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In collaboration with: **ZiuZ Visual Intelligence**, http://www.ziuz.com and Machine Vision Group**, Universitat Autònoma de Barcelona**, http://mv.cvc.uab.es/

Master Project: Detection and Segmentation of Polyps in Colonoscopy Images.

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1. INTRODUCTION

Colorectal cancer (CRC) is the third cause of cancer death worldwide. Currently, the standard approach to reduce CRC-related mortality is through efficient and regular colon screening to search for polyps; colonoscopy is currently the gold standard tool for colon screening [2]. Polyps are tumour, an abnormal growth of tissue projecting from a mucous membrane and is difficult to segment polyps because polyps are different of each other, polyps have similar colour and texture with the background of the image and polyps also do not have high contrast with the background of the image.

POLYP DETECTION AND SEGMENTATION: During a colonoscopy exploration, clinicians inspect the intestinal wall in order to detect polyps. Unfortunately, despite clinician's skills, some of the polyps are still missed, especially those small and/or hidden behind folds. Losing polyps may result in the lesion evolving badly and, taking into account the intervals between explorations, once it is found it might be too late for the patient. Thus, there is room for computational support systems to aid clinicians on this task [2]. Polyp *detection* is thus the task of generating an annotation (labelling) of an input colonoscopy image which says roughly where a polyp would be (if any). A more advanced form of this is polyp *segmentation* where the labelling is done in such a way as to closely surround the border of the polyp.

MACHINE LEARNING: Machine learning performs a structured learning component to understand the patterns of the input data to give output. Machine learning generates a mapping function and it is used to learn the target function. End-to-end machine-learning models have now found their ways to a variety of disciplines including natural language processing, drug discovery, and medical image analysis [3]. Our proposal is to use machine learning to detect and/or segment polyp patterns in colonoscopy videos.

There are many proposed techniques for detection and segmentation of polyp in colonoscopy images [4] and doctors have started to use just two techniques of polyp classification on two specific cases. We want to test machine learning for detection and segmentation of polyps in endoscopic images.

2. DATABASE

We have two databases of colonoscopy, one for segmentation and another for detection. The database comes from the MICCAI Endoscopic Vision Challenge 2017 [2] and it is available for research purposes only:

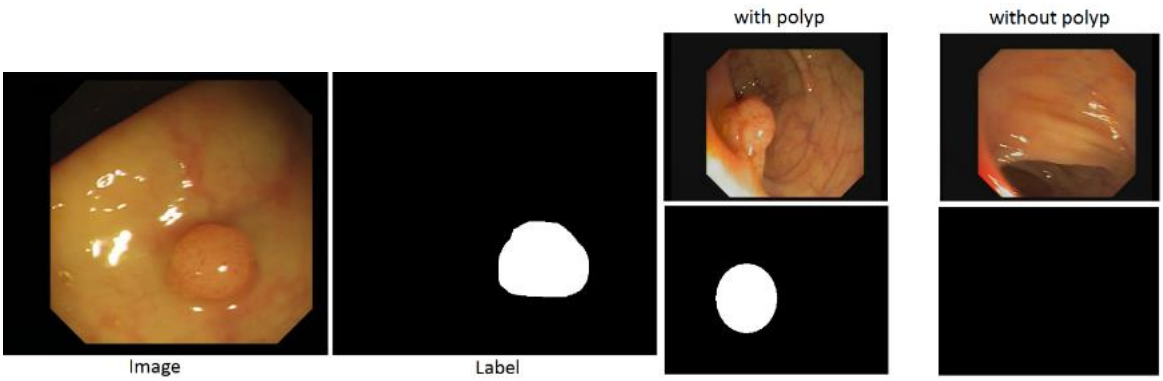
1. **Polyp segmentation [1, 2]:** database is composed by more than 300 frames (all of them showing a different polyp) extracted from routinely explorations at Hospital Clinic of Barcelona, Spain. This database aims to cover as many different polyp appearances as possible. As ground truth, the database provides a pixel-wise representation of the polyp region for all frames [2].
2. **Polyp detection [1, 2]:** CVC-VideoClinic-DB database is composed by more than 40 short and long sequences extracted from routinely explorations at Hospital Clinic of Barcelona, Spain. This database aims to cover all different scenarios that a given support system should face. The database provide an approximation of ground truth for all polyp frames, as shown in the next image. All annotations have been reviewed by clinical experts [2].

Table 1 presents the details about database.

Table 1. Database information

Database	**Label data**	**Task**	**Amount**
CVC-COLON-DB, Polyp Segmentation [1,2]	Yes *(border, lumen, polyp and specular)*	training	300
	Yes *(border, lumen, polyp and specular)*	test	612
CVC-VideoClinic-DB, Polyp Detection [1, 2]	Yes *(polyp)*	training	18 videos (each video has around 400 frames)
	not	test	18 videos (each video has around 1500 frames)

Figure 1 shows one image of each database as illustration.



(a) (b)

Figure 1: Illustration: (a) polyp segmentation, (b) polyp detection.

3. APPROACHES and TIMELINE

This task consists of developing an automatic system which is able to accurately detect or segment the polyp in the image. Techniques of machine learning are currently the most promising technique for this task. Specifically, we advise using convolutional neural networks (CNNS). For the first month the student are encouraged to research the state of the art and afterwards the student may proposed if he finds more promising to research a single general technique for detection and segmentation of polyp or just choose one case and goes more deeply in the technique.

3.1 STEP by STEP

The proposed timeline of the project is shown in table 1.

Table 1 – Timeline for the 6 month project

Activities	**1st Month**				**2nd Month**				**3rd Month**				**4th Month**				**5th Month**				**6th Month**			
State of the Art																								
Implementation of CNN																								
Pre- and post-processing																								
Tests/Comparison																								
Source code documentation																								
Report writing																								

3.1.1 State of the Art

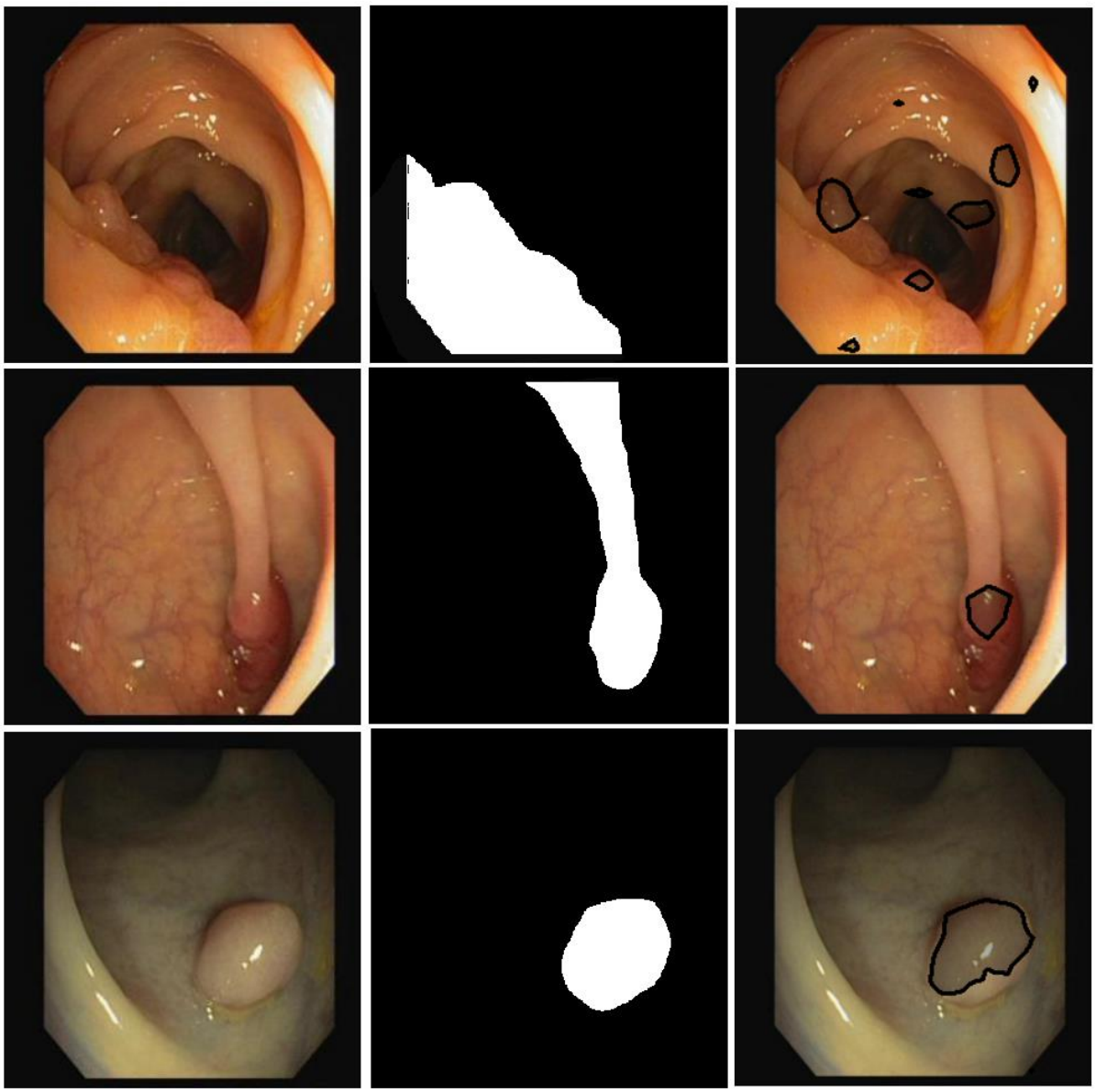
MICCAI endoscopy vision challenge 2015 [4] presents a comparative validation of polyp detection methods in video colonoscopy which the methods are presented in three categories: (1) CNN (Convolutional Neural Network), (2) hybrid approaches that combine two or more components that run and (3) hand-crafted methods which concentrates on local feature or holistic feature detector and descriptors [5]. The students are encouraged to start the state of the art by studying the results of MICCAI endoscopy vision challenge [4]. Besides MICCAI, we also encourage the student to search related works on scientific plataforms such as IEEE Xplore [9], ScienceDirect [10] and ACM [11]

3.1.2 Implementation of CNN

NVIDIA DIGITS [6] offers a user friendly interface for testing CNN's, however GPUs are necessary for this. TensorFlow [8] from Google and theano [7] with Python are good tools for testing CNN's and work on the CPU. DIGITS, TensorFlow and theano are all open source. After you set one of those tool [6, 7, 8], you must to set one CNN. There are several CNN's.

We encourage the student to use one of the presented tools [6, 7, 8] and to test the CNN's AlexNet for detection and UNet for segmentation. However the student is free to use another tools and CNN's if after the state of the art research he concludes that there are other betters.

Figure 1 present our currently results using the NVIDIA Digits [6] with the CNN AlexNet. Due of some reason(s) our results are not good yet and we want to improve it. We are wondering if the improvements must happen by pre- and post-processing filters or choose a correct CNN, or tuning the parameters of the CNN.



(a) (b) (c)

Figure 1. Result of the currenttly pipeline. (a) Input Image; (b) label of the polyp; and (c) Our currently results.

3.1.3 Pre- and post-processing

Pre- and post-processing the images may improve the final result. Image processing filters that can be used for removal of artefacts such as light scratches and “salt and pepper” noises or for get more edge contrast. The differences between neighbour frames might be also a good idea similar to the concept of 3D CNN [12, 13]. Image processing filters such as gaussian and morphological operators may improves the results of detection and segmentation of polyp using machine learning.

We encourage the student to generate new data from the currently data. This means applying image processing filters on the currently database in order to generate new data of Gaussian images for example. Generate a database of Laplacian, blackhat, tophap, opening, closing, gradient, sharp and unsharp image as the same for the Gaussian.

3.1.4 Tests/Comparison

The student should test the CNN using the database of original test images and the other databases created by image pre-processing filters as explained in sub-section 3.1.3. Results should be matched and compared with the ground truth. Students should evaluate the final results quantitatively by comparing the edges results.

4. DELIVERABLES

- **Software source code:** The student should share his implementation with the supervisor.
- **Source code documentation:** All explanations about how to install, run and use the software
- **Master Thesis:** Similar to a bachelor thesis. The student should explain all his/her work in writing.

5. RECOMMENDED SKILLS

- Language: proficiency in C/C++ or Python (preferred) or C#/Java
- Basic Knowledge of Image Processing
- Knowledge of Machine Learning is a plus

6. GRADING

The final evaluation is done according to the following weights:

- **Process:** 20% weight for *process*.
- **Thesis:** 25% weight for *thesis.*
- **Technical contributions:** 30% weight for *technical contributions*.
- **Scientific contribution:** 10% weight for *scientific contribution*.
- **Final presentation:** 15% weight for this element.

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