Tailoring Real-time Colorectal Polyp Detection Artificial Intelligence towards Clinician Difficulties

Student: Kallan Duong
School of Computer Science
The University of Adelaide
a1803476@student.adelaide.edu.au

Supervisor: Tim Chen
School of Computer Science
The University of Adelaide
tim.chen@adelaide.edu.au

Abstract

This project explores the use of AI to detect polyps from colonoscopies to assist clinicians in detecting early colorectal cancer. Polyp-detecting Artificial Intelligence (AI) has already been shown to be capable of detecting polyps with a high degree of accuracy, however, clinicians have specific requirements. Certain types of polyps with different characteristics may be more difficult for clinicians and AI respectively. This project aims to investigate which polyp cases may be difficult for humans and AI respectively and to use these differences (if any) to gain insight which could be used to improve the performance of AI systems.

1.1. Introduction

Colorectal cancer is one of the most common forms of cancer [1]. Long term outcomes can be improved for many patients if polyps are detected and removed before becoming malignant [2]. However, the accuracy of examination varies due to its reliance on the examiner's experience. Experience, professional background, time of day and procedure length can all contribute to a miss rate that has been measured as high as 22%-28% [3]. Clinician performance can be improved with the use of real-time Artificial Intelligence (AI). AI can detect polyps during the exam, which can improve accuracy. Automatic polyp detection systems can direct attention toward specific areas during real-time colonoscopy examination to alert examiners of high-risk areas for further examination. Figure 1 shows an example of a polyp detection system that alerts clinicians to specific areas shown by bounding boxes. AI has already been proven to have a high accuracy rate, that is particularly useful to assist clinicians during examination. However, examiners may find specific types of polyps difficult. An AI that can be tailored towards clinician's needs and difficulties would be useful for early detection of frequently missed types of polyps.

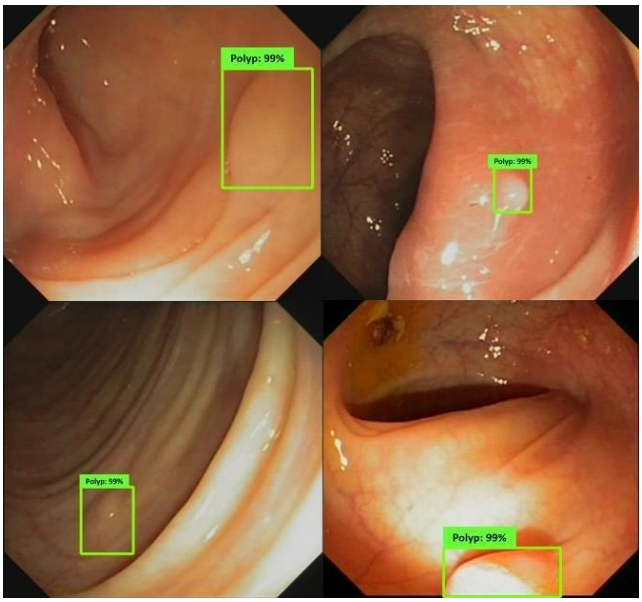

Figure 1. An example of a polyp detecting AI system [4]

1.2. Motivation

When clinicians examine colonoscopy results, AI has already shown to increase performance. However, clinicians may find specific types of polyps difficult. For example, the detection of smaller polyps may be more difficult for humans to detect. AI may also find certain types of polyps difficult to detect. This project aims to investigate what polyp characteristics humans and AI find difficult respectively and compare any differences, to gain insight. The reasons why AI finds specific characteristics difficult will also be investigated. This insight will be used to propose ways to improve current polyp detecting AI systems and tailor them for clinician requirements. For example, an AI that is specialised to detect polyps that other more general polyp-detecting AI, as well as human clinicians find difficult would help reduce the number of missed polyps. This project's findings will hopefully gain insight into ways to tailor AI for clinician requirements and difficulties.

2. Literature Review

The shortcomings and advancements within the field of polyp detecting AI were explored through the review of various research papers.

In 2015, the Automatic Polyp Detection sub-challenge was conducted at the international conference on Medical Image Computing and Computer Assisted Intervention (MICCAI). Jorge Bernal, et al. [5] provided a validation study comparing the results from different teams. The analysis showed that machine learning based methods had superior results and that some method's performances were close to the level of clinical application, as they were able to detect polyps in a small reaction time. However, this study also confirmed there was still room for improvement.

Following this, Gregor Urban, et al. [6] developed a convolutional neural network for colorectal polyp detection. The model achieved an excellent 96.4% accuracy, which shows a level of performance close to clinical application. However, real-time deep learning systems need to be validated in clinical trials to measure their impact during colonoscopies.

The first prospective randomized controlled trial analysing automatic polyp detection was conducted by Pu Wang, et al. [7]. This study showed an increase of Adenoma Detection Rate from 20% to 30%, due to a higher rate of small adenomas being detected. However, the study additionally highlighted the need for high sensitivity, specificity, and sufficient real-time processing time. Further improvements were needed before clinical application could be considered.

A wide range of real-time detection systems with high polyp detection accuracy and computational processing speeds have been developed recently. One such system was developed by Ruikai Zhang, et al. [8]. A fast object detection algorithm was firstly pre-trained with a large non-medical image database and then further fine-tuned with colonoscopic images extracted from videos. The detection results were further refined by incorporating a tracker. Evaluation on 17,574 frames extracted from 18 endoscopic videos resulted in a precision of 88.6% and a recall of 71.6% with a 6.5 frames per second processing speed. This displays good detection accuracy, as well as high computational processing power. However, the types of polyps clinicians and AI find difficult was not considered, which is a factor which may affect the effectiveness and real-world implementation of the system.

Jeremi Podlasek, et al. [9] also developed a convolutional neural network that detected real-time polyps. The testing results varied from an F1 score of 0.727 to 0.942. On full examination videos, it detected 94% of polyps with a 3% false-positive rate. This system was relatively accurate and succeeded in real-time on a wide array of hardware. This could help broaden the adaptation of new commercially available systems, as it does not require extensive computational power. However similarly to the previous study, polyp characteristics and their difficulties fails to be considered.

David Butler, et al. [10] additionally developed a polyp detection model using a combination of a Kalman Filtering tracker with a PP-YOLO detector. This resulted in a recall of 0.956, precision of 0.875, F_1 score of 0.914 and average precision of 0.952 when it was evaluated on a subset of annotated images from the Hyper-Kvasir dataset. This displays excellent results; however, polyp difficulty is also not considered.

Additional studies have implemented various other systems, including a deep learning model developed by Markus Brand, et al. [11], a polyp detection system using YOLOv5 developed by Jingjing Wan, et al. [12] and neural network for polyp localisation developed by James Weiquan Li, et al. [13]. Similarly, to previous studies, they also display good accuracy when detecting polyps during real-time colonoscopy videos, while maintaining adequate computational processing speeds. However, they all fail to consider how different polyp characteristics that clinicians and the model find difficult may affect real-world implementation.

A range of studies have also been conducted to investigate the characteristics of polyps commonly missed by endoscopists such as studies by Kim NH et al. [14], Lee, Jeonghun et al. [15], and Rijn JC et al. [16], however they do not include any reference to the use of polyp detecting AI as a solution.

The studies reviewed show that a range of different systems can achieve high detection accuracy, as well as sufficient processing speeds. This shows that the accuracy and processing speeds required for clinical application is achievable. However, there is a lack of research conducted on tailoring polyp-detecting AI towards the difficulties that clinicians face. The studies focus on the accuracy of polyp-detection but leave a gap for focusing on what examiners find difficult to detect. As the development of these systems continue to improve, clinical application is inevitable and tailoring the system towards the user's specific needs is an important part of real-world use.

3 Methodology

3.1. Research Questions

The following research questions were devised to assist the investigation.

Question 1: What types of polyps are more difficult to detect for AI?

Question 2: Why is AI uncertain about its difficult cases and which components of the image contribute the most to this uncertainty?

Question 3: How can this be applied to improve existing polyp-detecting AI systems?

Purpose

The purpose of question 1 will be to investigate and compare which specific characteristics of polyps cause difficulty for AI detection of polyps. Question 2 will expand upon this and investigate why these specific characteristics cause difficulty. Question 3 will be used to determine ways that these findings can be used to improve current polyp-detecting AI systems.

3.2. Measures of Difficulty

The difficulty of polyp cases was explored by analysing a polyp detector's performance on various colonoscopy images. The confidence of the model's prediction on each image was found and used to calculate entropy.

The entropy of the confidence of the model's prediction was used as an indicator of difficulty. Entropy is used as a measure of disorder and can be used to estimate the uncertainty of each image [17]. A higher entropy for a polyp case means that the model was more uncertain of whether the detected bounding box contains a polyp or not. Higher uncertainty was used as an indicator of higher difficulty. Thus, categories which had higher average entropy were considered to have higher difficulty.

The polyp detection model was run on image frames from each polyp case and the median confidence for each case was calculated from this.

Each case was then split into a category based on the polyp's characteristics. The median confidence and entropy were calculated for each category. A low entropy indicates that the model was certain in its prediction, while high entropy indicates that it was uncertain. Higher uncertainty was considered to show more difficulty for the model to make a prediction, while low uncertainty was considered less difficult. Based on the average entropy of each category, different polyp characteristics were split into a simple group and a difficult group. These characteristics can be used to rank polyps based on difficulty. A polyp with a higher number of easy characteristics is less difficult for the model to make a prediction. This was then compared with what previous studies have found endoscopists may find difficult to detect.

4. Experimental Setup

4.1. Datasets

The Showa University and Nagoya University (SUN) database was used to train the detector.[18][19]. The results were also obtained from detections run on images from the SUN dataset. The SUN database includes a multitude of images from 100 different positive polyp cases, each annotated with a bounding box. For each polyp, the dataset includes additional information that was used to rank the difficulty of each of the cases. These variables were polyp size, polyp shape, and polyp location. They were investigated to discover their effect on different measures of difficulty.

4.2. Polyp Detector

A polyp detector was trained using the SUN dataset. The polyp detector was trained using a YOLOv3 object detector with a Darknet-53 backbone. It produces bounding boxes with confidence that denotes the probability that the model is confident in the detection. The detector was quantitively assessed with precision, measured using $P = \frac{TP}{TP+FP}$, and recall $R = \frac{TP}{TP+FN}$. The confidence threshold defined for a true positive was 0.3.

4.3. Difficulty Evaluation

The object detector was run on image frames of each of the 100 polyp cases and the median confidence from the positive detections of each polyp was calculated. This median confidence was also used to calculate entropy.

For shape and location, each of the 100 polyps were split into categories. Separate categories for each variable were formed. Polyp shape was split into four different shape categories, classified using the Paris Polyp Classification System. The four shapes were IIA, IS, ISP, and IP polyps. Polyps were found in six different locations which were the rectum, sigmoid colon, descending colon, transverse colon, ascending colon, and cecum. Additionally, the bounding box size of each image was also investigated.

For each category, the median confidence and entropy of all polyps included in that category was calculated. The average entropies of the categories in each variable were then compared to analyse the effect that the variable had on entropy.

Entropy is used as a measure of unpredictability. A higher entropy for a polyp case means that the model was more uncertain of whether the detected bounding box contains a polyp or not. Higher uncertainty was used as an indicator of higher difficulty, as entropy measures unpredictability in the system. Categories were defined as easy or difficult to detect based on their average entropy.

The difficulties the AI model had with different categories in each variable were then compared to the results of studies investigating the difficulties human endoscopists had with certain polyp types.

4.4. Explaining Model Difficulty

It was then investigated why the model had difficulty with its difficult cases and simple cases. This was investigated using LIME. LIME is a python library used for explainable AI. For object detection, LIME can be used to highlight the most important part of the image for the model's prediction. This was used to investigate the importance of different components in different images. LIME was run on images that the model had low entropy predictions on, as well as images with high entropy predictions. The results were then compared to investigate whether there were any noticeable differences between what parts of the image the model finds important in low and high entropy images.

5. Results

5.1. Model Performance

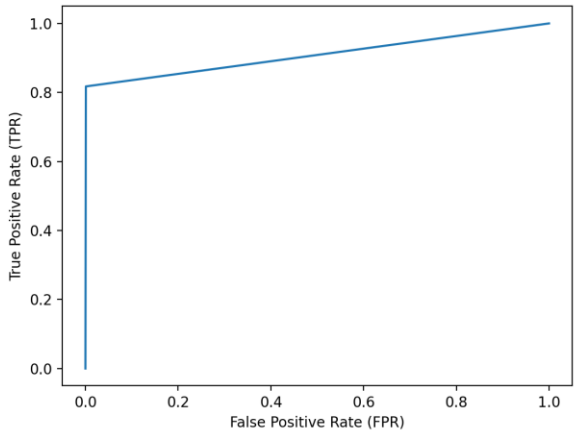

Figure 2. ROC curve of the polyp-detection model on the SUN dataset

The polyp-detection model was evaluated on the SUN dataset and was able to score a precision of 0.81, with a recall 0.997. This resulted in an F_1 score of 0.893. These results show that the detector was able to detect polyps with high accuracy and a low number of false positives.

A Receiver Operator Characteristic (ROC) curve was also created. Figure 2 shows that the model was able to perform well on the SUN dataset.

5.2. Polyp Size

A histogram was created to investigate the distribution of different bounding box sizes in the dataset.

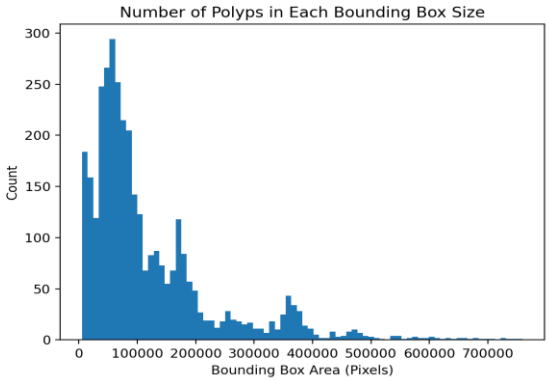

Figure 3. Histogram of bounding box areas

As seen in Figure 3, most of the data points had a bounding box area of under 200000 pixels. Therefore, the remainder of the investigation was conducted on points under 200000 pixels. This is because the lack of data points above 200000 pixels may skew results, as the model was trained on fewer of these types of points, which may result in a higher difficulty on detecting larger relative sized polyps.

A scatter plot was then created to investigate the relationship between bounding box area and average entropy.

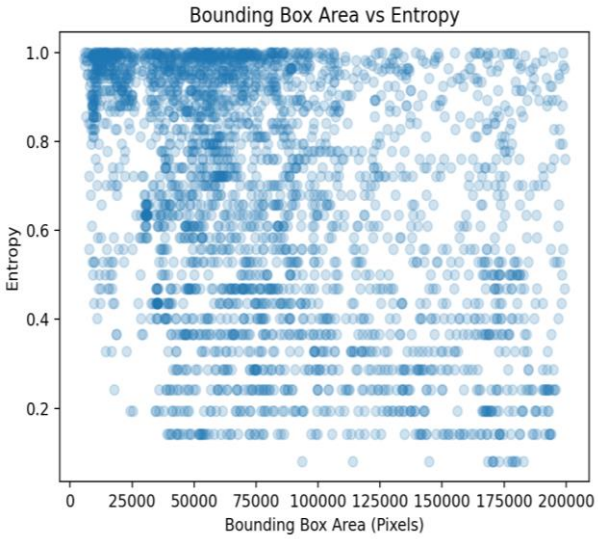

Figure 4. Scatter plot of bounding box area against entropy.

Figure 4 indicates a negative correlation between bounding box area and entropy, as the main cluster of points shown by the dark patches appear to decrease in entropy as bounding box area is increased. An r value of -0.29 was calculated from the data point.

5.3. Polyp Shape

To investigate the effect that polyp shape had on model difficulty, the average confidence and entropy was calculated. To reduce the effect that bounding box size had on entropy and isolate the effects of shape on entropy, only points with a bounding box area of under 100000 pixels were included. This was to keep the bounding box area relatively constant between data points.

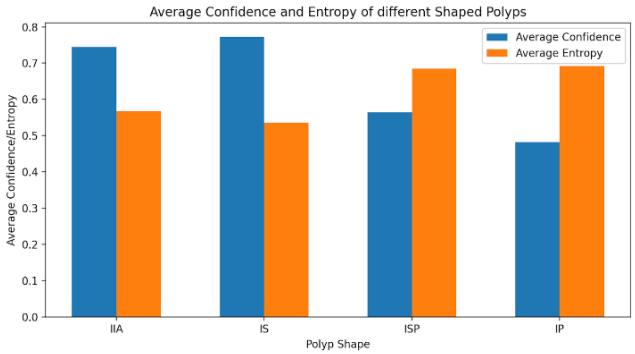

Figure 5. Average confidence and entropy of the model's predictions on different shaped polyps.

The SUN dataset categorised polyp shape using the Paris Classification System for polyps, containing polyps classified as IIA, IS, ISP and IP. Figure 5 displays that ISP and IP shaped polyps had a significantly lower average confidence than IIA and IS polyps. ISP and IP shaped polyps also had a significantly higher average entropy, while IIA and IS polyps had a lower average entropy.

5.4. Polyp Location

To investigate the effect that polyp location had on model difficulty, the average confidence and entropy was calculated. Similarly to shape, only points with a bounding box area of under 100000 pixels were included to keep bounding box area relatively constant between data points.

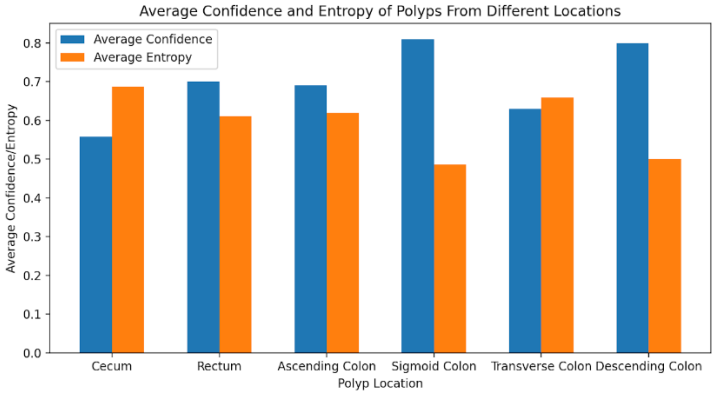

Figure 6. Average confidence and entropy of the model's predictions on polyps from different locations.

There were six different polyp locations in the SUN dataset. Figure 6 shows that polyps located in the cecum, ascending colon and transverse colon had low average confidence, while polyps located in the sigmoid colon and descending colon had higher average confidence. Polyps in the cecum, ascending colon and transverse colon had higher average entropy, while descending colon and sigmoid colon polyps had significantly lower average entropy. Rectum polyps also had slightly lower average entropy when compared to cecum, ascending colon, and transverse colon polyps.

5.5. LIME Image Explanation

LIME was used to investigate visual differences that the AI model may have in its respective difficult and simple cases. To achieve this, LIME was used on images with high entropy predictions and images on low entropy predictions. This was to highlight the most important part of the images for the model's prediction.

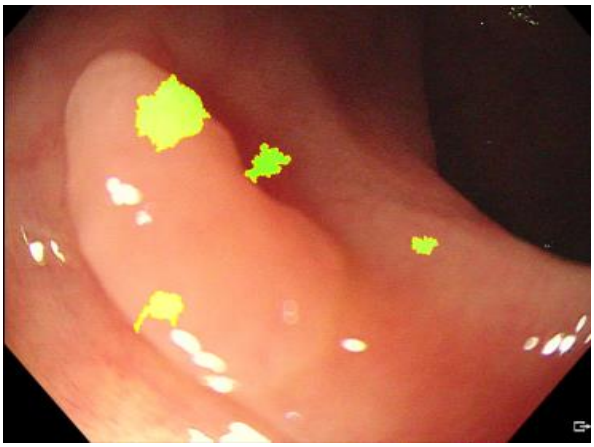

Figure 7. An example of a LIME explanation performed on an image with high entropy.

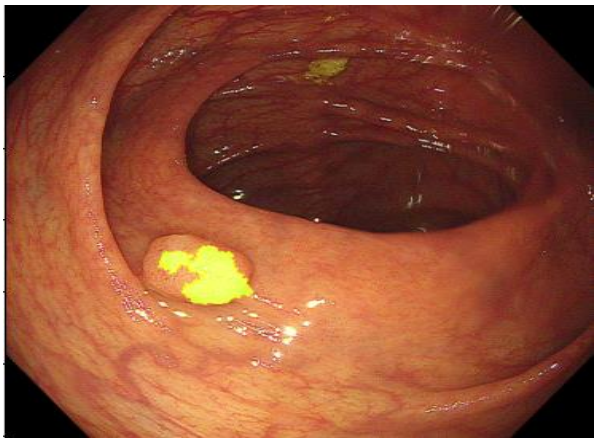

Figure 8. An example of a LIME explanation performed on an image with low entropy.

Figure 7 shows an example of one output of a high entropy image put through LIME, while Figure 8 shows an example of a low entropy image. The yellow highlighted parts represent the parts of the image that the AI model finds visually important for its prediction.

6. Discussion

6.1. Polyp Size

The actual diameter of polyps was initially investigated, however the results indicated that polyp diameter did not have a large impact on the model's detections. This may be because images were taken from different camera angles. Polyps with large diameter may be perceived as small, due to its relative size from a longer distance camera angle and vice versa with small diameter polyps. It was determined that relative size from the photo may have a larger impact on the model's detection.

The correlation shown in the scatterplot and r value indicates that the model may have had less difficulty in detecting polyps with a larger bounding box. This suggests that the AI model was less certain of smaller relative polyp sizes and more certain in its prediction of larger relative polyp sizes.

Endoscopists tend to miss smaller polyps more frequently than large polyps. In a study conducted by Kim NH et al. [14], polyps under 10mm (especially polyps under 5mm) were missed more frequently than polyps above 10mm in size. van Rijn JC et al. [16] also found similar results. The miss rate of adenomas larger than 10mm were 2.1%, while adenomas within the 5-10mm had a 13% miss rate. This increased to a 26% miss rate for adenomas smaller than 5mm. The AI model shares a high difficulty for smaller polyps,

6.2. Polyp Shape

Due to the high average entropy of IP and ISP shaped polyps, these cases were considered more difficult to detect, while IIA and IS shaped polyps were considered to have lower detection difficulty.

Endoscopists have higher difficulty in detecting flat and sessile polyps, when compared to pedunculated ones. In the study conducted by Kim NH et al. [14], it was found that flat and sessile polyps have a higher miss rate than pedunculated polyps. IIA polyps were defined as flat, IS polyps were defined as sessile while ISP and IP were defined as pedunculated. The study by Lee Jeonghun et al. [15], also found that 98% of missed polyps were sessile or flat.

The AI model's lower difficulty with IIA and IS polyps contradicts the endoscopist's difficulty with flat polyps. The model's difficulty with ISP and IP polyps also contrasts with the low miss rate of IP polyps by endoscopists.

One reason for this contradiction may be due to imbalances in the dataset. The dataset consisted of 83% IIA and IS polyps and only 17% ISP and IP polyps. As a result, the AI model was likely trained on a lower number of ISP and IP polyps than IIA and IS polyps. This may contribute to the difficulty it had with ISP and IP polyps, as it had less experience with those types of polyps.

6.3 Polyp Location

The polyps located in the cecum, ascending colon and transverse colon were considered to have higher detection difficulty, while rectum. descending colon, and sigmoid colon polyps were considered easier to detect than the other locations due to their lower average entropy.

Endoscopists share the AI model's difficulty with detecting polyps in the cecum, ascending colon, and transverse colon, while having less difficulty with polyps found in the rectum, sigmoid colon, and descending colon. In a study by Kim NH et al. [14], Polyps found in the cecum, ascending colon and transverse colon were found to have a higher miss rate of 26.8% when compared to polyps found in the descending colon, sigmoid colon, and rectum, which had a miss rate of 21.4%. This closely resembles the difficulties the AI model had with cecum, ascending colon, and transverse colon polyps.

6.4 LIME Explanation

High entropy images tended to have less total area of the polyp highlighted. They also seemed to have more non-polyp parts of the images highlighted. Low entropy images seemed to focus on the polyp itself and generally had more of the polyp highlighted with less distractions from other parts of the image. This indicates that the AI was able to focus on the polyp more easily on low entropy images.

6.5 Research Questions

For research question 1, the results indicate that smaller polyps, ISP, and IP polyps, as well as cecum, ascending colon, and transverse colon polyps were more difficult to detect for the model.

For research question 2, the LIME results showed that the AI tended to focus on the polyp edges more for lower entropy images. This indicates that the AI had difficulty identifying the polyp edges on high entropy images.

For research question 3, the results indicate that the AI may find similar types of polyps difficult to endoscopists. This indicates that the AI model may inherit human difficulties, as polyps are labelled by humans. These results mean that current AI systems may not be able to cover for endoscopists weaknesses. Therefore, a different kind of training/dataset may be required to train an AI that covers endoscopist weaknesses.

7. Code Link

The code used to train the detector and run the detections, as well as generate the results from the detections can be found here:
https://github.cs.adelaide.edu.au/a1803476/Kallan_Topics_2023.
The SUN database requires permission to use so images and annotations from the database have been omitted from the Github release. Details about permissions requests can be found at sundatabase.org.

8. Conclusions and Future Work

The results found indicate that polyps that are smaller from the perspective of the image tend to be more difficult to detect, while larger polyps are easier to detect. The results also indicate that the AI model found ISP and IP polyps more difficult to detect than flat IIA and IS polyps, however this could be due to a dataset imbalance. The AI model also found polyps in the cecum, ascending colon, and transverse colon more difficult to detect. There are some similarities and some differences between what the AI found difficult and what endoscopists find difficult. Endoscopists tend to similarly find smaller polyps, as well as polyps in the cecum, ascending colon, and transverse colon more difficult. However, endoscopists also find flatter polyps more difficult, which contrasts the AI's perceived difficulty with more protruded polyps.

There are additional factors that may have affected the results of the experiment. The model used may have biases which can cause certain types of polyps to be easier to detect. Models with different biases may find different results, so the procedure should be replicated using different model types to see whether similar results are replicated. The dataset also has different numbers of polyps in each category, which may also cause some biases in categories with a low sample size of polyps. A similar short investigation using a different dataset would be useful to determine whether similar variable categories are difficult.

After these experiments with alternate polyp-detection models and datasets are completed, a greater understanding of what polyp characteristics contribute the most to detection difficulty for AI. This insight could be used in future to tailor AI for detection of specific types of polyps that endoscopists have difficulty with. An AI that has been trained to perform well on specific types of polyps would be an interesting investigation. This could help detect specific types of polyps that are frequently missed by humans, to lower polyp miss rates overall.

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