CURRENT POSTGRADUATE STUDENT

SURNAME	LO
NAME	Wan Yee (Winnie Lorraine)
PROGRAM	MPhil in Surgery
DATE OF REGISTRATION	1 AUG 2018
SUPERVISOR	Professor Carmen Poon
FIELD OF RESEARCH / INTENDED THESIS TITLE	Biomedical and process engineering
KEYWORDS FOR RESEARCH	

RESEARCH STUDY:

CONFERENCE TITLE / ABSTRACT / POSTER:

1. Posters on Colorectal polyp detection and screening (one of the designers/ drawers)

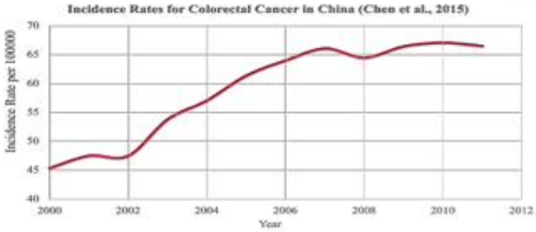
Localisation of Colorectal Polyps by Convolutional Neural Network Features Learnt from White Light and Narrow Band Endoscopic Images of Multiple Databases

Yali Zheng, Ruikai Zhang, Ruoxi Yu, Yuqi Jiang, Tony W. C. Mak, Sunny H. Wong, James Y. W. Lau, and Carmen C. Y. Poon

Colorectal Cancer

Torre et al., 2012; Chen et al., 2015; Hong Kong Cancer Registry, 2017

- 3rd most common cancer in the world
- 376,300 new incidence and 191,000 died in China, 2015
- 1st in new incidence, 2nd in cause of cancer death in Hong Kong



Current Limitation

Hasenbach et al., 2008; Ren et al., 2017; Tajbakhsh et al., 2016; Park et al., 2012; Tajbakhsh et al., 2016

- 10-30% miss-polyp rate during colonoscopy
- Existing polyp detection algorithms
  - Not efficient for real-time analysis
  - Performance compromised by training and testing on same database

Methodology

Redmon et al., 2016

- Implemented a real-time object detector YOLO to localize polyp with bounding boxes on endoscopic images
- Pre-trained with non-medical databases and fine-tuned with colonoscopic images
- Evaluated on several colonoscopy databases with different combination of images selected and augmented

Experimental Setup

Bernal et al., 2012; Bernal et al., 2012; Silva et al., 2014

- 3 public databases (CVC-ColonDB, CVC-ClinicDB & ETIS-Larib)
- 1 self-collected database (PWH-ColonDB)

TABLE 1. FOUR COLONOSCOPY IMAGE DATABASES USED IN THIS STUDY

Database	Images	Image resolution (w×h)	Number of images with polyps	Ground Truth
CVC-ClinicDB	612 sequential WL images from 25 short videos	384×288	612	Bounding box created from binary mask
CVC-ColonDB	380 sequential WL images from 15 short videos	574×500	380	Bounding box created from binary mask
ETIS-Larib	196 WL images	1225×966	196	Bounding box created from binary mask
PWH-ColonDB	798 NB images	1244x1080; 1034x900; 460x400; 227x227	798	Bounding box

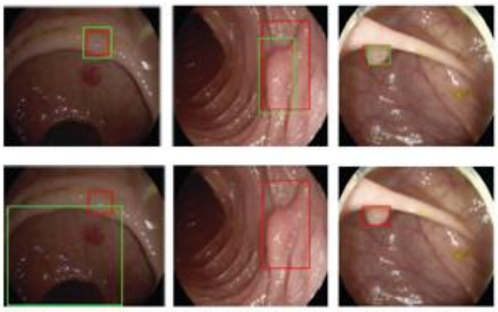


Figure 1. Examples that were correctly localized by YOLO when trained with CVC-ClinicDB (a) while were not localized by YOLO when trained with PWH-ColonDB (b). Green boxes are predicted, and red boxes are the ground truth.

Experimental Results

- Augmentation of the training data can improve the localization performance of YOLO by 5%.
- By pulling WL (white light) images from different database from CVC-ClinicDB for training.
- NB (narrow-band) and WL images should be considered separately for the training.
- YOLO has great potential for real-time polyp localization.

TABLE 2. THE OPTIMAL PERFORMANCE OF THE FIVE TRIALS

Trial No.	Training dataset	No. of training images	Optimal weights	Threshold	TP	FP	FN	Prec	Sens	F1	F2
1	CVC-Clinic	612	2000.weights	0.2	122	40	86	75.3%	58.7%	65.9%	61.4%
2	PWH	798	3000.weights	0.2	49	59	159	45.4%	23.6%	31.0%	26.1%
3	CVC-Clinic-Aug	2448	2000.weights	0.2	139	44	69	76.0%	66.8%	71.1%	68.5%
4	CVC-Aug	3968	5000.weights	0.2	154	45	54	77.4%	74.0%	75.7%	74.7%
5	CVC-Aug-PWH	4766	4000.weights	0.25	149	40	59	78.8%	71.6%	75.0%	73.0%

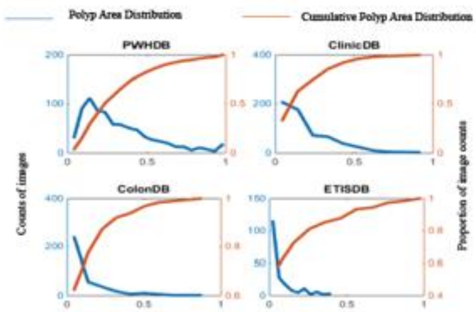


Figure 2. Distribution of relative polyp area in four databases.

Uniqueness and Competitive Advantages

★ Minimized Chances of Missed Polyps

- By locating potential polyp region

★ Reduced Cost and Burden

- By providing real-time pathology decision for 1) Resect-and-Discard and 2) Diagnose-to-Leave strategies