Training Data Enhancements for Robust Polyp Segmentation in Colonoscopy Images

Victor de A. Thomaz

César A. Sierra-Franco

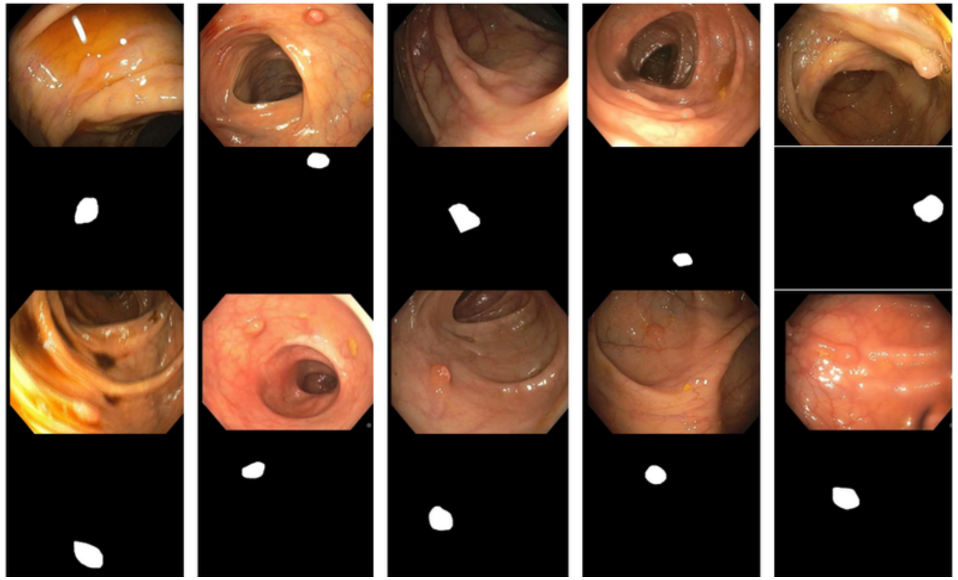
Alberto B. Raposo

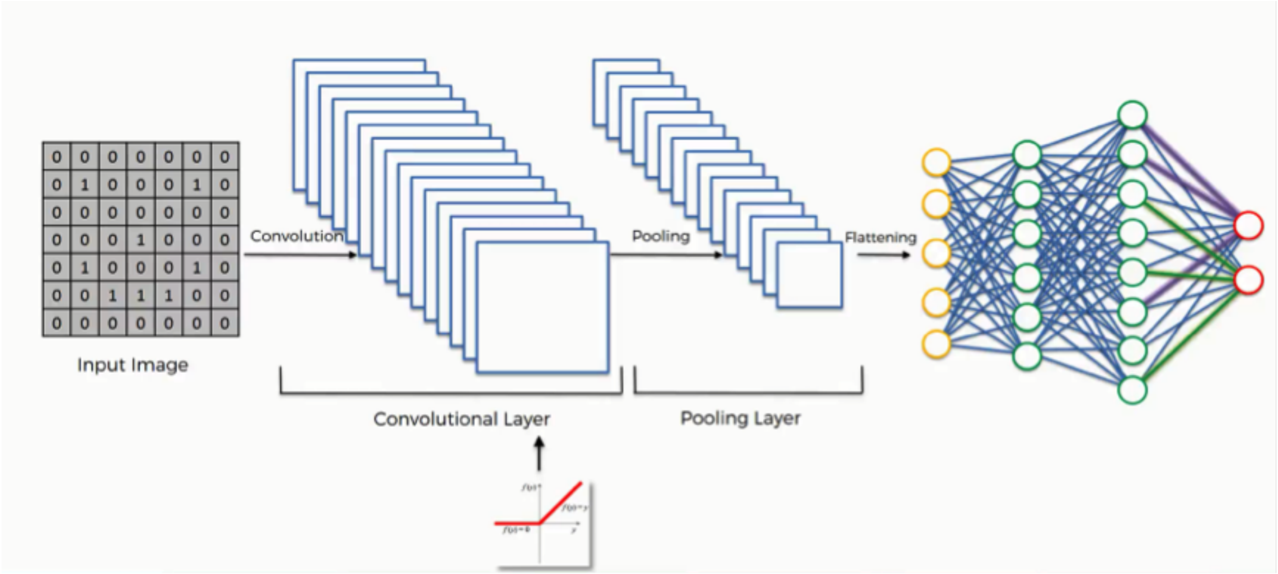
Pontifical Catholic University of Rio de Janeiro (PUC-Rio)
Department of Informatics

Contribution

Dataset enrichment

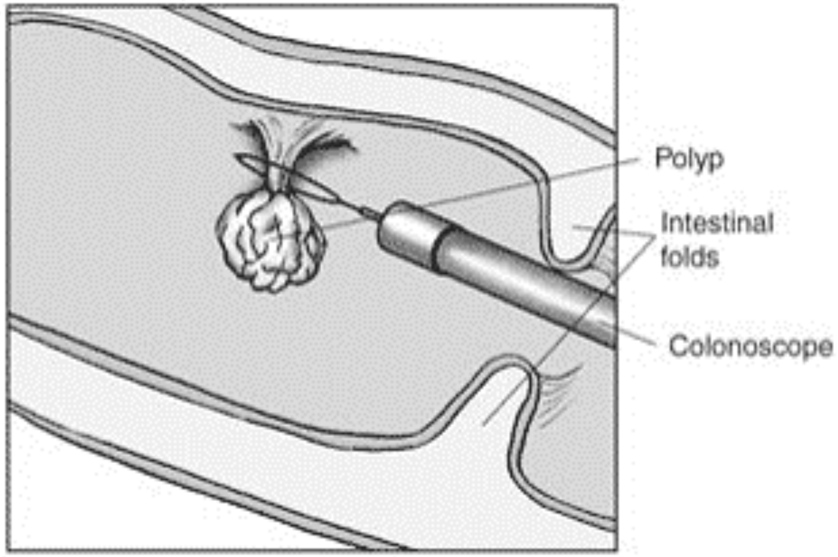
--> to improve the performance of convolutional deep learning approaches





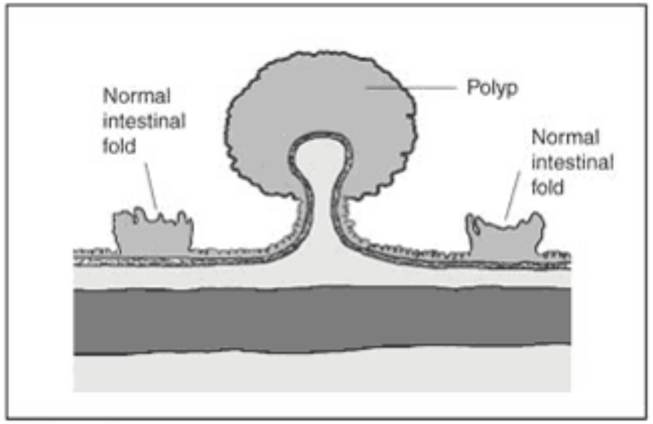
Colorectal cancer

Major cause of cancer-related death.



Colonoscopy

→ reduce the risk by the disease by 70% or more.



Detecting cancer in early curable stages

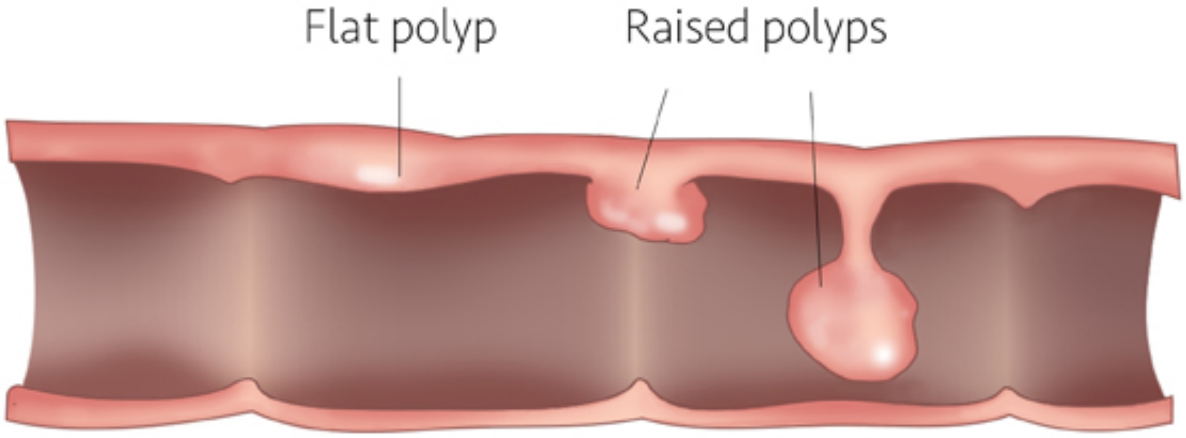
Finding and removing benign polyps

Objective: reduce the polyp/adenoma miss rate

Ideal case --> Doctor find and remove every polyp during the colonoscopy.

Some colon polyps can be tough to spot.

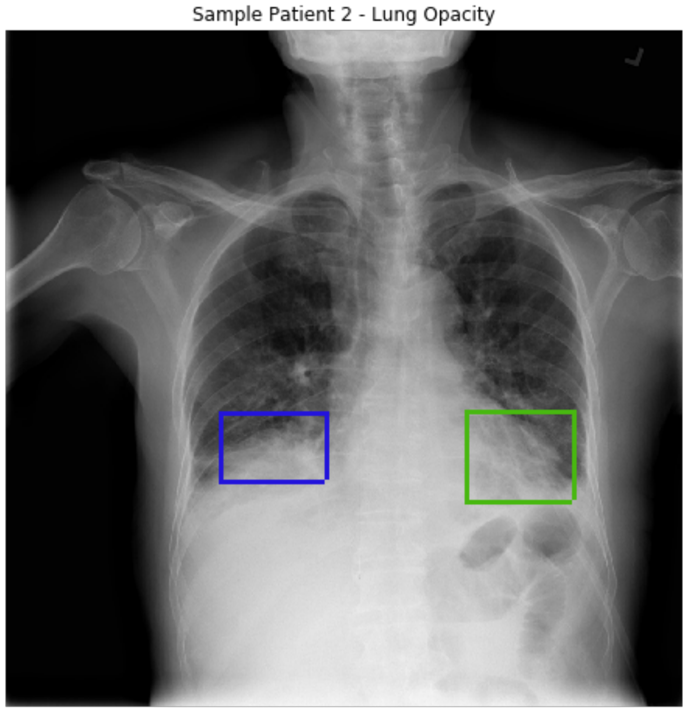
- They may be partly hiding behind a fold
- They are so flat that they're barely visible to the eye.



Computer visions systems may help/assist doctors in polyp detection

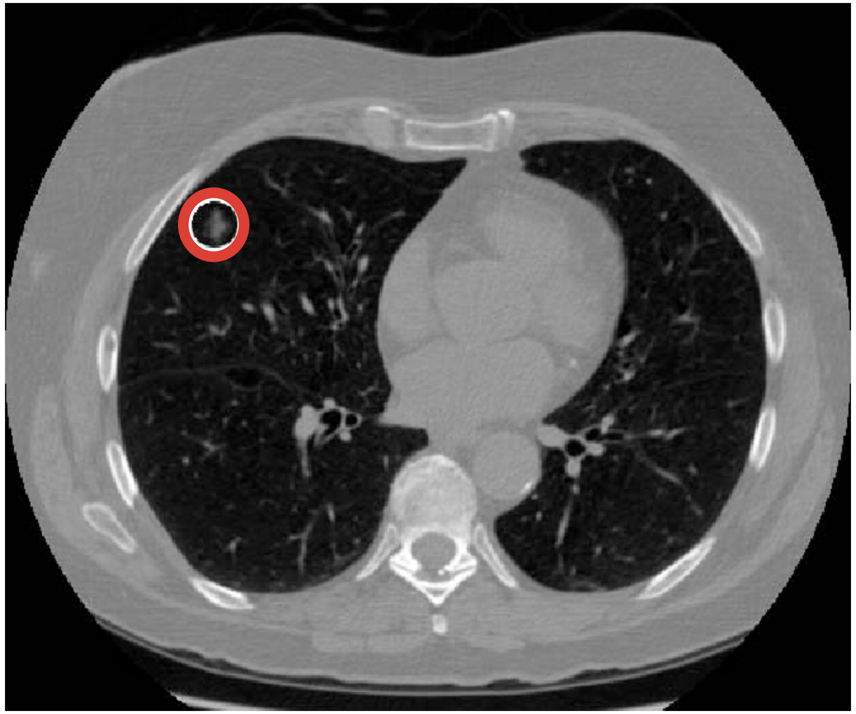
Deep learning in medicine

Large contributions in medical image analysis



Pneumonia detection on X-Ray

Successful applications on X-Ray and MRI analysis.

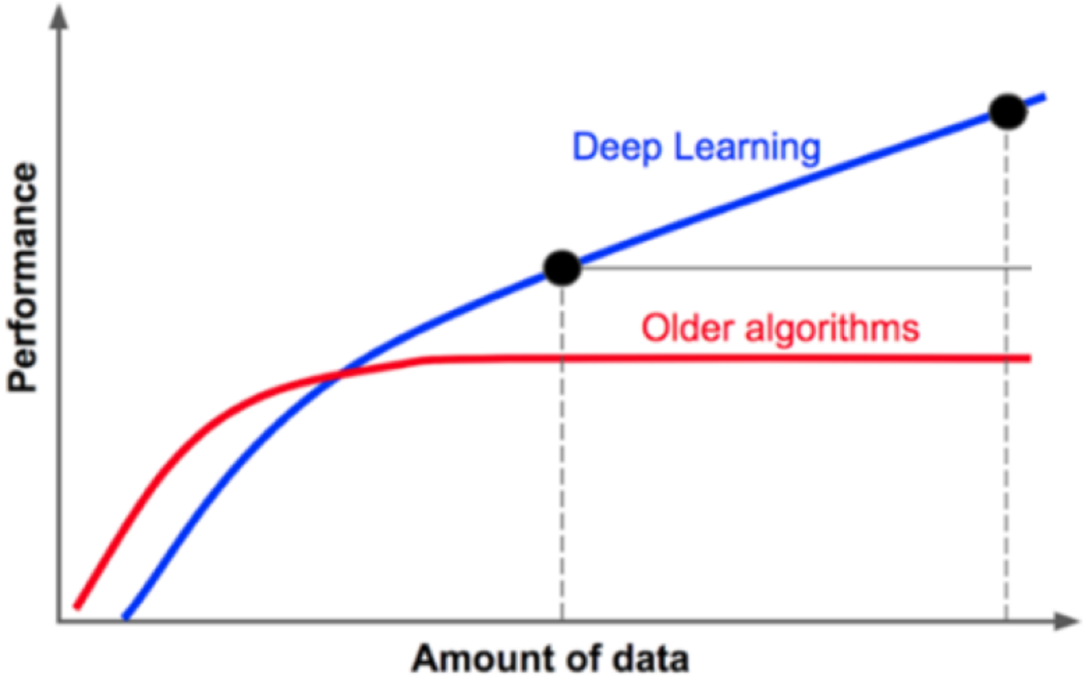


Lung cancer detection on tomographies.

Deep learning challenges

Deep Learning:

- Great for image analysis
- Better performances than other computer vision techniques

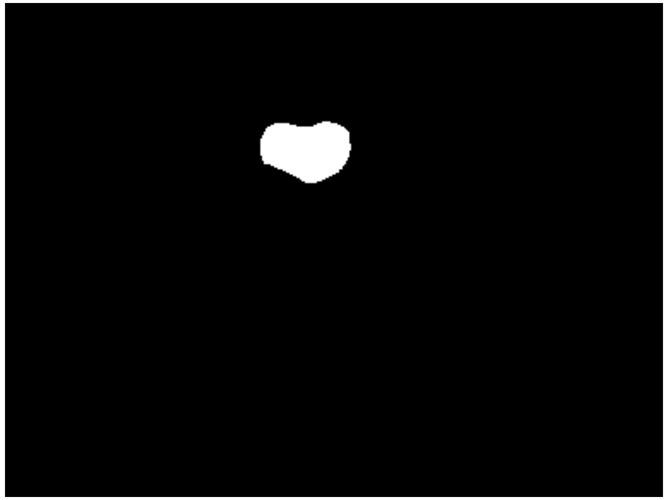


Source: Ng, Andrew. "Nuts and bolts of building AI applications using Deep Learning." NIPS, 2016

Challenge: Quantity and quality of training data

Example: polyp segmentation

Colonoscopy image



Mask (label)

- Need of obtain massive amount of data
- Datasets should be properly annotated

We need the sample with its corresponding maks

Data challenges in the medical context

- **Data privacy.**
  Medical data is personal and not easy to access (ethical issues).

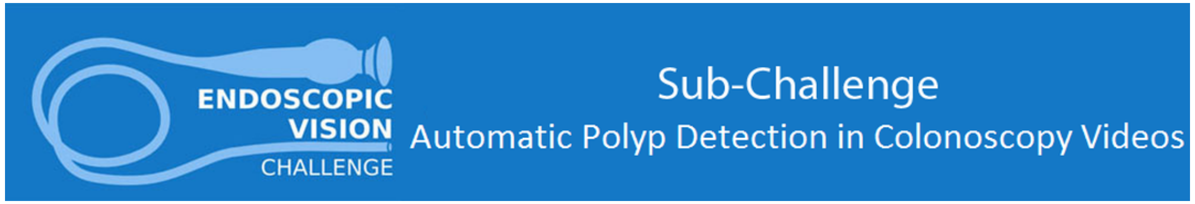
- **Size of annotated data**.
  Annotation process is hard to outsource and only expert physicians can analyze medical images

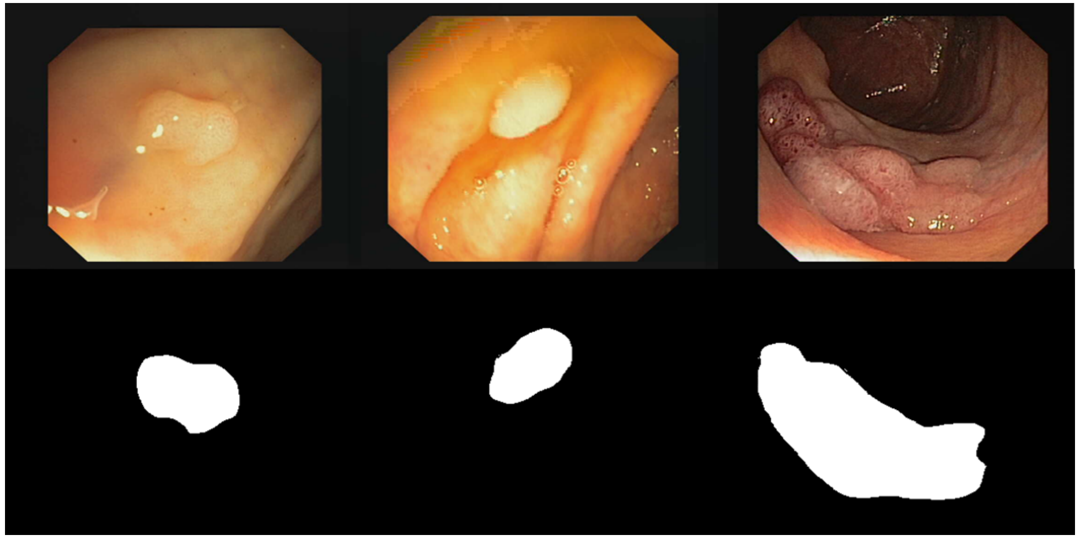
↓

High labeling costs → **Lack of annotated data.**

Colonoscopy dataset:
CVC-ClinicDB

Publicly available dataset restricted for research and educational purposes





(Bernal et al., 2015)

- 612 still images from 29 different colonoscopy videos.
- Provide the ground truth for the polyps --> a mask corresponding to the region covered by the polyp in the image

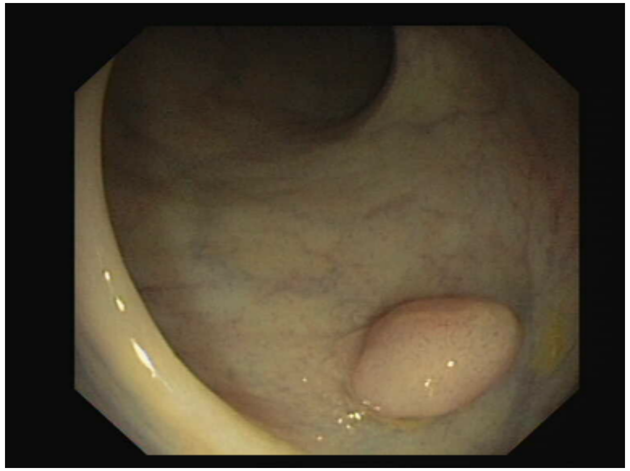
How to generate new training data (images/labels), to improve a polyp segmentation task through deep learning approaches?

General approach

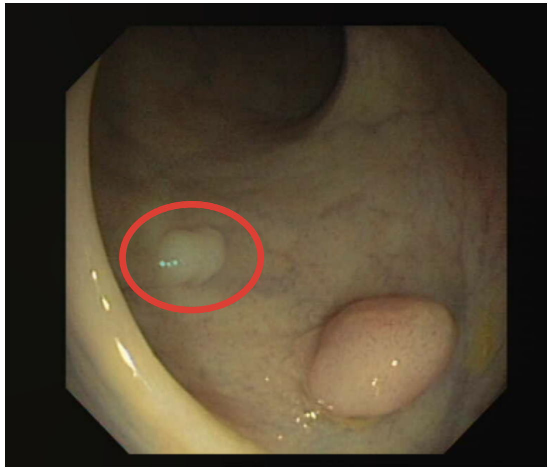
Beyond transfer learning and traditional data augmentation techniques

method → combing features from different samples to get new ones.

A polyp from a source image



We inserted it into a non-polypoid region of another image



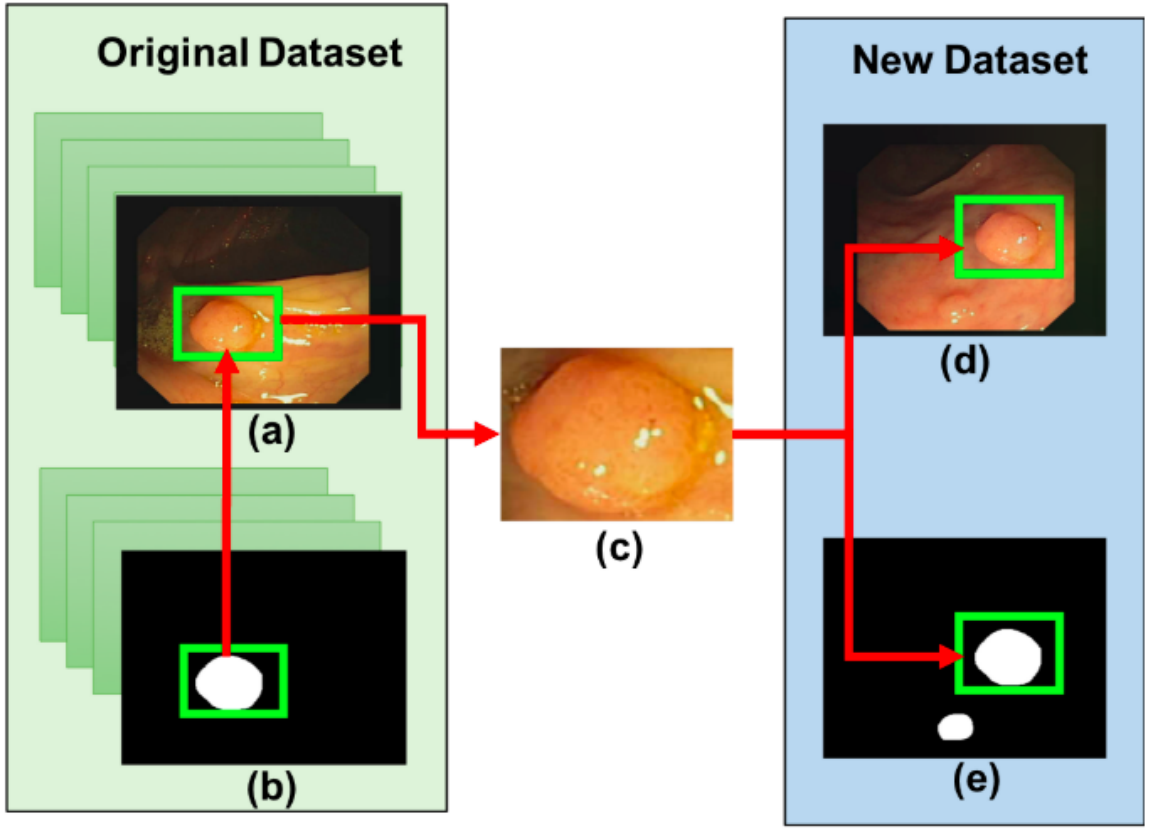
Preserving the realism into the destination image.

Process for data generation

1 - **Polyp selection**
Selecting which ones are appropriate for image extraction.

2 - **Polyp integration**
- Deciding the region/area which can receive a polyp.
- Polyp placement
- Create the new mask

- Preserve consistency
- Preserve realism --> real colonoscolpy



Process for data generation:
2. polyp integration

2.1 Region selection

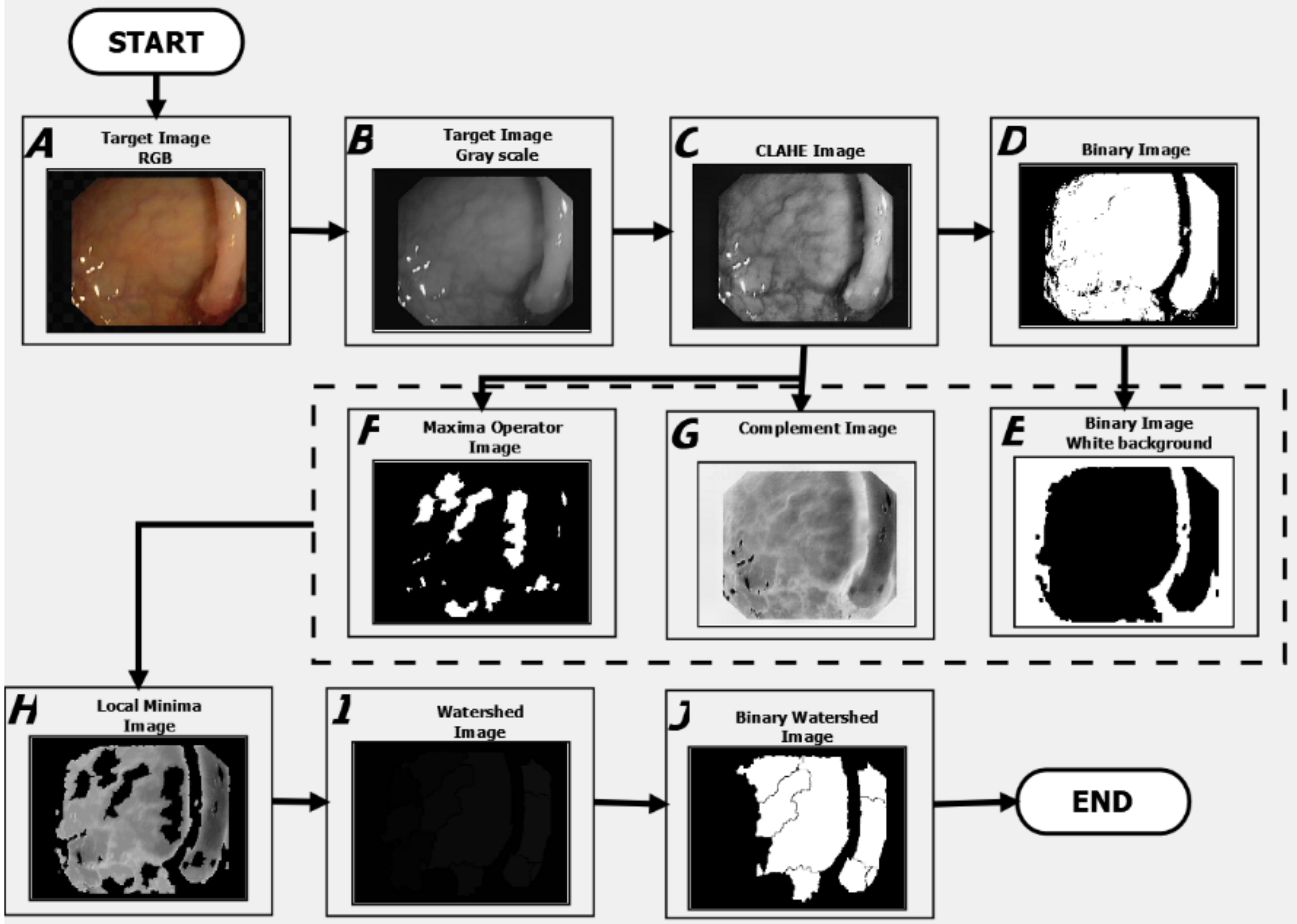
Goal: to find the possible areas (regions) to place the copied polyp.

Based on ***Watershed Transform*** *technique*

↓

Process the image like a topographic map

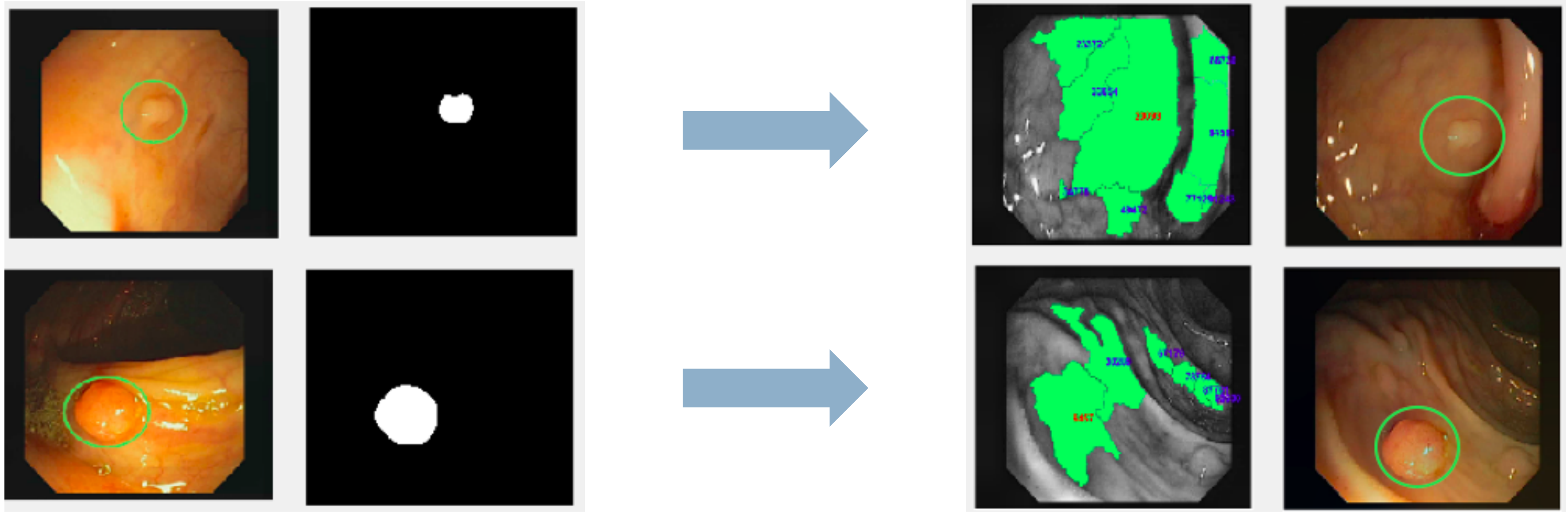
- Light pixels – high elevation
- Dark pixels – low elevations



Process for data generation:
2. polyp integration

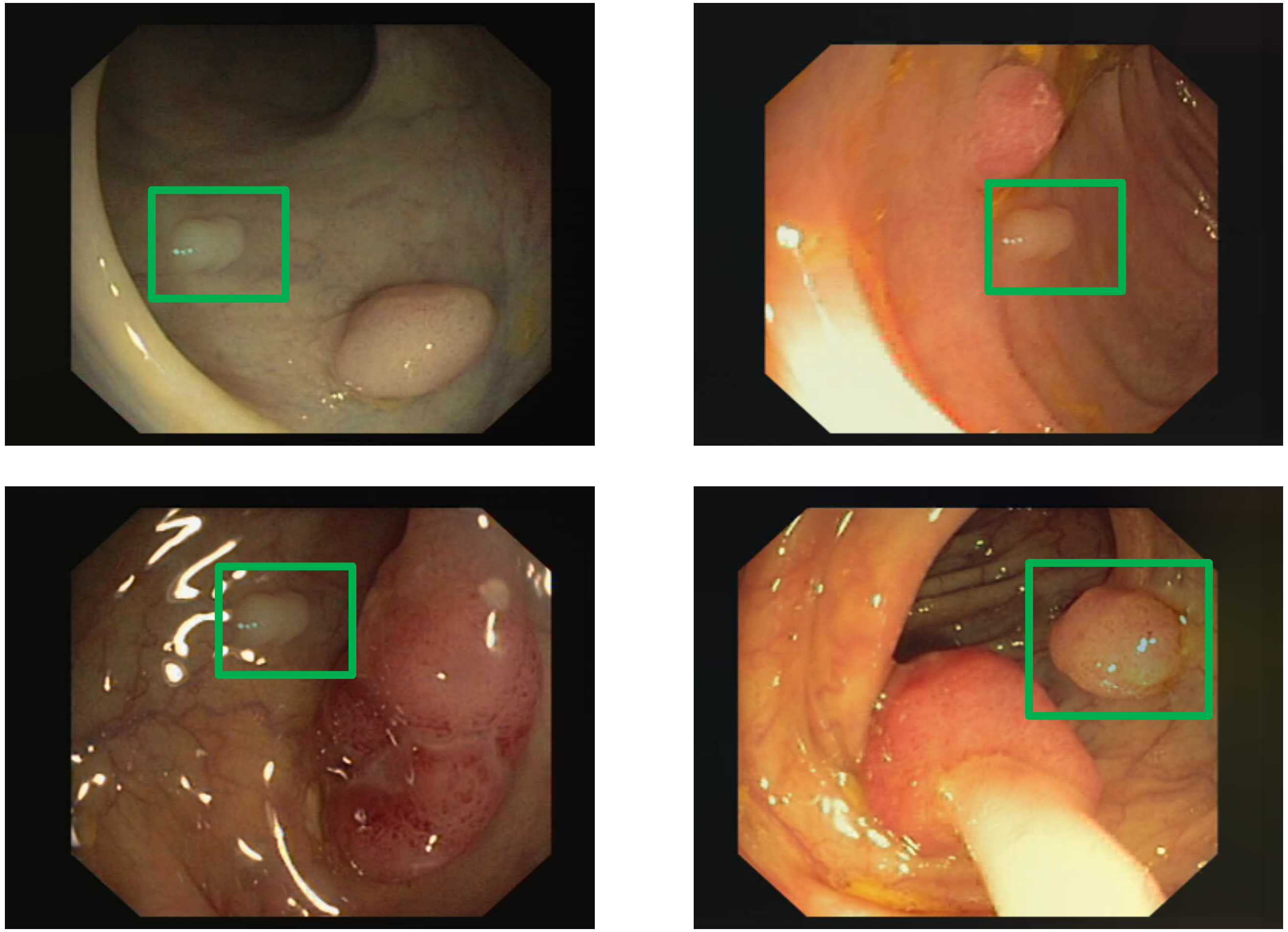
2.2 Polyp placement

Source image Mask Watershed **Target image**

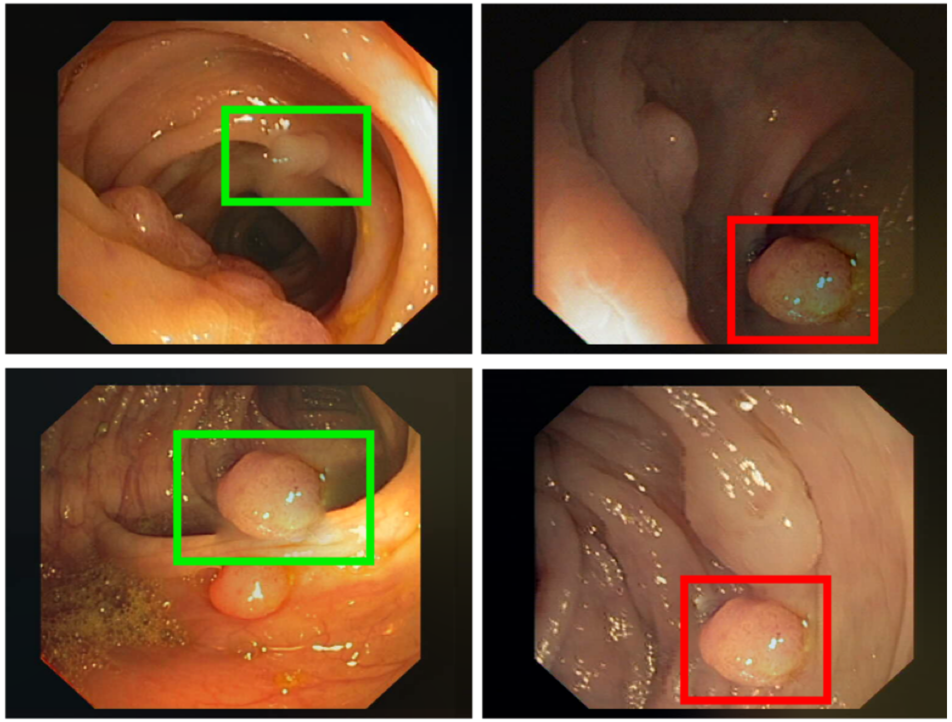


Poisson image editing

Visual results



Visual results (problems/limitation)



Incorrect region:

- Polyp over a colon fold.

Differences in image quality:

- Illumination/bright issues.
- Out of focus

Deep learning experiments (evaluate the proposed method)

Semanting segmentation: U-net network

- Original dataset
- Traditional data-augmentation techniques
- Our syntetical enhanced dataset

Dataset

Train set: CVC-ClinicDB

- 612 images

Test set: ETIS-LaribPolypDB

- 192 images

ID training set (TS)	Training dataset	Number of samples
TS A	CVC-ClinicDB (original)	612
TS B.1	CVC-ClinicDB (traditional data augmentation)	1071
TS B.2	**CVC-ClinicDB + two polyps types (our proposed method)**	**1071**
TS C.1	CVC-ClinicDB (traditional data augmentation)	3873
TS C.2	**CVC-ClinicDB + seven polyps types (our proposed method)**	**3873**

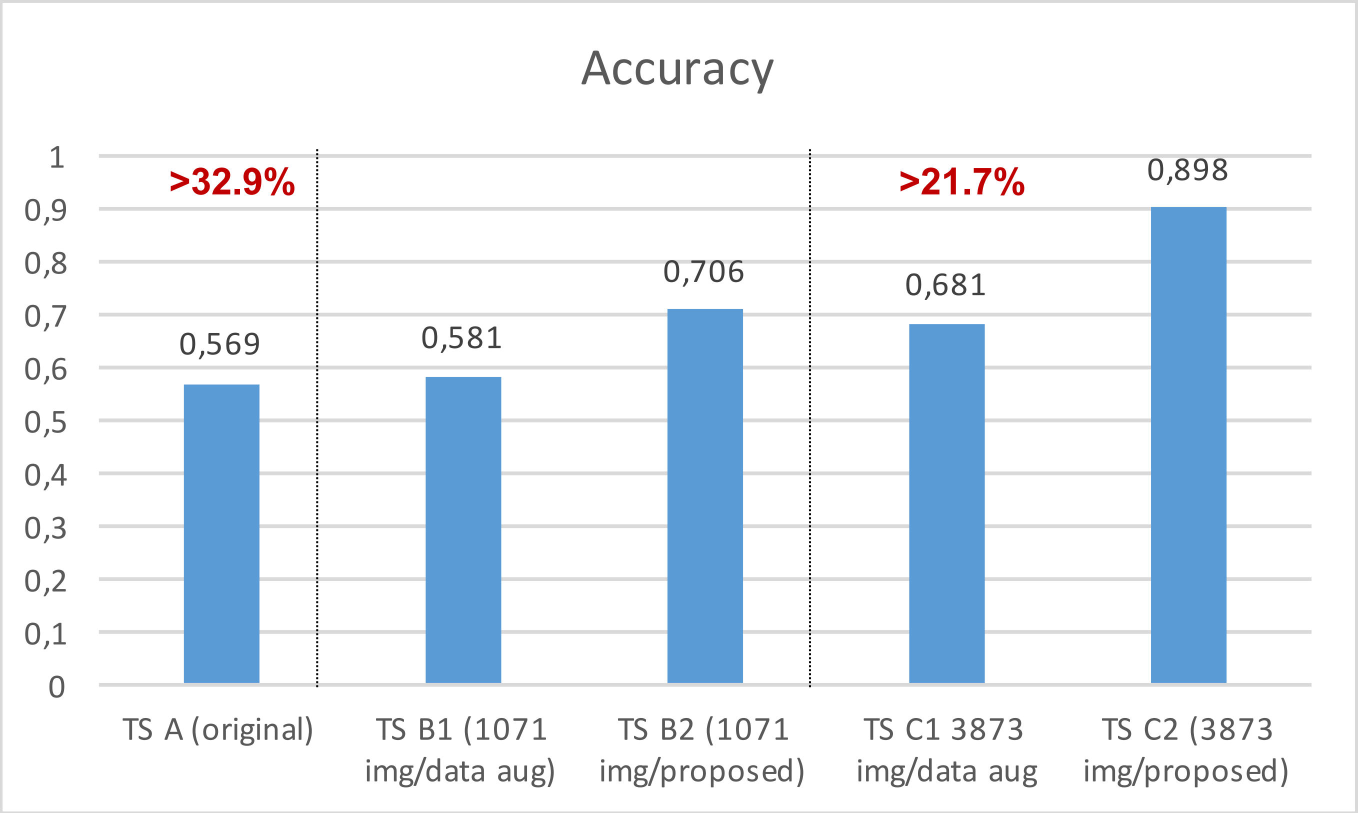
Deep learning experiments – Evaluation metrics

ID training set (TS)	Training dataset	Number of samples
TS A	CVC-ClinicDB (original)	612
TS B.1	CVC-ClinicDB (traditional data augmentation)	1071
TS B.2	**CVC-ClinicDB + two polyps types (our proposed method)**	**1071**
TS C.1	CVC-ClinicDB (traditional data augmentation)	3873
TS C.2	**CVC-ClinicDB + seven polyps types (our proposed method)**	**3873**

Evaluation metrics

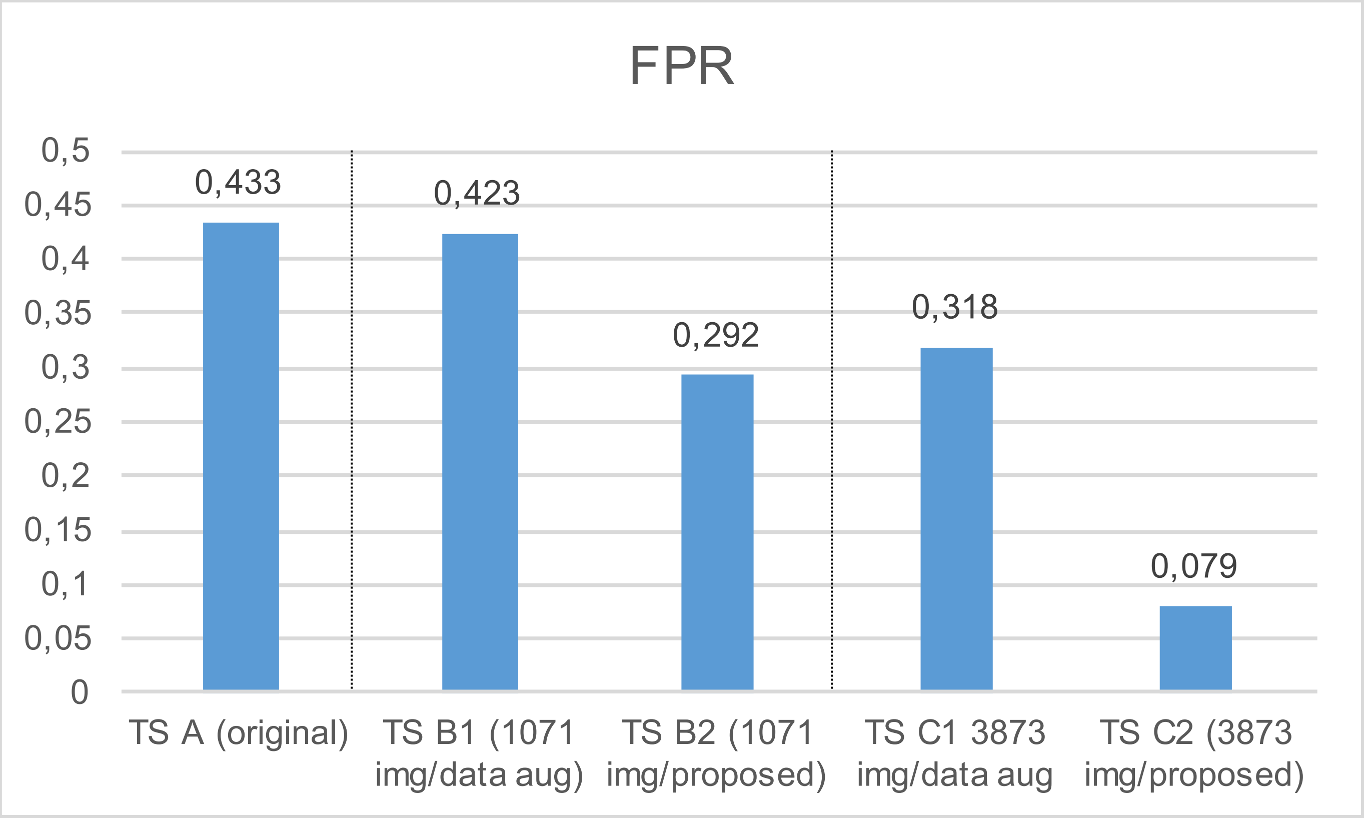
- Accuracy
- False positive rate

Results



- Our method (B2 and C2) present better accuracy than traditional data augmentation techniques (B1 and C1).
- More noticeable with the quantity and variability sample increase.

Results – False positive rate



Big improvements when increasing the quantity and variability of the dataset.

Conclusion

- We propose a method to enrich a colonoscopy dataset in terms of samples quantity and variability (from the existing images).
- We evaluated our method (enhancing/training) over CVC-ClinicDB and testing over ETIS-LARIBPOLYPDB.
- U-Net Semantic segmentation results over the enhanced datasets showed an improved performance over traditional data augmentation techniques.
- Our polyp insertion process can be a useful alternative to traditional data augmentation techniques.

Next steps

- Improve polyp generation process with enhanced synthetic. approaches.
- Generation with desired features: shape, size, textures.
- Generate new realistic colonoscopy images (backgrounds) to increase the data variability.

Contact information:

PhD. candidate – Victor de Almeida Thomaz
thomaz.thomaz@gmail.com

PhD. César A. Sierra Franco
casfranco@tecgraf.puc-rio.br

Prof. PhD. Alberto B. Raposo
abraposo@tecgraf.puc-rio.br