Semantic Segmentation of Colon Polyps in Colonoscopy Images

YOUTUBE LINK: https://www.youtube.com/watch?v=9xskFU8ldbc&feature=youtu.be
BACK UP: https://bit.ly/2WrxWGQ

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Overview

The Problem

- In colonoscopy procedures, the miss rate for colon polyps is 22% [1].
- Colon polyp segmentation is more often explored with computer-aided detection methods. Few end-to-end deep learning attempts at this task exist.

Our Solutions

- Use synchronous image-mask data augmentation to train a U-Net or a SegNet.

Real-World Application

- Future work could entail introducing automatic polyp segmentation software into a colonoscope.

Data/Features

Dataset

- *CVC-ClinicDB:* 612 frames (RGB, 384x288) collected from 29 colonoscopy video independent sequences with corresponding ground truth masks [2].
- Insights: Adjacent images in sequences look similar, separate sequences into train/dev/test, not individual images.
- Train/dev/test split:
  train: 435 images (sequences 9-29)
  dev: 50 images (sequences 1-2)
  test: 127 images (sequences 3-8)

Pre-processing

- Images were pre-processed to be grayscale and 128x128 resolution. To the eye, the colon polyps are distinguishable after this transformation.

Data Augmentation

- Due to the cylindrical geometry of the colon wall and the nature of the video taking procedure, rotations are justified (0-360 degrees).
- Vertical/horizontal flips and slight brightness shifts also applied for a greater ability to generalize.

Key References

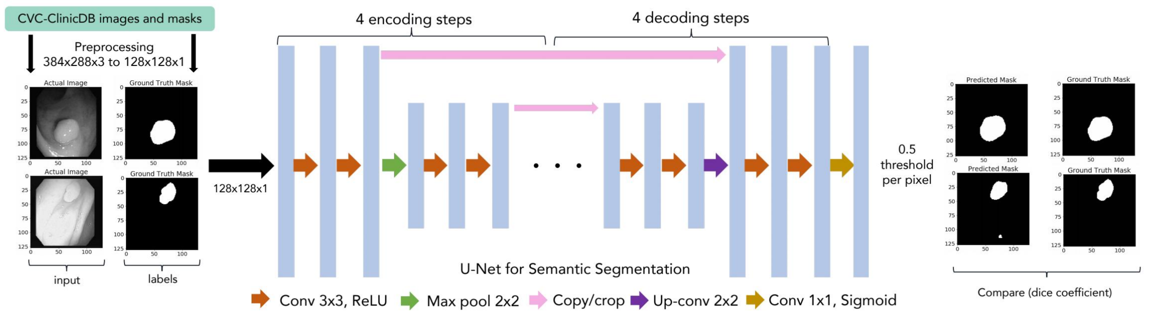
[1] Jeroen C. van Rijn, Johannes B. Reitsma, Jaap Stoker, Patrick M. Bossuyt, Sander J van Deventer, and Evelien Dekker. Polyp miss rate determined by tandem colonoscopy: A systematic review. American Journal of Gasotroentereology, 101, 2006.

[2] Bernal et. al. Wm-dova maps for accurate polyp highlighting in colonoscopy: Validation vs. saliency maps from physicians. Computerized Medical Imaging and Graphics, 43, 99-111, 2015.

[3] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. CoRR, abs/1505.04597, 2015.

[4] Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. Computer Vision and Pattern Recognition, abs/1511.00561, 2015.

Models and Methods



Architectures

U-Net [3]: Primary architecture of this work. Fully convolutional network consisting of an encoder and a decoder with "skip connections" to connect encoder levels with the equal resolution decoder levels to merge local and global information -- a necessity for segmentation tasks.

SegNet [4]: Convolutional encoder-decoder network. Differs from U-Net in that non-linear up-sampling is achieved the decoder's use of the pooling indices of the corresponding encoder step (5 steps each) [2].

Metric and Loss

$$D = \frac{2|A \cap B|}{|A| + |B|}$$

Dice coefficient: Effectively an intersection over union calculation. Above, A is the prediction mask and B is the ground truth mask.

Loss: Negative dice coefficient. Performed significantly better than binary cross-entropy in the baseline.

Results and Analysis

Tuned Models

Model	Learning Rate	Opt. Algorithm	Batch Size
U-Net	0.0001	Adam	8
SegNet	0.0001	Adam	1

Results

Model	Train (Dice)	Test (Dice)
U-Net	0.56	**0.48**
SegNet	0.33	0.23

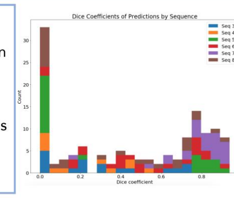
U-Net trained for 300 epochs. SegNet trained for 102 epochs.

Note: Baseline U-Net used no data augmentation. Train/Test dice: 0.92/0.29. Data augmentation dramatically reduced variance.

Results and Analysis

Qualitative Error Analysis

- Predictions are visually satisfactory when: polyps in frame are roughly circular, high contrast in image.
- Predictions visually unsatisfactory when: polyps too large/too small in frame, low contrast in image.



Future Work

Improve Current Models

- U-Net: Use a larger encoder-decoder along with higher resolution, RGB images. Reason: some polyps have a distinct color contrast compared to colon wall.
- SegNet: More extensive hyperparameter tuning, longer training.

Explore New Models and Techniques

- Implement transfer learning with FCNs trained on ImageNet.
- Survey sequence models for real-time colon polyp segmentation.

Long-term

- Develop colonoscope with embedded polyp segmentation software.