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: 412 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.

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.

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. Differ from U-Net in that non-linear up-sampling is achieved by using the pooling indices of the corresponding encoder step (5 steps each) [2].

Metric and Loss
- 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

<table>
<thead>
<tr>
<th>Model</th>
<th>Learning Rate</th>
<th>Opt. Algorithm</th>
<th>Batch Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>U-Net</td>
<td>0.0001</td>
<td>Adam</td>
<td>8</td>
</tr>
<tr>
<td>SegNet</td>
<td>0.0001</td>
<td>Adam</td>
<td>1</td>
</tr>
</tbody>
</table>

Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Train (Dice)</th>
<th>Test (Dice)</th>
</tr>
</thead>
<tbody>
<tr>
<td>U-Net</td>
<td>0.56</td>
<td>0.48</td>
</tr>
<tr>
<td>SegNet</td>
<td>0.33</td>
<td>0.23</td>
</tr>
</tbody>
</table>

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

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.