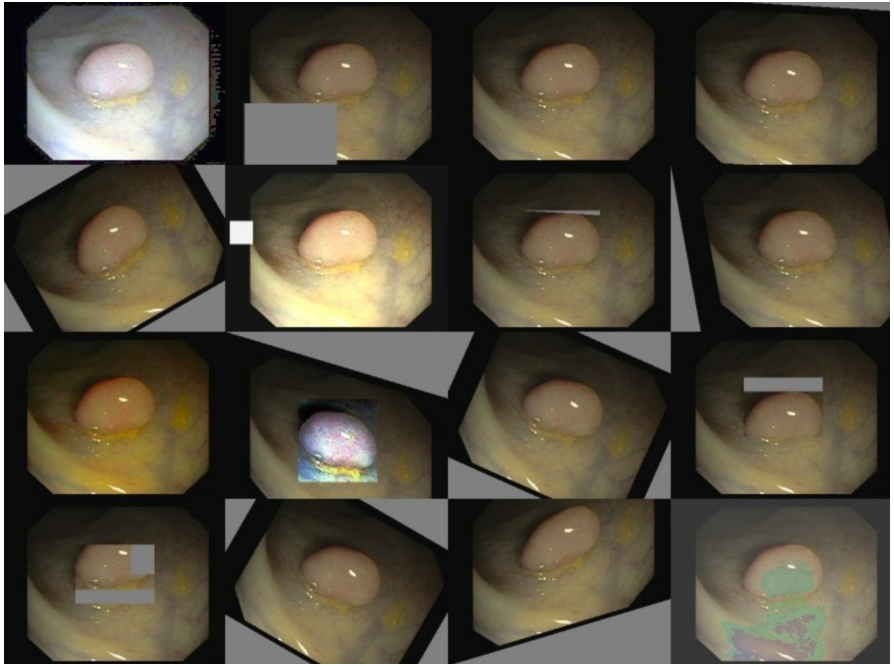
Detector Experimental settings:
Stochastic Gradient Descent (SGD) with 0.9 momentum.
LR with initial value is set to 3e-4 and will be decreased to 3d-5 from the iteration 900k.
Number of anchor boxes is 12 (4 scales, i.e., 64 × 64, 128 × 128, 256 × 256, 512 × 512 and 3 aspect ratios, i.e., 1 : 2, 1 : 1, 2 : 1).



Data Augmentation
Sec3.2

Data augmentation can be split into two types: self-defined data augmentation (a.k.a traditional augmentation) and auto augmentation.

Our work:
Validate learned augmentation policies on polyp detection.
Make a benchmark table in prior to compare different augmentation type.
Workaround make some study in combine several data augmentation types.



Experiments

Table 3 shows the comparative results between different augmentation strategies.
Table 4 presents the comparative results between the auto augmentation in our model and other state-of-the-art results. Among compared methods, CUMED, OUR and UNS-UCLAN are end-to-end deep learning-based approaches.

	TP	FP	FN	Prec	Rec	F1	F2
TDA	142	58	66	71.0	68.3	69.6	68.8
AA	152	52	56	74.5	73.1	73.8	73.4
AA-TDA-1	144	59	64	70.9	69.2	70.1	69.6
AA-TDA-2	148	67	60	68.8	71.2	70.0	70.7
AA-TDA-3	148	47	60	75.9	71.2	73.5	72.1

Table 3. Comparison among traditional data augmentation (TDA), auto augmentation (AA) and their combinations.

	TP	FP	FN	Prec	Rec	F1	F2
CUMMED[3]	144	55	64	72.3	69.2	70.7	69.8
CVC-CLINIC[3]	102	920	106	10.0	49.0	16.5	27.5
ETIS-LARIB[3]	103	1373	105	6.9	49.5	12.2	22.3
OUS[3]	131	57	77	69.7	63.0	66.1	64.2
PLS[3]	119	630	89	15.8	57.2	24.9	37.6
SNU[3]	20	176	188	10.2	9.6	9.9	9.7
UNS-UCLAN[3]	110	226	98	32.7	52.8	40.4	47.1
RetinaNet[10]	134	**48**	74	73.6	64.4	68.7	66.1
Our model	**152**	52	**56**	**74.5**	**73.1**	**73.8**	**73.4**

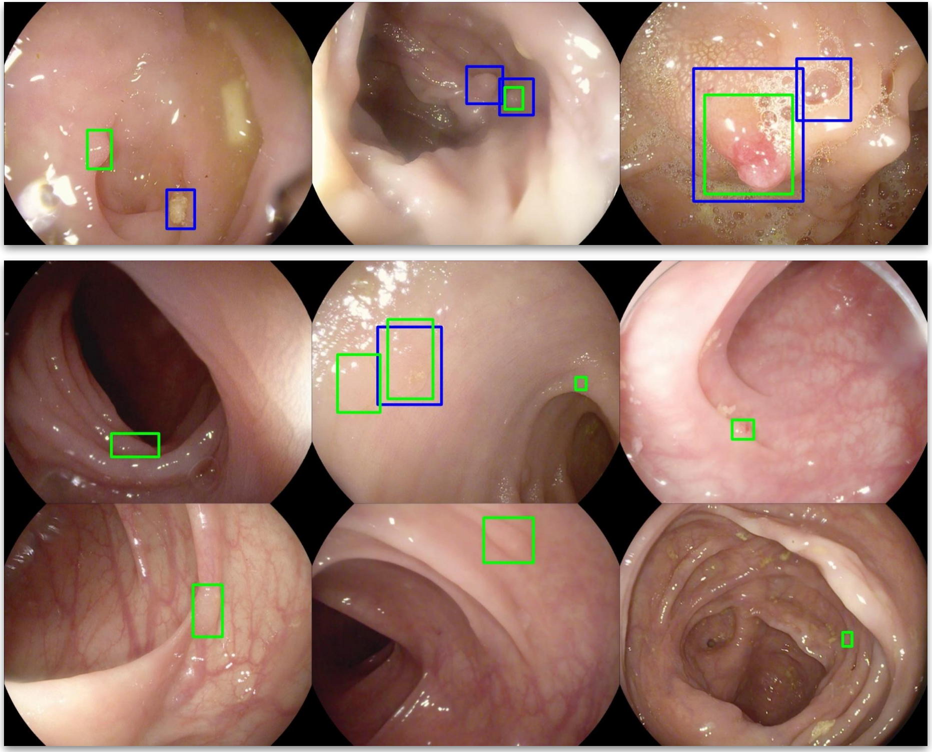
Table 4. Comparative results between our model and the state of the art.

Failed Cases

Note: blue boxes are the predicted locations, and green boxes are groundtruths.

False Positive: failed results above caused by shortcoming in bowel preparation (i.e., leftovers of food and fluid in colon).

False Negative: failed results caused by the variations of polyp type and appearance (i.e., small polyp, flat polyp, similarities of polyp and colon vein)



Conclusions

In this paper, we adapt a deep learning-based object detection method with auto data augmentation for polyp detection problem. Different augmentation strategies are evaluated.

The experimental results show that the learned auto augmentation policies learned from the general object detection dataset are well transferred to polyp detection problem.

Thank you.

Please feel free if you have any question.