



# A Novel Computer Vision Program Accurately Identifies Colonoscopic Colorectal Adenomas

Taibo Li<sup>1</sup>, SB, Jonah Cohen<sup>2</sup>, MD, Michael Craig<sup>1</sup>, MS, Kleovoulos Tsourides<sup>1</sup>, MS, Nadim Mahmud<sup>3</sup>, MD, Tyler M. Berzin<sup>2</sup>, MD

<sup>1</sup>Massachusetts Institute of Technology, Cambridge, MA, <sup>2</sup>Division of Gastroenterology, Beth Israel Deaconess Medical Center and Harvard Medical School, Boston, MA,

<sup>3</sup>Department of Medicine, Brigham and Women's Hospital, Boston, MA

## BACKGROUND

- Colonoscopy with polypectomy reduces the risk of developing colorectal cancer. However, clear evidence demonstrates variability among endoscopists with regard to adenoma detection rates, and interval colon cancer after colonoscopy remains an important public health challenge.
- Sessile serrated adenomas (SSAs) are recognized as particularly difficult lesions to identify because of their frequently flat morphology and subtle surface features.
- Computer vision represents a promising modality to improve endoscopic lesion detection but to date, technical challenges have limited its applicability to clinical endoscopic practice.

## AIMS

- To develop a novel computer vision program and assess its performance in detecting the presence of adenomatous colon polyps including SSA.

## METHODS

- We curated 26 endoscopy videos totaling more than 390 min of footage. We captured 509 frames which contains adenomatous polyps and 6,875 polyp-free frames. We applied data augmentation and generated 15,270 adenomatous polyp-positive images, of which 2,310 are SSA, and 20,625 adenomatous polyp-negative images.
- Exclusion Criteria: images that are blurred or contain polypectomy devices were not included.
- We trained a large, deep convolutional neural network on 90% of images (Fig 1). We tested the performance of the program on the remaining 10% of the images unseen by the program during training.

## RESULTS

We trained the model on 32,305 images and tested its performance on 3,590 images with the same proportion of SSA, non-SSA polyp-positive, and polyp-negative images (Table 1).

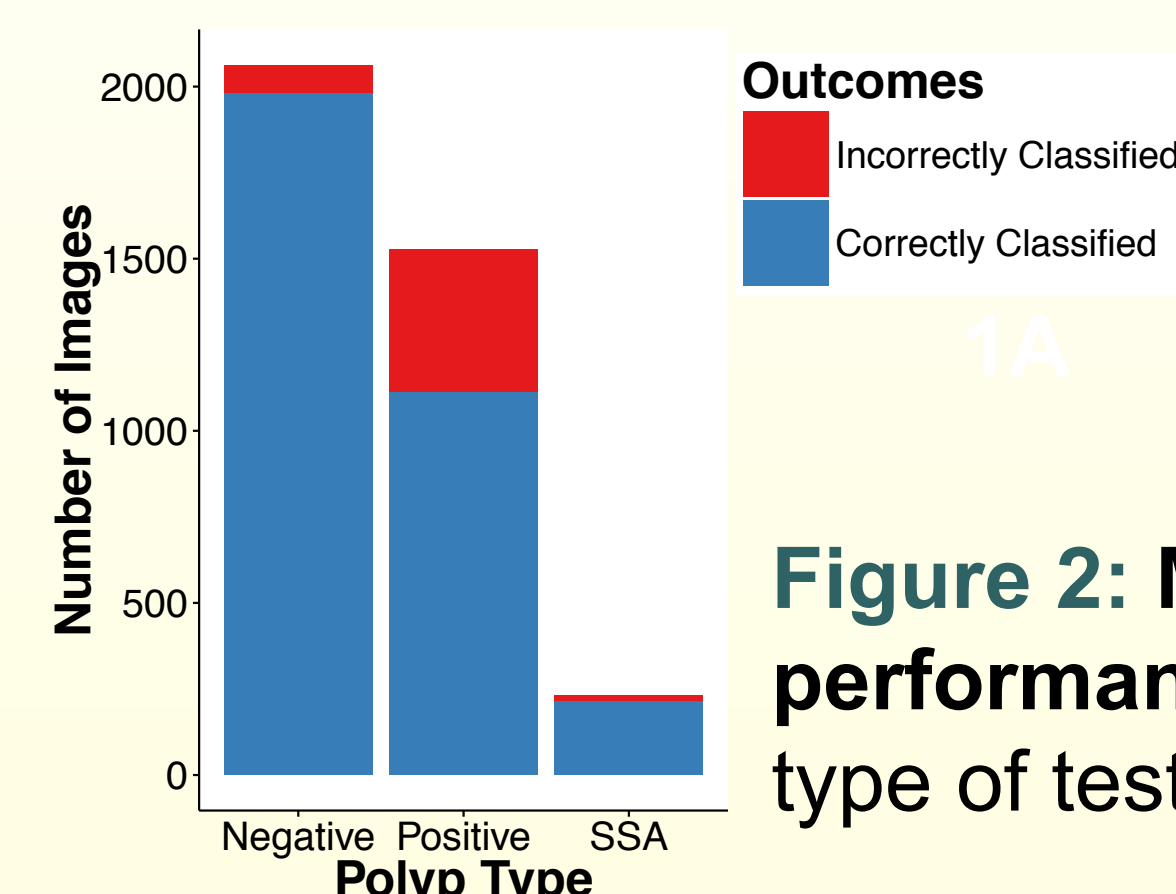
**Table 1: Number of images used in this study.**

		Training	Validation
Polyp-Positive	SSA	2,079	231
	Non-SSA	11,664	1,296
Polyp-Negative		18,562	2,063
<b>Total</b>		<b>32,305</b>	<b>3,590</b>

The overall accuracy is 0.86. Classification results for each category is shown in Table 2 and Fig 2. Receiver operating curve (ROC) is shown in Fig 3.

**Table 2: Model performance tested on 3,590 images.**

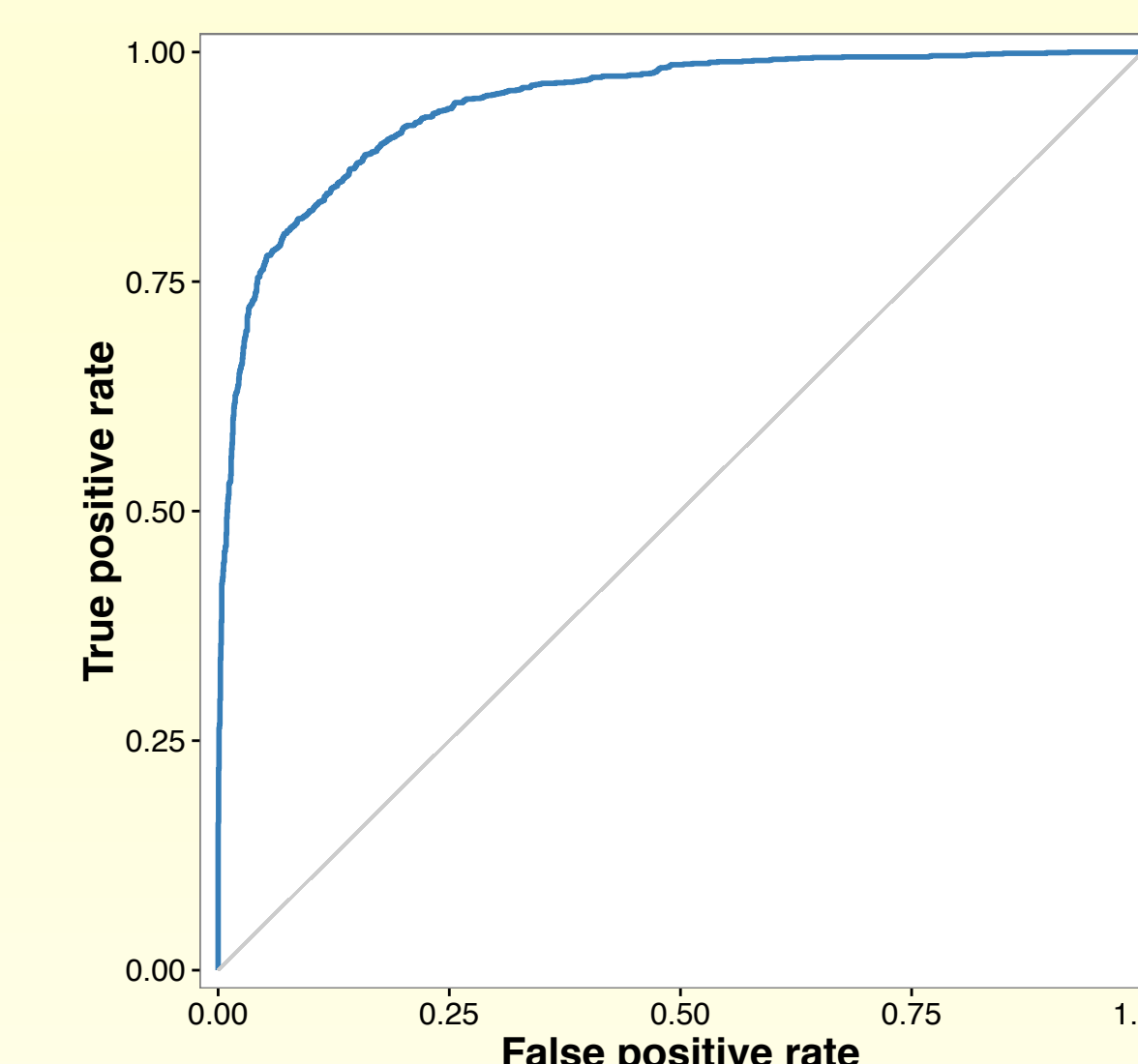
			Predicted Condition	
	Total N = 3,590		Predicted Positive	Predicted Negative
	Condition	Overall	1,114	413
	Positive	SSA	214	17
True Condition	Condition Negative		80	1,983



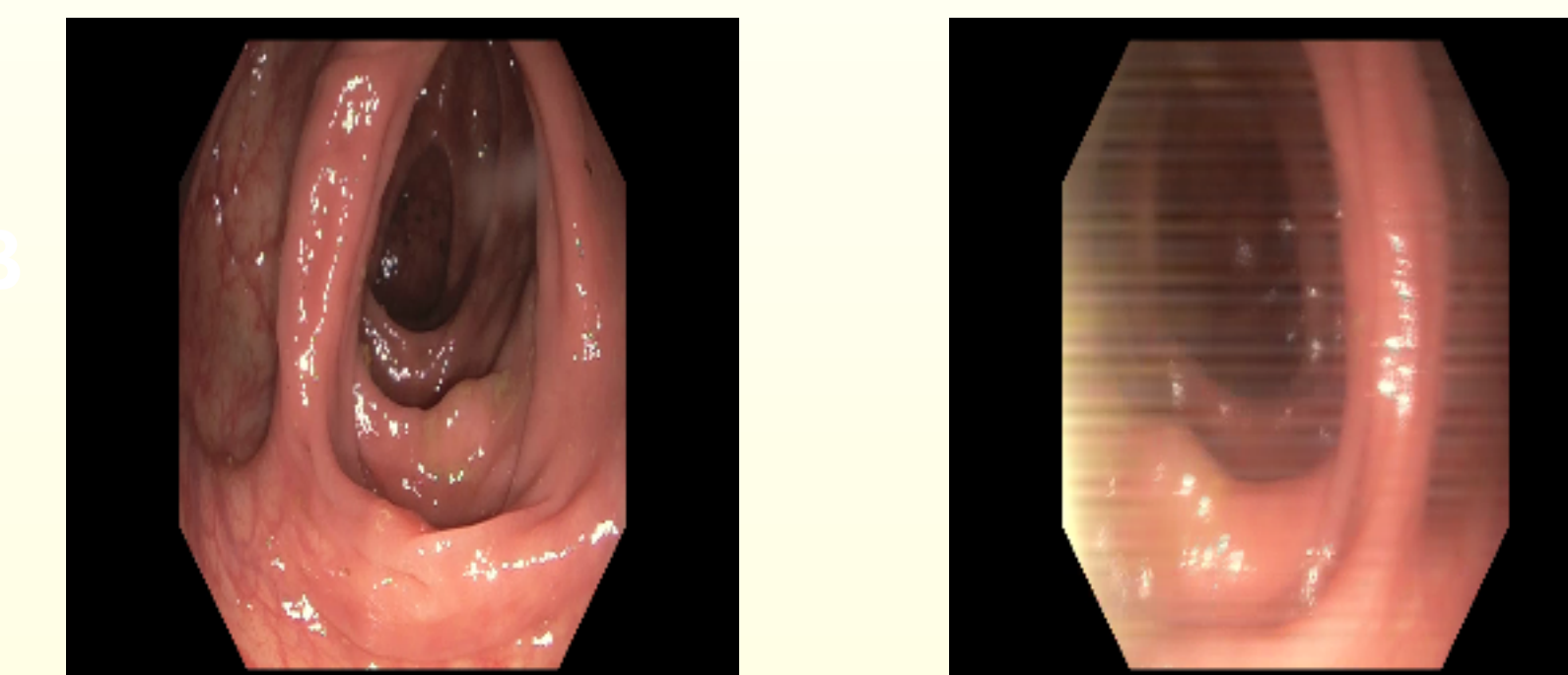
**Figure 2: Model performance for each type of test images.**

The sensitivity is 0.73, and the specificity is 0.96. The positive predictive value is 0.93, and the negative predictive value is 0.96.

Area under the ROC curve is 0.94.



**Figure 3: ROC analysis showing an area under curve (AUC) of 0.94.**

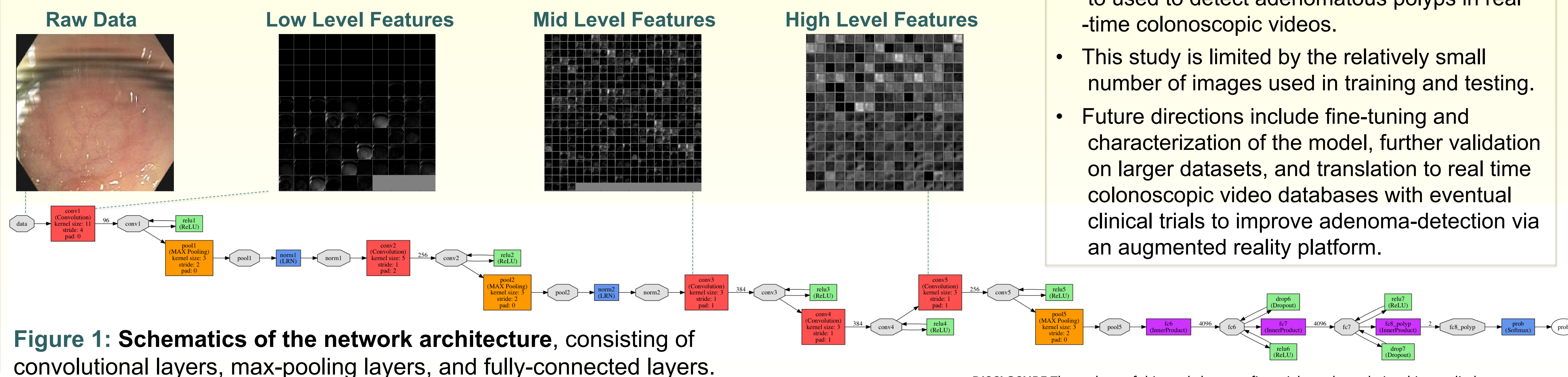


**Figure 4: Example images of correctly classified (left) and incorrectly classified (right) SSAs.**

For SSAs, the accuracy is 0.93. Two example SSA images used in the model are shown in Fig 4, where we observed that the model can be susceptible to motion-induced blurring in endoscopic videos.

## CONCLUSIONS

- We have shown that a novel computer vision program using convolutional neural network can identify the presence of colorectal adenomas including SSA from colonoscopic images with high accuracy.
- Because all images were captured from endoscopy videos, this model has the potential to be used to detect adenomatous polyps in real-time colonoscopic videos.
- This study is limited by the relatively small number of images used in training and testing.
- Future directions include fine-tuning and characterization of the model, further validation on larger datasets, and translation to real-time colonoscopic video databases with eventual clinical trials to improve adenoma-detection via an augmented reality platform.



**Figure 1: Schematics of the network architecture, consisting of convolutional layers, max-pooling layers, and fully-connected layers.**