

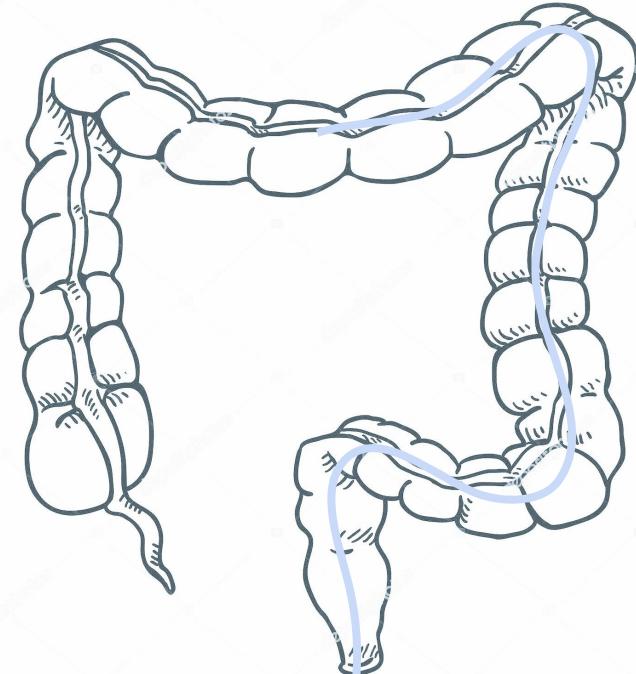
MIE 1075

Artificial Intelligence & Robotics

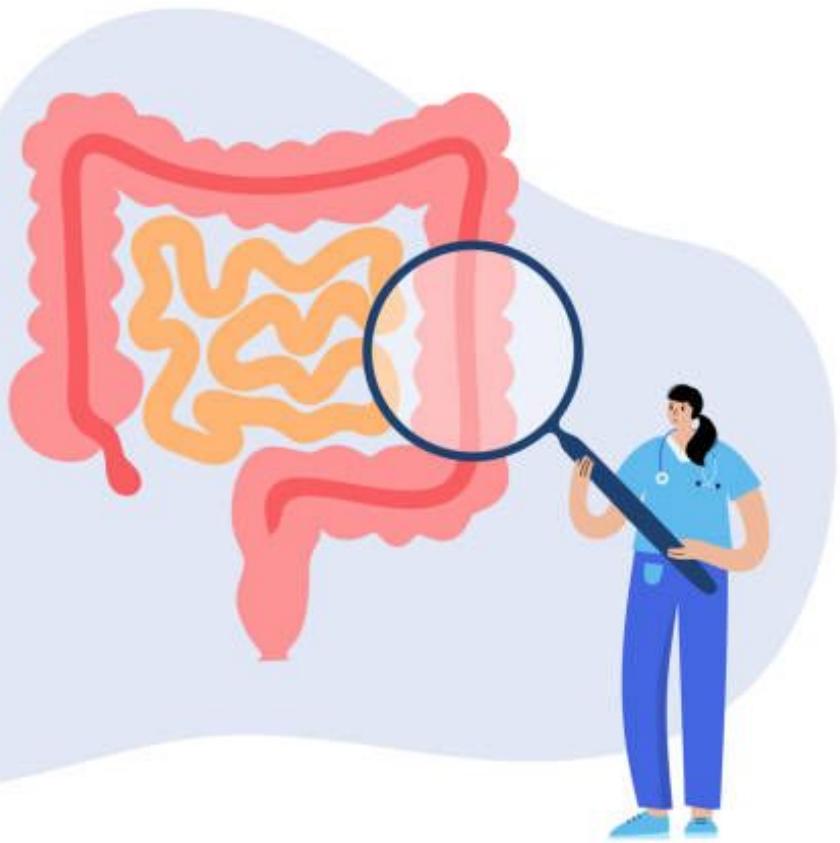
An autonomous colonoscopy robot
for colorectal cancer surveillance and
polyp removal

Matthew Teichman, Min Woo (David) Kong, Manthan Patel, Shawn Khan

December 9, 2021



Colorectal Cancer



Prevalence

- Third most common cancer worldwide
- Prevalence decreasing overall with adoption of routine colonoscopy
- More people being diagnosed at age 30-40

Prognosis

- Early detection leads to better outcomes, current practice is to screen at age 50 with routine colonoscopy
- Colonoscopy is the most effective method of identifying lesions and preventing colorectal cancer

Problem Statement

- To design an autonomous colonoscopy robot to identify and manipulate polyps

Bylsma LC, Gillezeau C, Garawin TA, Kelsh MA, Fryzek JP, Sangaré L, Lowe KA. Prevalence of RAS and BRAF mutations in metastatic colorectal cancer patients by tumor sidedness: A systematic review and meta-analysis. *Cancer medicine*. 2020 Feb;9(3):1044-57.

Conventional Colonoscopy

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Methods

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Discussion

Conclusion



- Conventional colonoscopy is performed by either a general surgeon or a gastroenterologist
- Patient requires bowel preparation
- Camera inserted through the rectum all the way to the end of the large intestine
- Doctor looks for polyps which are pre-cancerous growths

Access to Colonoscopy

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Original Article

Inequitable Access to Surveillance Colonoscopy Among Medicare Beneficiaries With Surgically Resected Colorectal Cancer

Janeth I. Sanchez, PhD, MPH  ^{1,2}; Veena Shankaran, MD, MPH²; Joseph M. Unger, PhD, MS^{1,2}; Margaret M. Madeleine, PhD, MPH^{1,2,3}; Subodh R. Selukar, BS  ⁴; and Beti Thompson, PhD^{1,2}

BACKGROUND: After colorectal cancer (CRC) surgery, surveillance with colonoscopy is an important step for the early detection of local recurrence. Unfortunately, surveillance colonoscopy is underused, especially among racial/ethnic minorities. This study assesses the association between patient and neighborhood factors and receipt of surveillance colonoscopy. **METHODS:** This retrospective, population-based cohort study used Surveillance, Epidemiology, and End Results-Medicare linked data (2009–2014). Beneficiaries with surgically resected stage I or III CRC between the ages of 66 and 85 years were identified, and multivariable logistic regression was used to assess the effect of factors on receipt of colonoscopy. **RESULTS:** Overall, 57.5% of the patients received initial surveillance colonoscopy. After adjustments for all factors, Blacks and Hispanics had lower odds of receiving colonoscopy than non-Hispanic Whites (NHWs; 29.6% for Blacks, $P = .002$; 12.9% for Hispanics, $P > .05$). NHWs with Medicaid coverage had 35% lower odds of surveillance colonoscopy than NHWs without Medicaid coverage. Minority patients with Medicaid were more likely to receive colonoscopy than their racial/ethnic counterparts without Medicaid coverage ($P > .05$). Hispanics residing in neighborhoods with incomes of $\geq \$90,000$ had significantly lower odds of surveillance colonoscopy than Hispanics residing in neighborhoods with incomes of $\$0$ to $\$30,000$. **CONCLUSIONS:** Receipt of initial surveillance colonoscopy remains low, and there are acute disparities between Black and NHW patients. The association between factors that assess a patient's ability to access colonoscopy and actual receipt of colonoscopy suggests inequitable access to surveillance colonoscopy within and across racial/ethnic groups. *Cancer* 2021;127:412–421. © 2020 American Cancer Society.

KEYWORDS: cancer health disparities, colorectal cancer, surveillance.

INTRODUCTION

Up to 50% of all patients with colorectal cancer (CRC) will experience recurrence or metachronous (second primary) CRC after surgical resection.^{1,2} The identification of recurrent cancers when potentially curative treatment is still possible is a critical aspect of cancer surveillance and an important predictor of survival among patients with CRC.^{2,3}

National guidelines recommend an initial surveillance colonoscopy within 1 year after surgery for patients diagnosed with stage II or III CRC.⁴ Postoperative colonoscopy surveillance improves survival in this population by detecting synchronous colorectal tumors that may have been missed during the preoperative workup, local and anastomotic recurrences, and metachronous CRCs.^{1,2,5}

Despite its benefits, only approximately 50% of eligible patients with CRC receive surveillance colonoscopy as recommended.^{6–8} Patients who are older, patients who have more comorbidities, and patients without adjuvant treatment are less likely to receive surveillance colonoscopy.^{6,7,9,10} Previous studies also suggest that elderly Black and Hispanic patients with CRC are 10% less likely to receive surveillance colonoscopy within the first 2 years following surgery than non-Hispanic White (NHW) patients.^{6,9}

Few studies have evaluated whether patient- and neighborhood-level factors contribute to observed racial/ethnic disparities in CRC surveillance.^{6,7,9} These racial/ethnic differences may be driven, in part, by the dynamic interdependence of multiple levels of influence, including the characteristics of patients and the neighborhoods in which they reside.¹¹ For example, racial/ethnic minorities tend to experience socioeconomic disadvantages, such as living in poverty and/or residing in resource-deprived neighborhoods, that may reduce their access to health care and their likelihood of

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¹Department of Health Services, School of Public Health, University of Washington, Seattle, Washington; ²Public Health Sciences Division, Fred Hutchinson Cancer Research Center, Seattle, Washington; ³Department of Epidemiology, School of Public Health, University of Washington, Seattle, Washington; ⁴Department of Biostatistics, School of Public Health, University of Washington, Seattle, Washington

We acknowledge the dedication and contributions of the staff at the Hutchinson Institute for Cancer Outcomes Research in facilitating access to the data.

Additional supporting information may be found in the online version of this article.

DOI: 10.1002/cncr.33262. Received: June 26, 2020; Revised: August 14, 2020; Accepted: September 3, 2020; Published online October 23, 2020 in Wiley Online Library (wileyonlinelibrary.com)



- Study by Sanchez et al. (2021) found inequitable access to screening colonoscopy
- Black and Hispanic populations had lower odds of receiving colonoscopy than non-Hispanic White populations
- Patients without Medicaid insurance had 35% lower odds of surveillance colonoscopy

Sanchez JI, Shankaran V, Unger JM, Madeleine MM, Selukar SR, Thompson B. Inequitable access to surveillance colonoscopy among Medicare beneficiaries with surgically resected colorectal cancer. *Cancer*. 2021 Feb 1;127(3):412–21.

Overview of AI Techniques

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Task	Goal of Task	Type of AI Implemented
Path planning and actuation of endoscope	To inform the direction of autonomous movement, such as turning, without collision and/or injury	Mask R-CNN
Localization and orientation of endoscope	To understand where the robot is moving in relation to the colon	Stereo SLAM
Maintenance of sufficient insufflation pressures	To maintain steady insufflation pressures in the colon to allow for adequate visualization	N/A
Assess adequacy of bowel preparation	To ensure patients have undergone bowel preparation to clear the bowel of the stool and ensure sufficient visualization and safety of the procedure.	N/A
Tissue identification and localization	To identify and localize lesions discrepant from normal anatomy (polyps, lumen, stool, cecum, appendiceal orifice, ileocecal valve)	Mask R-CNN for image processing
Characterization of polyp	To indicate whether a lesion is likely to be cancerous, precancerous, or benign (non-malignant)	CNN
Polyp manipulation and removal	To allow for biopsy and extraction of polyp	Mask R-CNN, reinforcement learning

Stereo SLAM & Orienting Colonoscope Position

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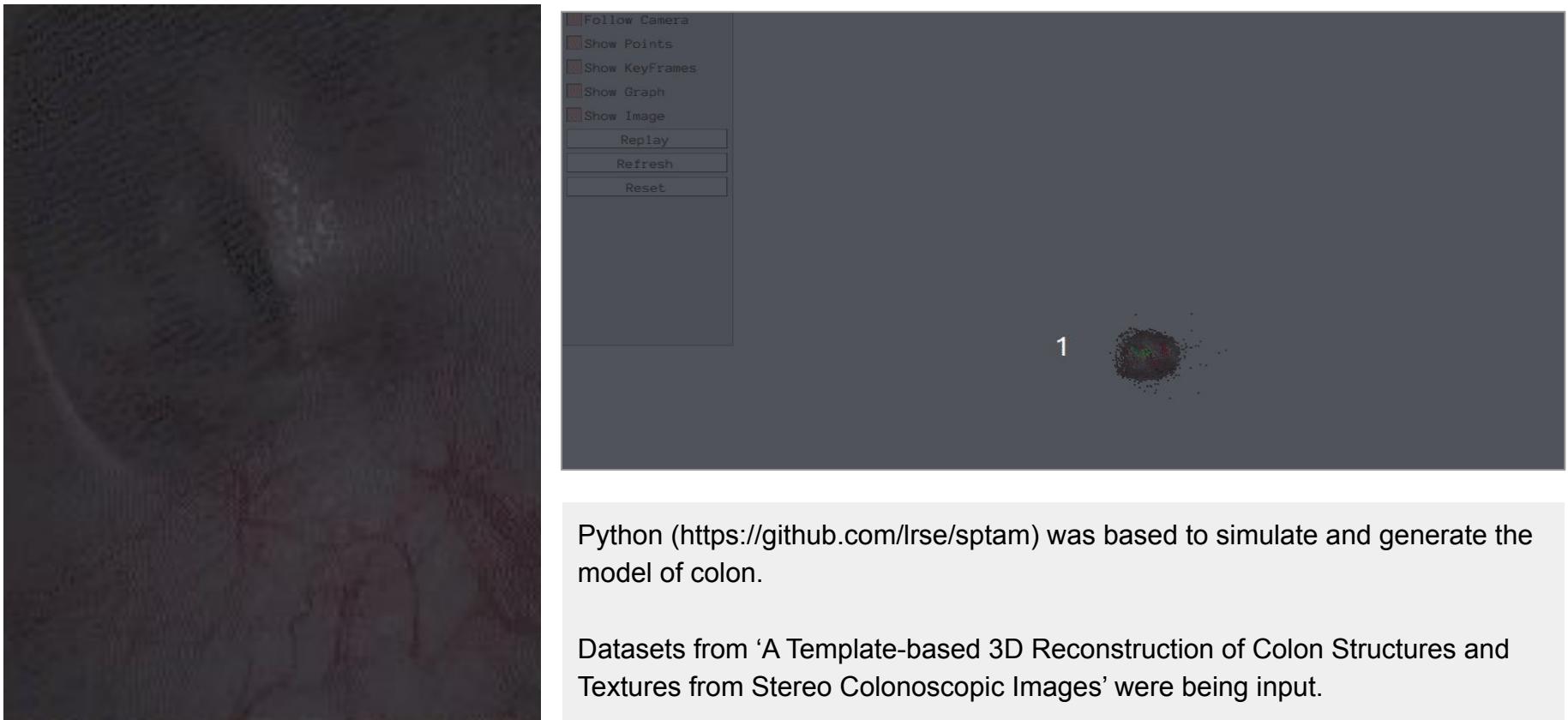


Fig. Stereo SLAM

[1] Taihú Pire, Thomas Fischer, Gastón Castro, Pablo De Cristóforis, Javier Civera and Julio Jacobo Berlles. S-PTAM: Stereo Parallel Tracking and Mapping Robotics and Autonomous Systems, 2017.

[2] Taihú Pire, Thomas Fischer, Javier Civera, Pablo De Cristóforis and Julio Jacobo Berlles. Stereo Parallel Tracking and Mapping for Robot Localization Proc. of The International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, 2015.

Demonstrations - Localization of Endoscope

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```
class ColonDataset():
    """
    path example: 'path/to/simulator/case1'
    """
    def __init__(self, path):
        Cam = namedtuple('cam', 'fx fy cx cy width height baseline')
        self.cam = Cam(90, 90, 160.0, 180.0, 480, 640, 1)

        path = os.path.expanduser(path)

        timestamps = np.loadtxt(os.path.join(path, 'LMB_Camera Position L Data.txt'), delimiter=", ", usecols=(0, 1, 2), unpack = True)
        self.left = ImageReader(self.listdir(os.path.join(path, 'left')),
                               timestamps[0,:])
        self.right = ImageReader(self.listdir(os.path.join(path, 'right')),
                               timestamps[0,:])

        assert len(self.left) == len(self.right)
        self.timestamps = self.left.timestamps
```

Fig. Python sample code for the calibration

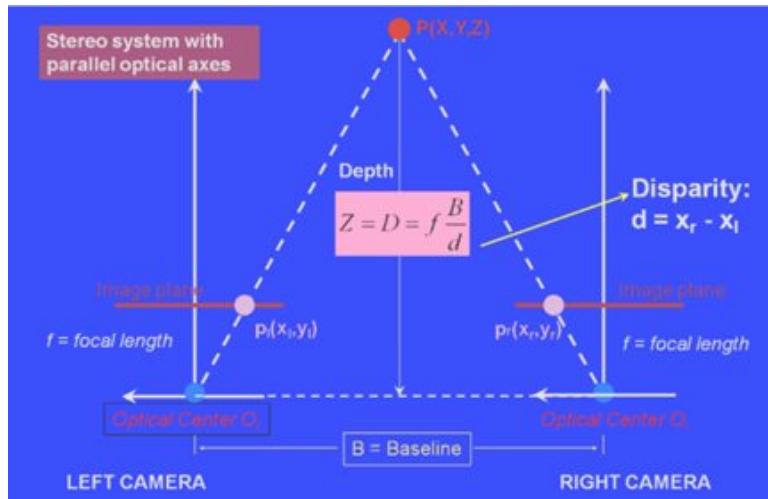


Fig. Stereovision geometry

Accurate calibration values (focal length values, optical centre, width of baseline) are needed to properly generate SLAM.

[1] Taihú Pire, Thomas Fischer, Gastón Castro, Pablo De Cristóforis, Javier Civera and Julio Jacobo Berlles. S-PTAM: Stereo Parallel Tracking and Mapping Robotics and Autonomous Systems, 2017.

[2] Taihú Pire, Thomas Fischer, Javier Civera, Pablo De Cristóforis and Julio Jacobo Berlles. Stereo Parallel Tracking and Mapping for Robot Localization Proc. of The International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, 2015.

Demonstrations - Polyp Identification

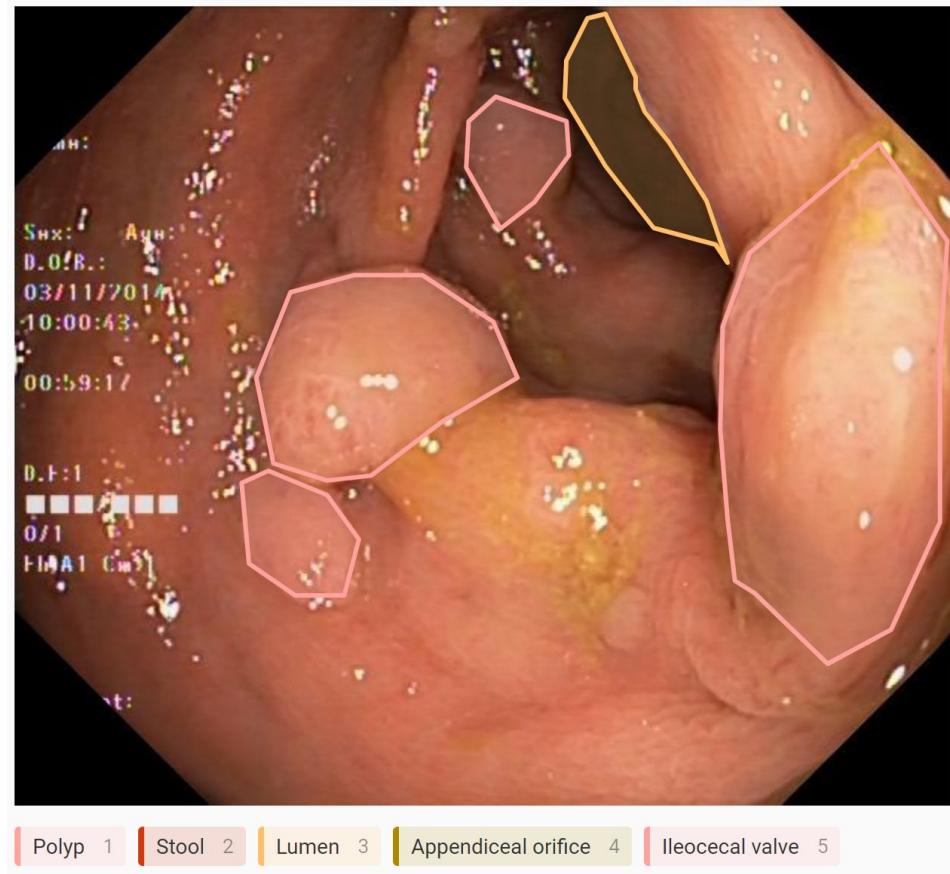
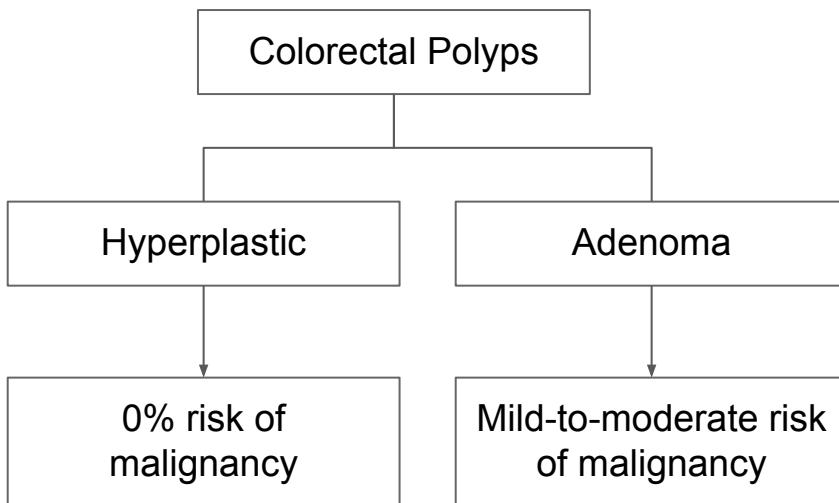
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Demonstrations - Polyp Characterization

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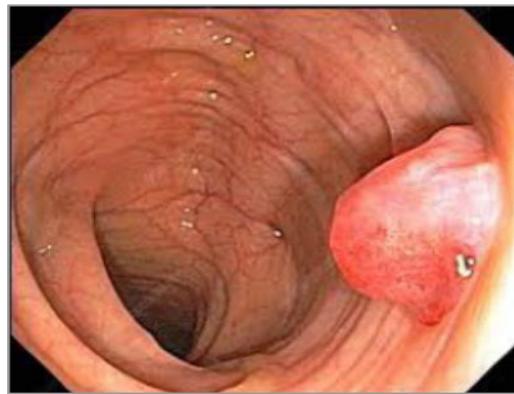
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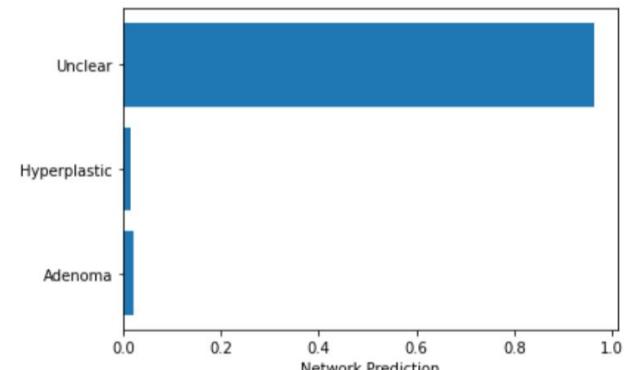
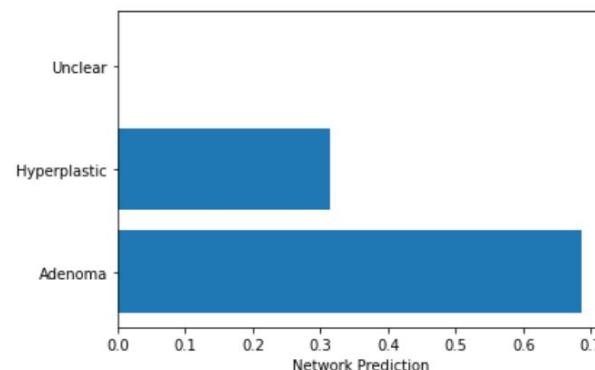
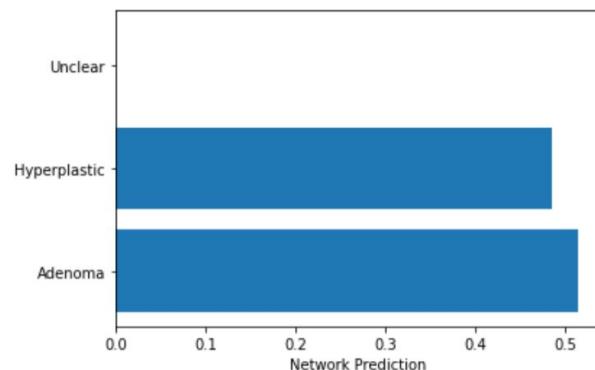
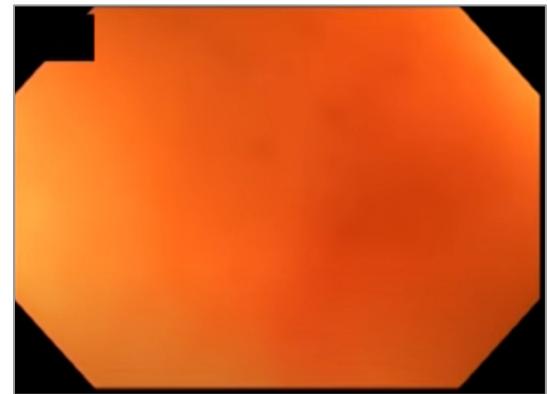
Hyperplastic Polyp



Adenomatous Polyp



Other/Unclear



Confusion Matrix of Polyp Network

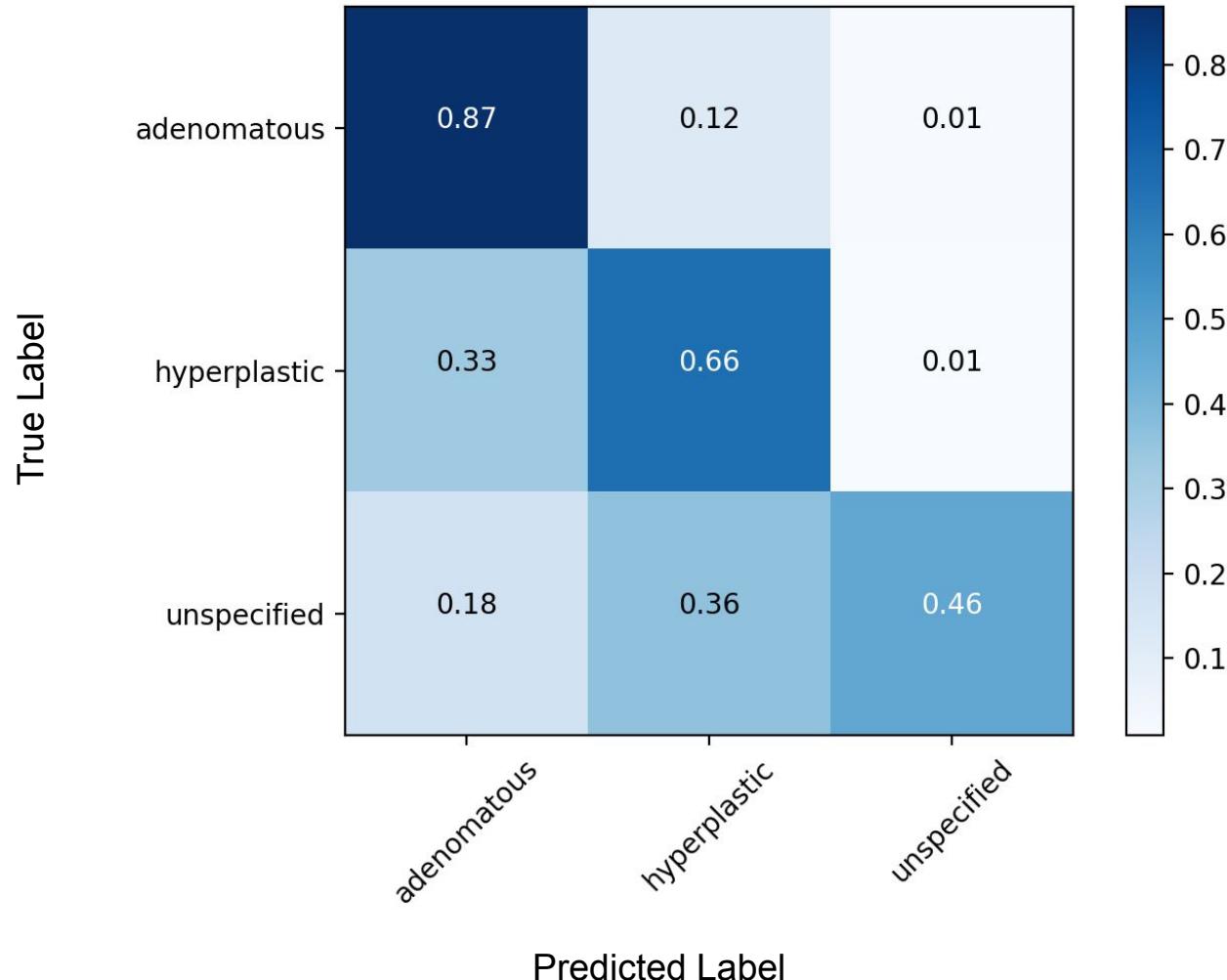
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Google Inception v3 Network

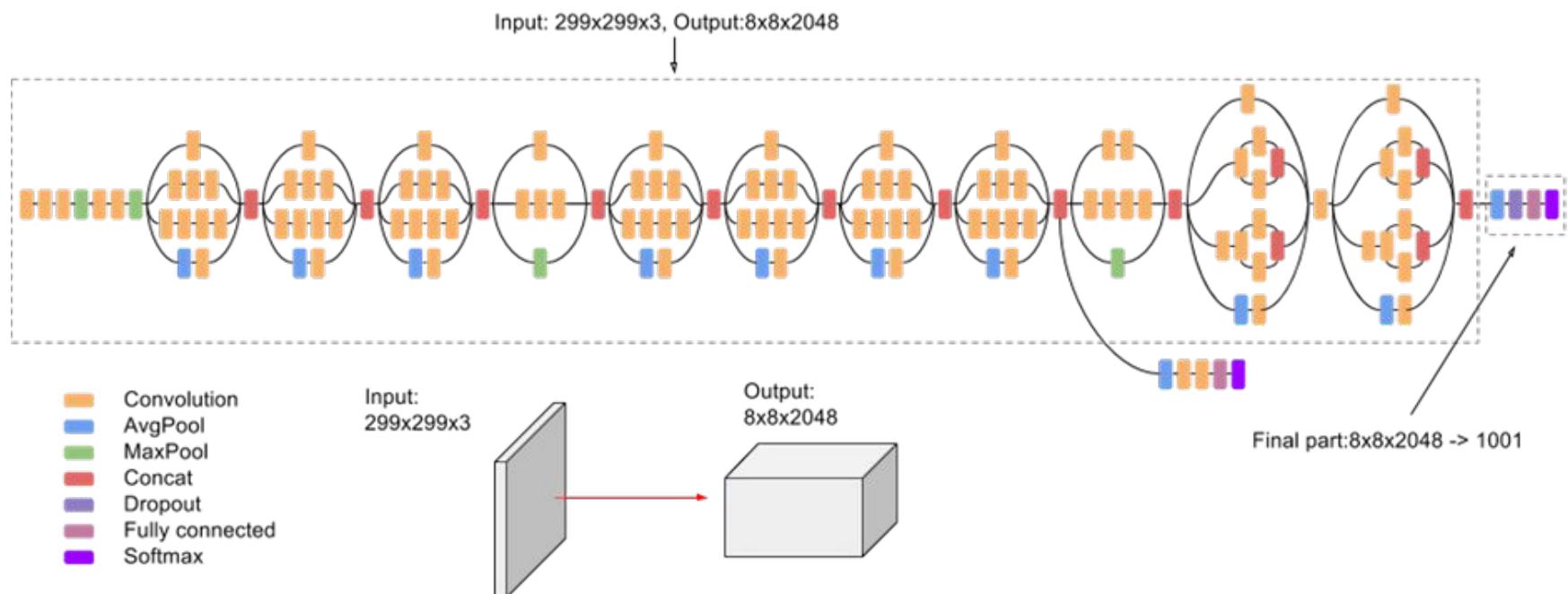
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Identifying Stool

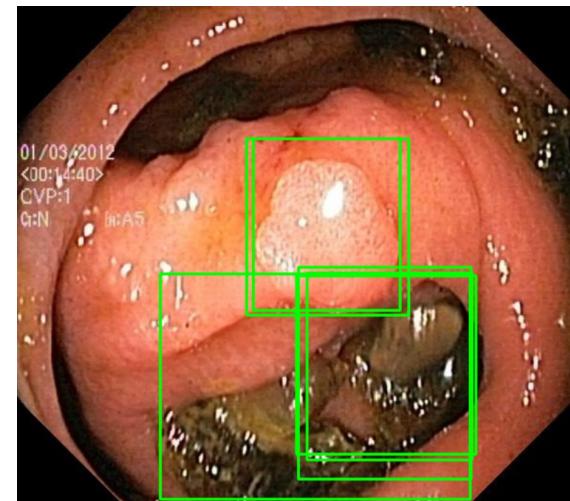
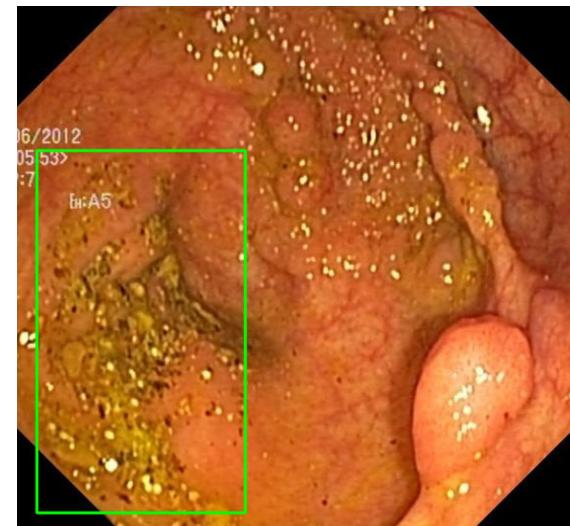
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Identifying the Colonic Lumen

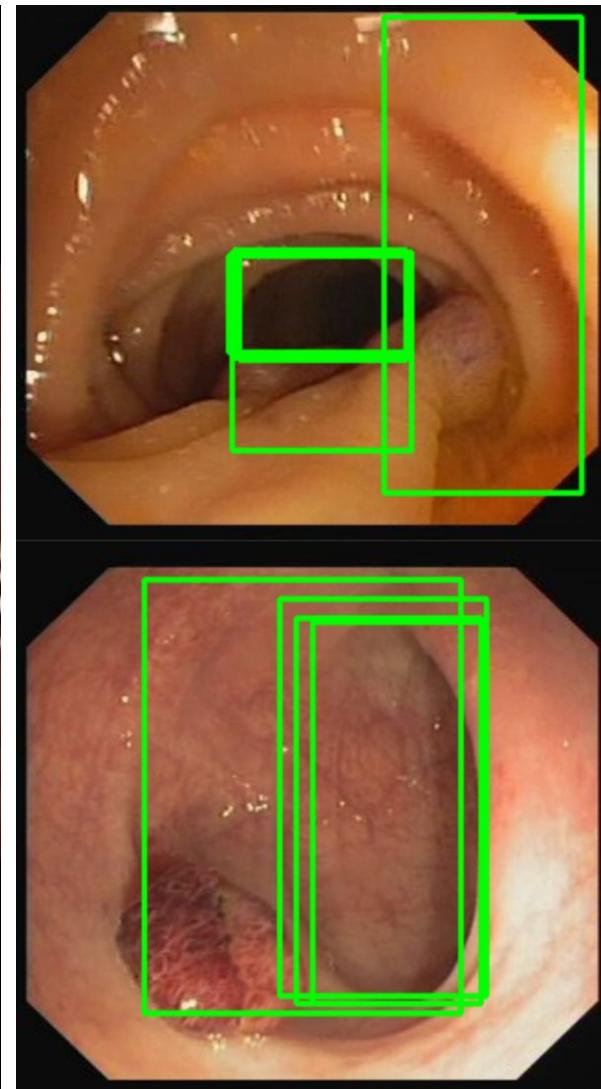
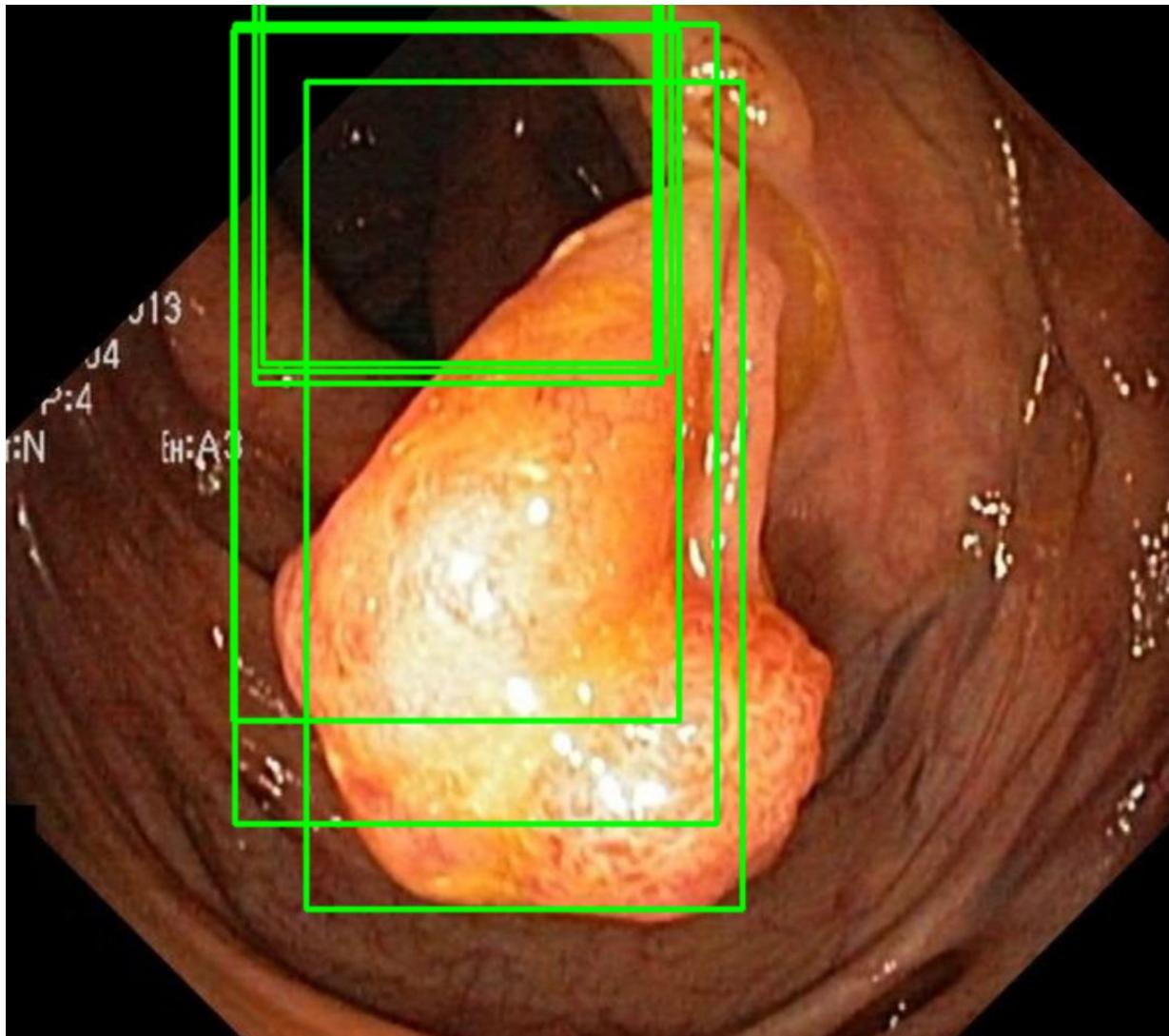
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Identifying & Localizing Polyps

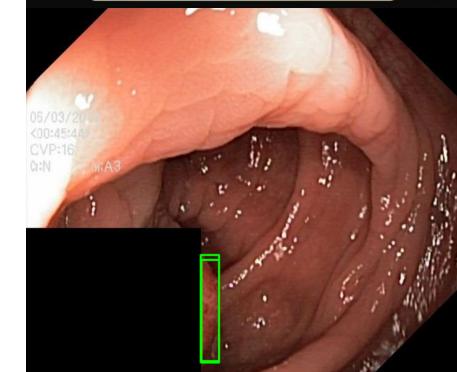
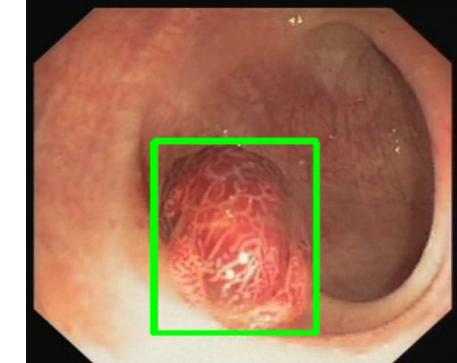
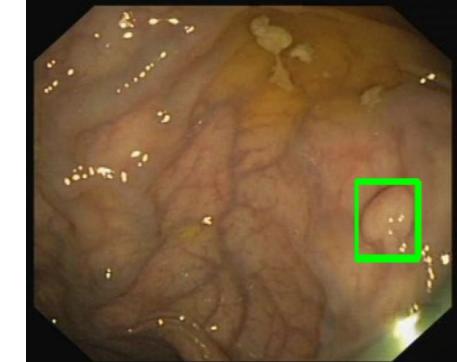
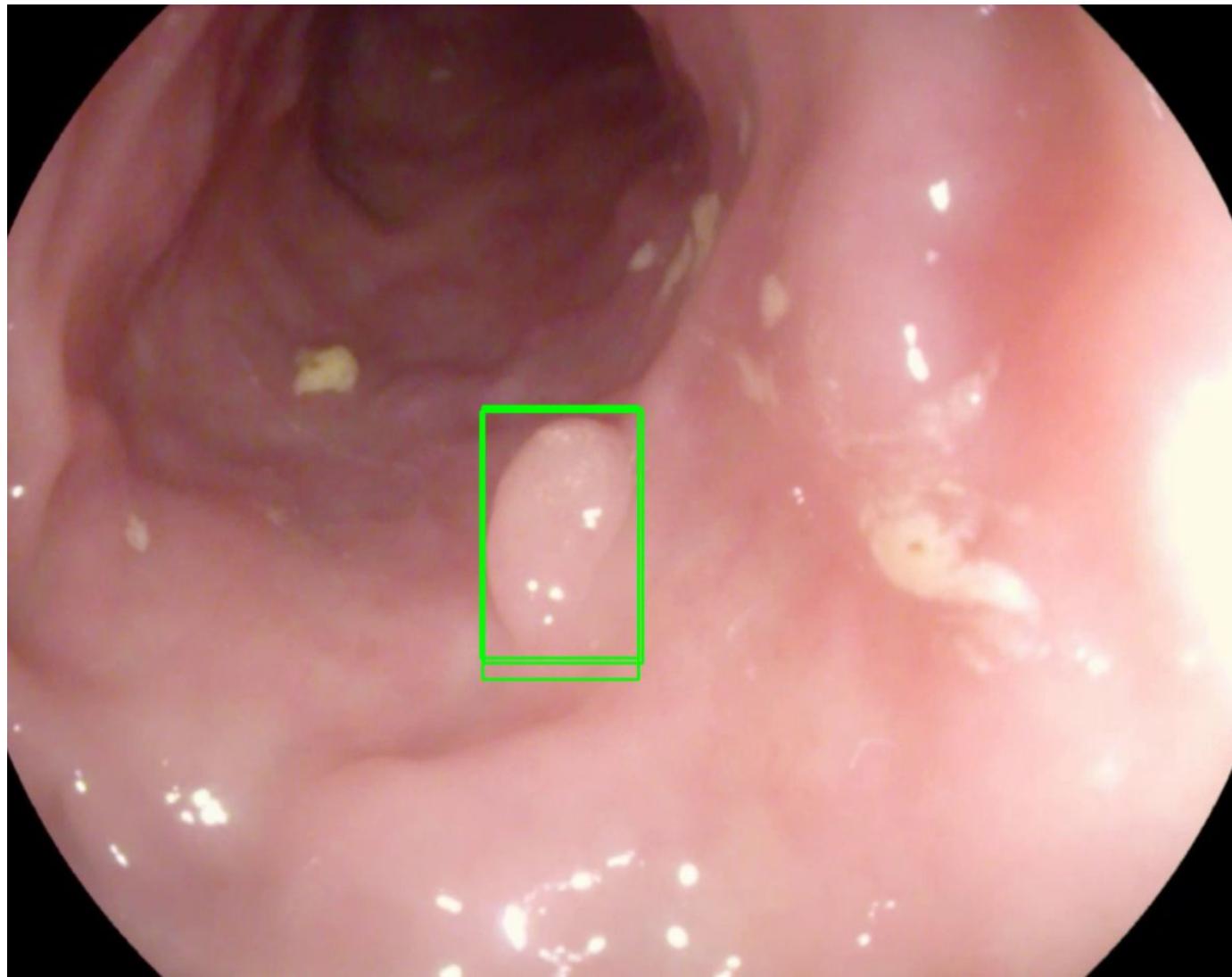
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Mask R-CNN & Feature Localization

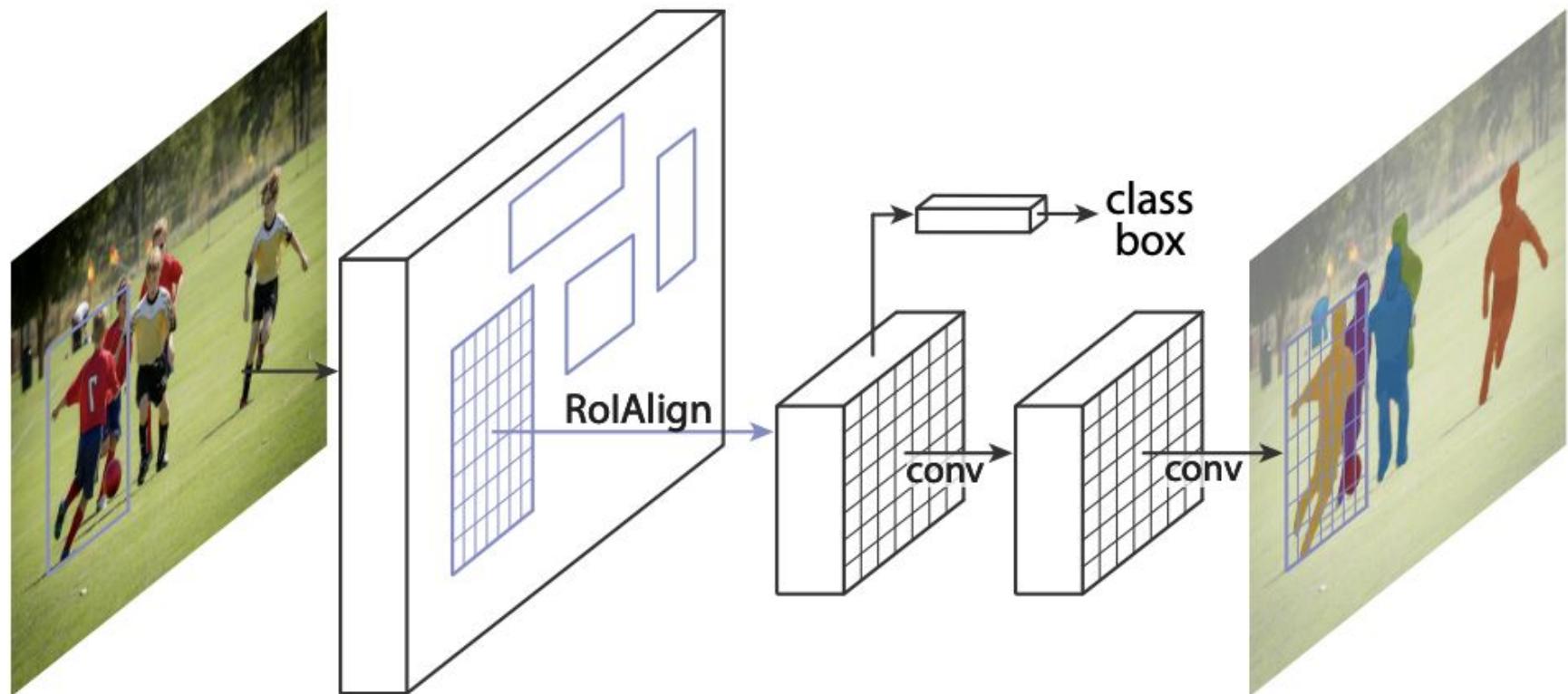
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Demonstrations - Polyp Manipulation

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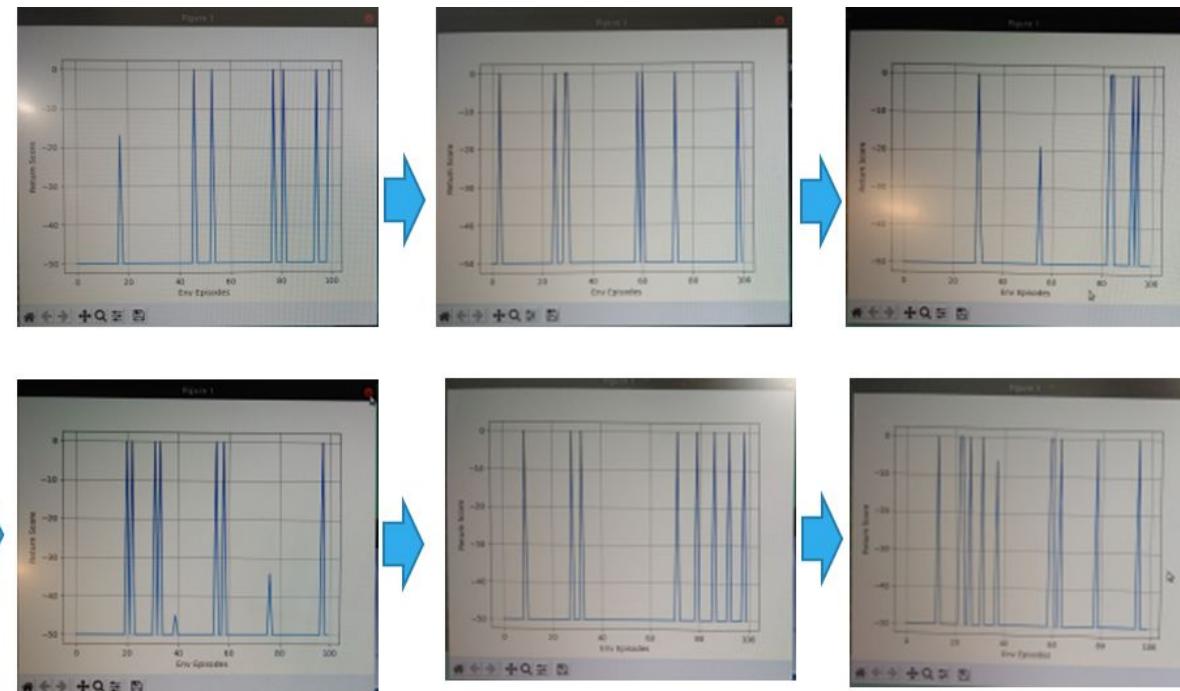


Fig. Return Score (sum of rewards) vs. Env Episodes

3D plot by Python (Mujoco and Open gym) was used to train the robot.
As the robot gets being trained, it appeared to have more chances to receive return score of 0.

Demonstrations - Polyp Manipulation

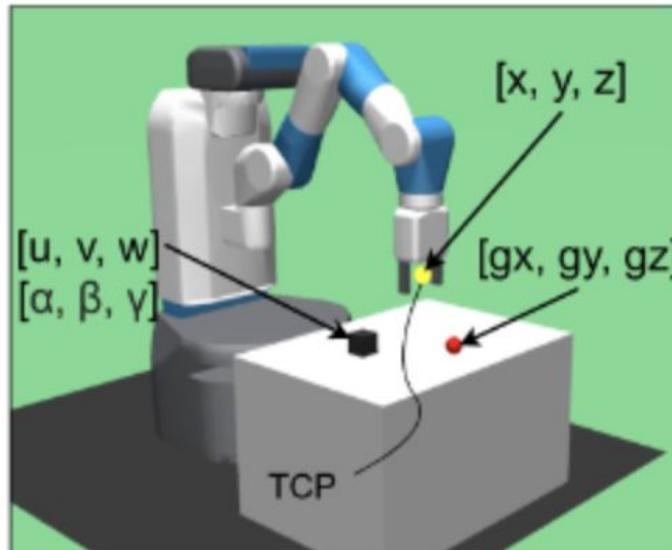
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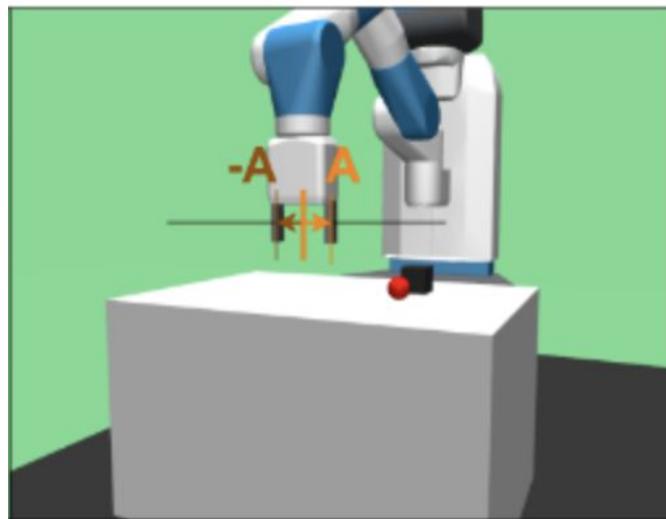
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	FetchReach-v1	FetchPickAndPlace-v1
Goal position	$[gx, gy, gz]$	$[gx, gy, gz]$
Achieved goal	$[x, y, z]$	$[u, v, w]$
TCP position	$[x, y, z]$	$[x, y, z]$
Object position	-	$[u, v, w]$
Object relative position	-	$[u - x, v - y, w - z]$
Gripper state	$[A, A]$	$[A, A]$
Object rotation	-	$[\alpha, \beta, \gamma]$
Object velocity	-	$[\dot{u}, \dot{v}, \dot{w}]$
Object relative velocity	-	$[\dot{u} - x, \dot{v} - y, \dot{w} - z]$
TCP velocity	$[\dot{x}, \dot{y}, \dot{z}]$	$[\dot{x}, \dot{y}, \dot{z}]$
Gripper velocity	$[-\dot{A}, \dot{A}]$	$[-\dot{A}, \dot{A}]$



```
def compute_reward(self, achieved_goal, goal, info):
    # Compute distance between goal and the achieved goal.
    d = goal_distance(achieved_goal, goal)
    if self.reward_type == 'sparse':
        return -(d > self.distance_threshold).astype(np.float32)
    else:
        return -d
```

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Algorithm 1 Soft Actor-Critic

Initialize parameter vectors $\psi, \bar{\psi}, \theta, \phi$.
for each iteration **do**
 for each environment step **do**
 $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t | \mathbf{s}_t)$
 $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1} | \mathbf{s}_t, \mathbf{a}_t)$
 $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$
 end for
 for each gradient step **do**
 $\psi \leftarrow \psi - \lambda_V \hat{\nabla}_\psi J_V(\psi)$
 $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$
 $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$
 $\bar{\psi} \leftarrow \tau\psi + (1 - \tau)\bar{\psi}$
 end for
end for

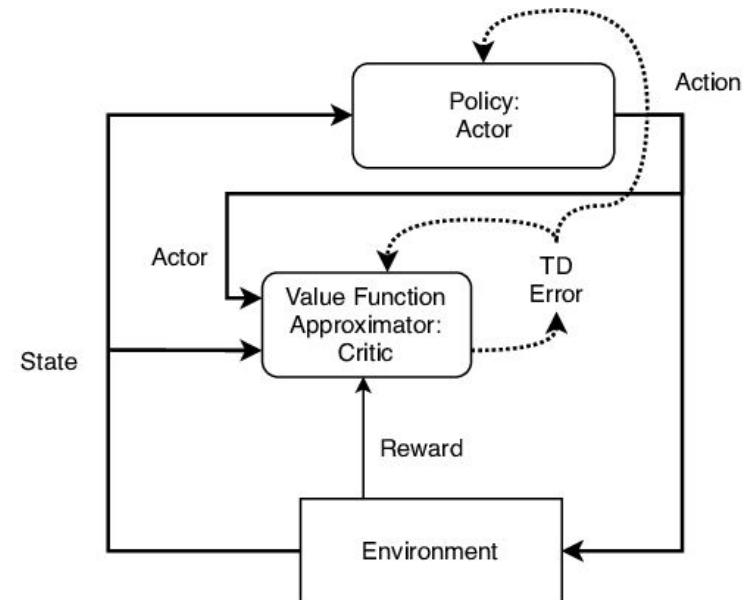


Fig. Policy optimization framework

Demonstrations - Polyp Manipulation

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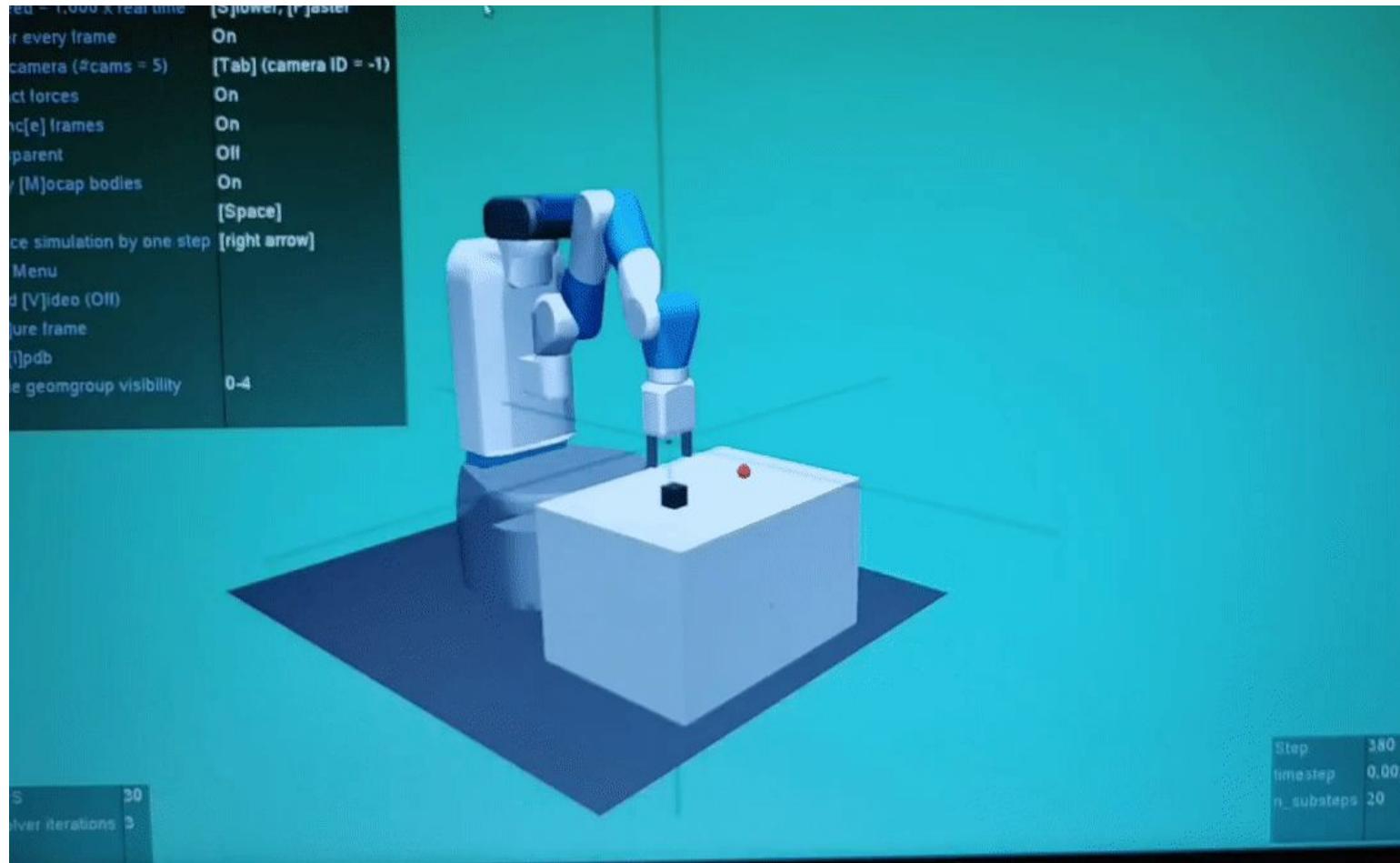


Fig. Grasping

Demonstrations - Path Planning

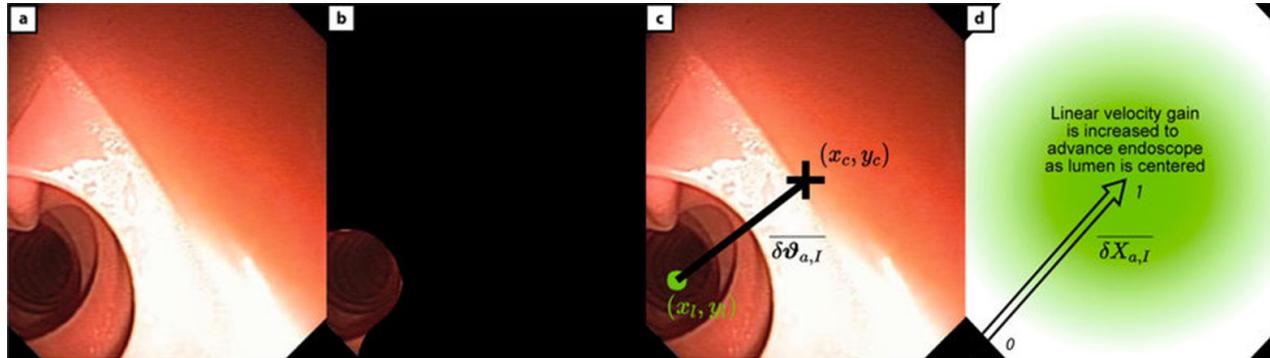
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- As input segmented images will be received on which mask RCNN is applied
- This segmented images will contain lumen which is inside space of colon
- Algorithm will find positional delta between endoscope focus and lumen
- Delta will be considered as vector to follow lumen
- Once it coincides, it will increase velocity

Reinforcement Learning - DQN Algorithm

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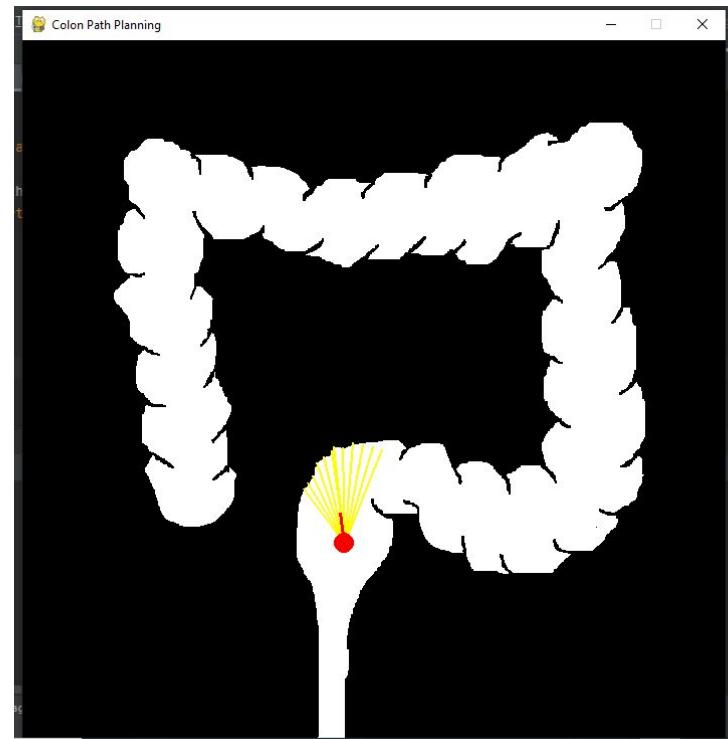
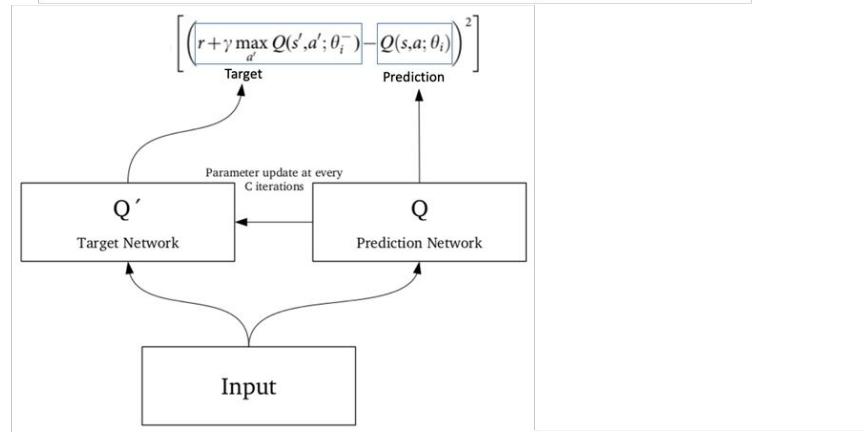
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DQN Algorithm

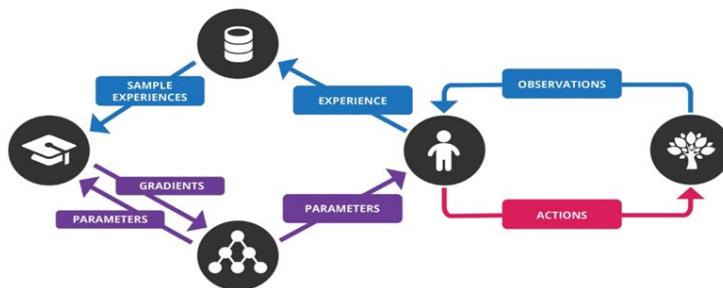
$$Q(s, a) = r(s, a) + \gamma \max_a Q(s', a)$$

$$Q(s, a) \rightarrow \gamma Q(s', a) + \gamma^2 Q(s'', a) \dots \dots \dots \gamma^n Q(s'' \dots n, a)$$

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right]$$



Flow Chart



PARAMETERS

Buffer = 100
Batch = 32
Gamma = 0.99
Tau = 0.0001
Learning rate = 0.0001
Update = 1

Demonstrations - Path Planning

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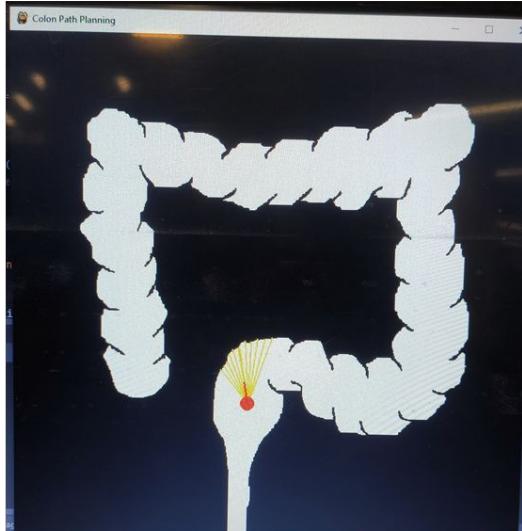
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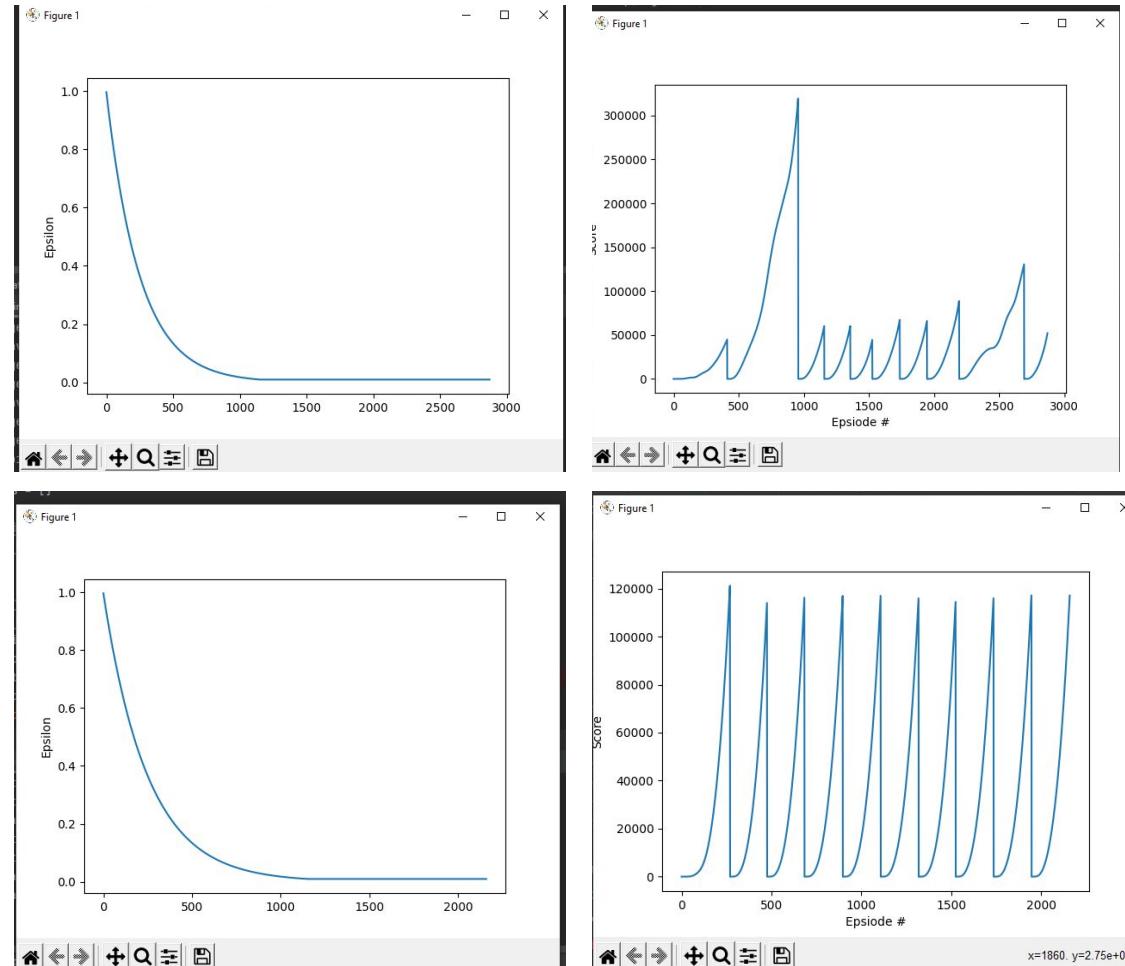
- Plots for training
- Reward value Plots and Reward Function

```
def __reward(self):  
    if self.__collision() == True:  
        reward=-30  
    if 158 <= self.x[0] <= 178 and 472 <= self.x[1] <= 492:  
        reward = 200  
    else:  
        reward = 1.5*(abs(self.x[0] - 320) + abs(self.x[1] - 500))**1.5  
    return reward
```

- Logistical needs for Memory



Epsilon and Reward Plots for Training



Vine Robot - Steering Mechanism

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Methods

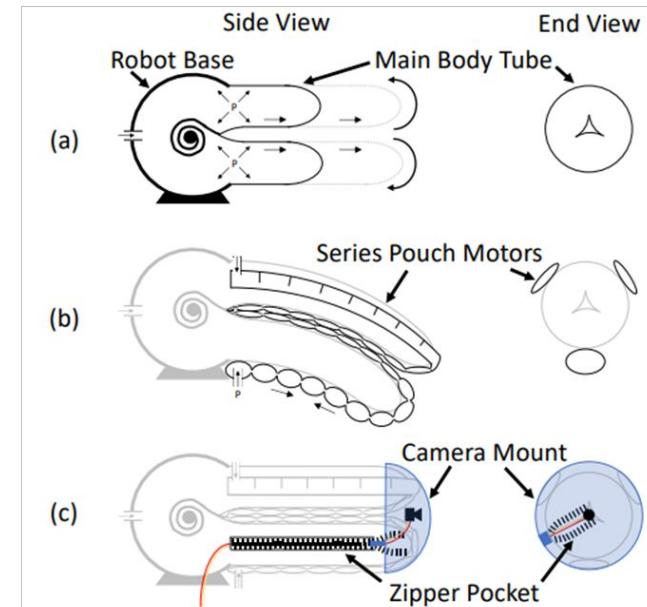
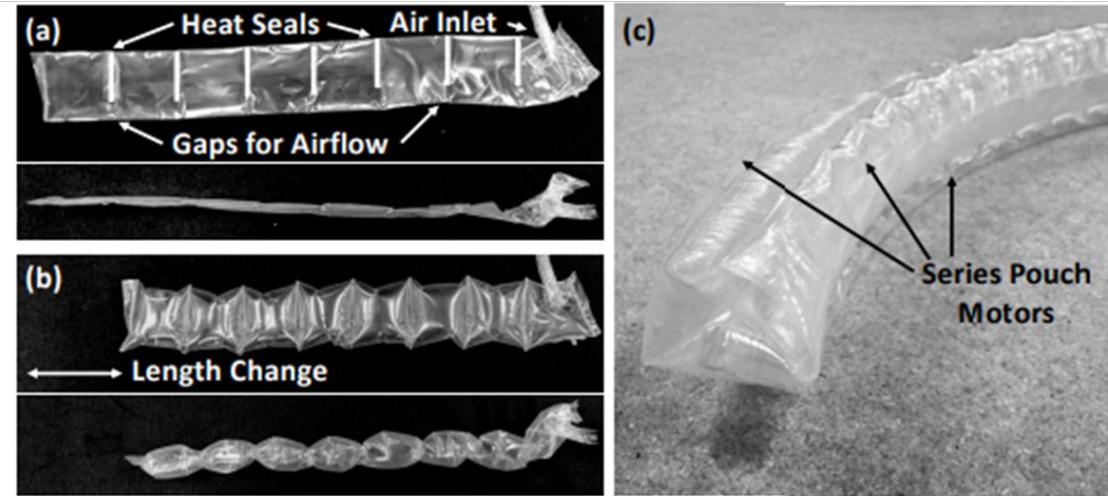
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- Partially heat sealed at regular intervals to create a series pouch motor
- Pneumatic Actuator at the end to inflate Heat Seals
- AI will give output signal as 4 parameters for steering:
 1. 3 series pouch motor actuation pressure
 2. Spool unwinding velocity for eversion of vine robot in colon.

Ref. "Vine Robots: Design, Teleoperation, and Deployment for Navigation and Exploration , IEEE Robotics & Automation Magazine. PP. 10.1109/MRA.2019.2947538."



Future Directions - Implementation of Vine Mechanics

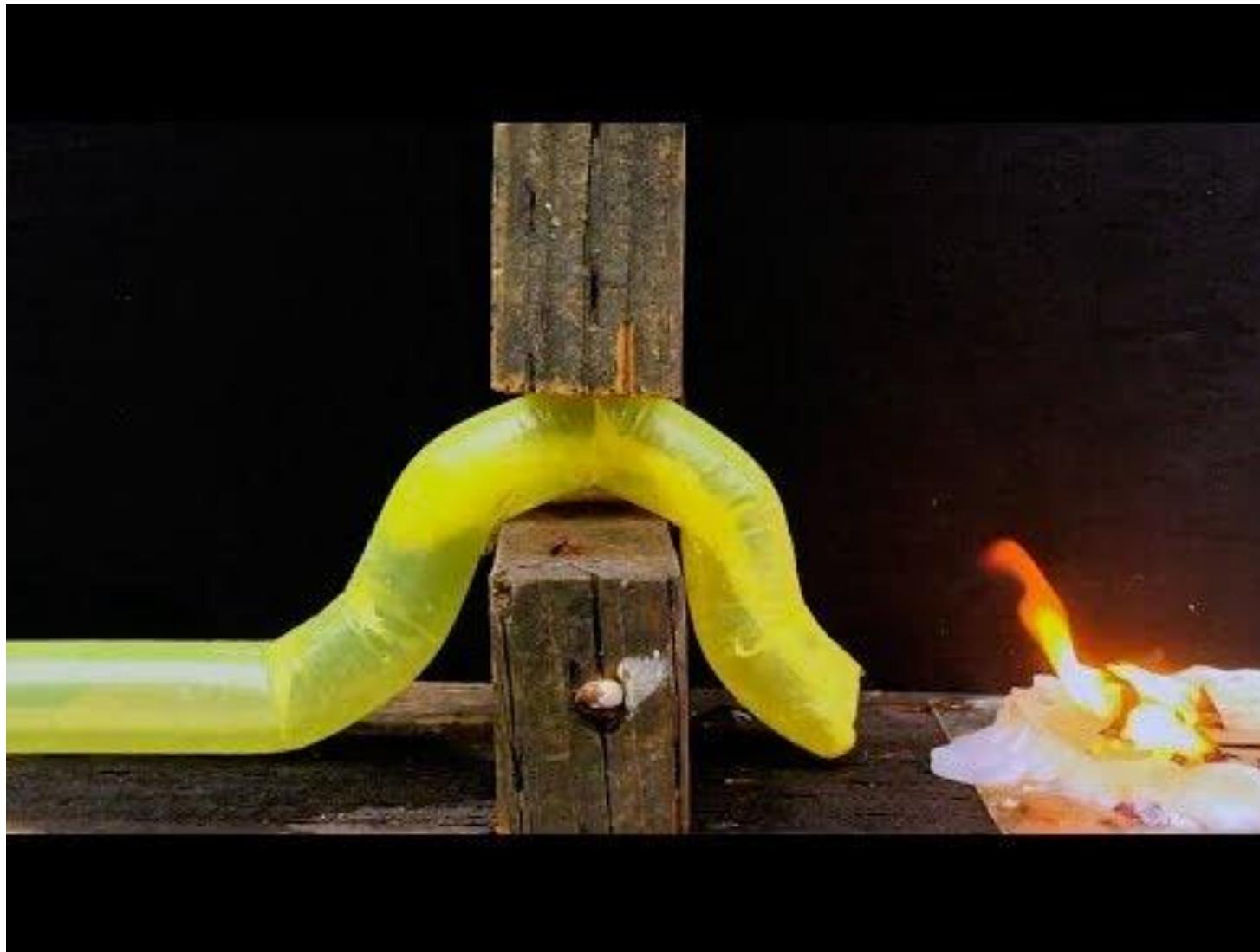
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Future Directions - Vine Robot

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From: Allison Mariko Okamura <aokamura@stanford.edu>

Sent: December 5, 2021 10:48 AM

To: Shawn Khan <shaw.khan@mail.utoronto.ca>

Subject: Re: Vine **robot**

Dear Shawn,

Thanks for reaching out! My former postdoc Elliot Hawkes, who is now at UC Santa Barbara, has worked in this area and may be able to provide relevant links: <https://me.ucsb.edu/people/elliot-hawkes>.

Best,
Allison

Future Directions - Deep Space Healthcare Challenge

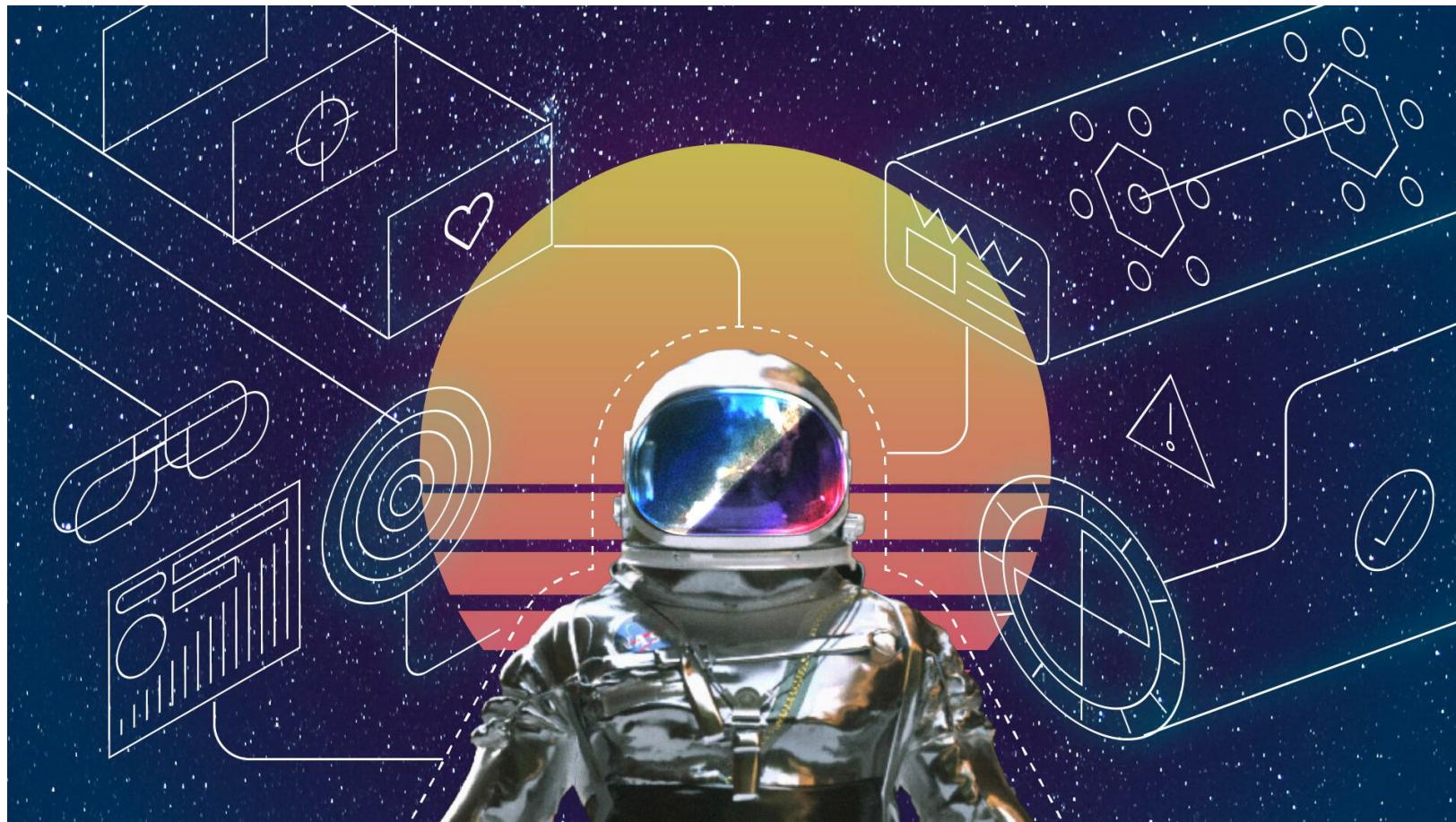
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<https://impact.canada.ca/en/challenges/deep-space-healthcare-challenge?fbclid=IwAR0gacrrUSla54grnSBfmb-W5XrbIoUDHjVyMtqBA2WIvm25PPGD9IL46Xg>

Conclusion

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- Autonomous colonoscopy has important applications in increasing accessibility to screening cancers
- Each task utilizes artificial intelligence to adapt to the dynamic of the colon
- Pressure-driven eversion may allow for safe navigation in the colon
- Further training data required to improve overall performance
- Integration of each component in a system to assess safety and efficacy in a model environment

Thank you for your attention!