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# ARTIFICIAL INTELLIGENCE BASED COLONOSCOPY DETECTION

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***Abstract**: Gastrointestinal endoscopy has proven to be an excellent context for developing artificial intelligence (AI) frameworks that can assist endoscopists in many of their daily activities. Detection of lesions during colonoscopy (computer-aided detection, CADe) and characterization of lesions (computer-aided characterization, CADx) are AI clinical programs in gastrointestinal for which the most published evidence has been published. These are the simplest programs for which specialized groups have developed several machines currently available on the market and can be used in scientific practice. We summarize the past and current development of colonoscopy video analysis strategies, specializing in two classes of artificial intelligence (AI) technology used in scientific trials. These are (1) abnormal diagnosis and feedback to improve colonoscopy and (2) detection of abnormalities. Our survey's carefully crafted craft features include techniques using traditional machines for learning algorithms and deep existing knowledge of methods. Finally, we bridge the gap between the state-of-the-art generation and acceptable clinical features and conclude with future guidelines for expanding endoscopic AI technology to fill the current gap.*

***Keywords**: Artificial Intelligence, colonoscopy, Computer aided diagnosis, medical image analysis, machine learning.*

## I. INTRODUCTION

Automated analysis of endoscopic images recorded during colonoscopy has become an important research area in recent decades. Colonoscopy is the gold standard for the prevention of most colorectal cancers (CRCs), as, at some point during the colonoscopy, the endoscopist can examine the entire colon and remove all precancerous lesions. Therefore, timely enrollment in a colonoscopy-based screening program should prevent you from developing CRC at an early stage. However, despite many countries' comprehensive stool-based screening programs and colonoscopies, CRC continues to cause morbidity and mortality. In 2020, 935,173 deaths worldwide and about 53,200 in the United States. In

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recent years, few areas of medicine have not been affected by the emergence of artificial intelligence (AI) systems, especially since convolutional neural networks were developed, which gave machines some cognitive abilities. Allowed to collect data that can be used. In multiple clinical fields. Indeed, we are on the brink of a revolution for many, if not all, modern pharmaceutical drug settings. Gastrointestinal endoscopy has proven to be an excellent context for developing AI systems that can be useful for endoscopists in many parts of their daily activities. AI is the right tool to improve in all subdomains of endoscopy [4], thereby standardizing the exercise by guaranteeing a minimum priority that is impossible to move below.

For the detection of lesions during colonoscopy (laptop-aided detection, CAD) and characterization of lesions (laptop-aided characterization, CADX), there are AI clinical programs in the gastrointestinal that have published conclusive evidence for some remote assistance. This is an excellent program for which different companies have developed multiple devices currently available on the market and used in clinical practice. This may be because large amounts of data (i.e., images and videos) are needed to train and test reliable AI systems, especially in Western international settings., where colorectal cancer screening programs are widely implemented, a large number of colonoscopies are performed each day, and the overall incidence of colorectal polyps is high enough that it is possible to collect a large number of colonoscopies. Various "pathological" images or videos are used to train the device while being equally clean to test the device, even in a real-life situation.

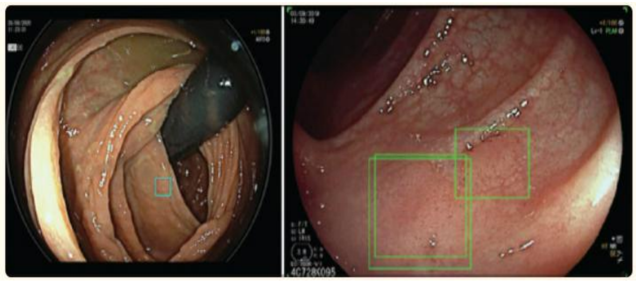

Fig.1 Examples of computer-aided detection

In the early years of colonoscopy imaging evaluation, image processing was typically used to extract carefully designed features as input to traditional decision-making system learning techniques. The past decade has seen a significant boom in supervised deep learning (DL) strategies for a colonoscopy that involve machine learning of features from raw school images for prediction. Computer researchers wrote two surveys focusing on the development of diagnostic techniques. Readers are interested in screening techniques for colonoscopy are referred to, including pre-and post-procedure analysis

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(e.g., content-based video retrieval, green storage, green video interaction, and scanning), as well as a variety of low-Overviews of minimally invasive endoscopic surgeries. Avid readers of deep learning strategies for polyp photodetection, localization, and neighbourhood segmentation of polyps by 2020 are mentioned. The latest survey also includes publicly available polyp datasets and records of overall performance measurements.

## II. LITERATURE SURVEY

Many methods have been proposed and evaluated over time. Because few annotated data sets are publicly available, many researchers used private data sets for general performance assessments. Publicly available datasets are usually for polyp detection and segmentation. They are extremely small and are photographed in perfect condition. They are not yet a major form of colonoscopy imaging in clinical use. Because of these constraints, we do not review existing strategies simultaneously but chronologically. In addition to the topic of colon navigation strategies via 3D reconstruction, we also ignore overall performance reports based on evaluations that primarily use small personal test datasets (i.e., less than 3,000 images or less).

Rex DK et al. [2017] Pairing colonoscopy devices with image-enhanced technology (i.e., white-light endoscopy and chromoendoscopy) has improved the quality of care to patients by increasing the precision of colonoscopy procedures. Recently, research efforts have focused on integrating computational power and previously collected data to enhance the simultaneous detection and classification of colonoscopy images or videos and support endoscopists in their decisions about the presence and/or histology of a polyp.

van der Sommen et al. [2020] Machine learning is a subset of AI that allows mathematical methods to develop an algorithm based on given data (e.g., polyp images or videos) to predict the same pattern or a specific task in unseen or unknown data.

Ahmad OF et al. [2019] The final output of these systems (e.g., detection or classification of polyps) is based on pre-defined features or extraction of the most relevant image features (e.g., polyps), which may help in the specification, detection, or classification of a new image. In conventional machine learning (i.e., handcrafted models), a researcher manually introduces the clinically relevant polyp features to the machine learning

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algorithm. In contrast, in the most advanced machine learning method, which is called deep learning, polyp features, clinically relevant or not, are automatically extracted by the algorithm without prior introduction by a researcher. As a result, the output is based on the capture and summary of complex polyp characteristics, either for detection (i.e., discrimination of polyp from background mucosa) or prediction of histopathology (i.e., neoplastic or non-neoplastic)[17]. Schachschal G et al. [2016] Deep learning employs deep neural networks (DNNs), which imitates the complex interconnected neural network in the human brain. These artificial neurons are positioned in several detections and pooling layers, taking weighted data (from the precedent layer), processing it, and passing the output (processed data) to the next layer. Each layer performs as a “step of abstraction[17]”, which forms a hierarchy of common features that grow in complexity throughout the layers (i.e., edge- > basic shape- > object- > class prediction). In other words, each layer would extract useful and relevant features from a given data that would facilitate the classification of the images. When data are presented, the DNN performs the repetitive iterations of a previously chosen model (i.e., support vector machines, random forests, or neural networks) throughout the deeper layers, so-called hierarchical feature learning.

Vleugels et al. [2019] For computer-assisted colonoscopy, the development of the AI model is primarily based on supervised data, where data are retrospectively labeled by one or a group of expert endoscopists. For example, in CADx, colonoscopy images or videos will be labeled as neoplastic or non-neoplastic based on the reference standard of pathology results (Figure (Figure1),1), which would have been reviewed and finalized following consensus by several pathologists.

Anderson et al. [2018] In CADe, polyp images or videos will be reviewed by experienced endoscopists, and polyp borders will be delineated based on consensus by endoscopists. Ultimately, the output of the AI algorithm will identify the presence of a polyp, or be able to discriminate between a neoplastic and non-neoplastic polyp (Figure (Figure22). However, there are some shortcomings and barriers to the development and implementation of CAD systems in real-time endoscopy practice, as discussed below.

## III. PROPOSED SYSTEM

Objective measurements of quality of colonoscopy are important to reduce subjective biases and differences among endoscopists. We focus on three key measures of quality of colonoscopy: the amount of blurry (non-informative) images during the withdrawal phase, the quality of bowel preparation by patients prior to colonoscopy and the effort to remove remaining debris by the endoscopist, and the quality of the endoscope navigation inside the colon. The latter remains very challenging to solve, but has recently gained more interest due to its significance to the clinical outcome

**Informative Frame Analysis**

An informative body in a colonoscopy video can be described as a mass recognition body useful for diagnosing colonic mucosa. Most of the mucosa may not have been adequately examined if the maximum number of frames throughout the removal process is uninformative or blurry. In addition, early discrimination of uninformative from informative frames can improve the accuracy of analysis of colonoscopy video frames for other abnormality detection functions. Several capabilities can distinguish uninformative from informative frames:

- Characteristics of corners and sides that match the previous frame.
- The ratio of background pixels.
- The implicit and advanced deviation of depth in the HSV shadow area (hue saturation value).

A random forest classification was changed to use for the class. A more desirable facet detection-based method was proposed. Non-informative frames usually don't have many borders anymore. However, very bright areas due to specific reflections can cause false edges. Therefore, the proposed method uses bright neighbourhood segmentation to perceive and discard false edges.

A convolutional neural network (CNN) model has been used for the first time for this problem. Improper or poor bowel training due to uninformative frames is characteristic of the ultimate fouling and cleaning agent. SimpleNet (a CNN built from scratch by the authors), AlexNet, GoogLeNet, and ResNet were compared in terms of accuracy and speed using a dataset of approximately 12,000 frames. Experimental results confirmed that CNN methods fast detect uninformative frames with an accuracy of 70 to 95%.

**Bowel Preparation and Cleansing**

Bowel preparation (cleansing) is a key precondition for a successful colonoscopy. The degree of bowel cleansing affects successful disease detection. Therefore, an accurate assessment of bowel preparation quality is important. The Boston Bowel Preparation Scale (BBPS) is a widely used bowel preparation quality assessment score. BBPS measures the individual cleanliness of three colon segments (ascending colon, transverse colon and descending colon) with a score ranging from 0 (dirtiest) to 3 (cleanest); the addition of the segmental scores provides the overall BBPS score. Informative frames were classified by Support Vector Machine (SVM) into frames with and without remaining debris. A CNN with two DenseNet layers which have a feature reuse mechanism embedded before the SoftMax classifier was proposed to estimate BBPS scores an accuracy of 90% based on the public Nerthus dataset. EndoAngel based on a CNN architecture outputs bowel preparation scores every 30 seconds during the withdrawal phase of colonoscopy; an accuracy of 89% was achieved over 20 colonoscopy videos

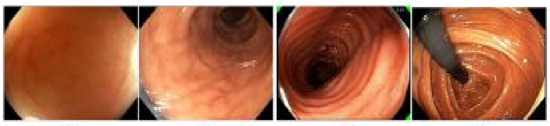


Fig.2 Examples (a) wall view; (b) lumen view; (c) spiral score and feedback; (d) retroflexion for viewing a difficult-to-reach area.

## IV. MEDICAL TRIALS WITH REAL-TIME AI-ASSISTED COLONOSCOPY

Although AI for colonoscopy has received much study attention over the years, few structures have been tested in clinical trials. There are 9 scientific trial reports of real-time AI-assisted colonoscopy, seven clinical trials from one center, and two from three centers. Four trials provided comments on the best of colonoscopy. Structures within the last 4 trials provided their full feedback for the polyps. All of these trials show that AI-assisted structures improve colonoscopy endpoints, either by increasing rarer or by detecting larger polyps. The first clinical trial, conducted in 2012, used EMIS software that robotically detected the start and end of each technique in real-time. It measured several fine-grained metrics within the procedure: clean voiding time with no obscuring frames, amount of stool visualized on the image during insertion and voiding, BBPS scores, and spiral scores. The expression provided contains only the aforementioned "spiral punctuation." Current comments commonly used in scientific trials indicate packaging containers around detected polyps but not the shape of target polyps. In ideal occasions, polyps are removed with a margin of thick tissue surrounding the polyp. Consequently, polyp detection is

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more important than polyp segmentation. However, segmentation may be necessary to assess the integrity of the resection.

## V. FUTURE OF AI FOR COLONOSCOPY

Leading experts are optimistic about using AI systems in daily practice for real-time assistance during colonoscopies. However, they have concerns about three issues: robustness, transparency, and integration with clinical workflow. We'll take a closer look at the first two issues, but we'll limit the discussion to the last one because of the breadth of the topic. Finally, we will briefly discuss the potential of AI as a driving force for autonomous or robotic entities. Since DL systems are standard technologies for AI for colonoscopy, the availability of large datasets of floor facts under ideal and sub-optimal conditions is crucial to increase the overall performance of AI-assisted systems. And despite the availability of excellent real-world data sets, we must determine the exact limits of use and recognize that results based solely on AI may be of limited value. Models based on unique data sets will want to show the patterns that the models capture and show the dominance of those patterns within the data set. This will help to understand the limitations of models tested on such private data sets.

**Autonomic and Robotic Instruments**

Knowledge of location of the endoscope tip and the location and nature of any lesions allows steering of endoscope and instruments. We foresee a gradual introduction of DL-based automation, initially under direct human supervision. Eventually standalone instruments completely driven by autonomous software may result in colonoscopy robots. For instance, current manipulation of the endoscope tip is manually via dials in order to steer the tip of the endoscope in the direction of the upstream lumen; there is no reason to believe that DL cannot do this as well if not better than human operators. Patient movement, breathing and pulsating heart or vessels may move the endoscope tip away from a polyp that needs to be removed; DL-based software may automatically correct for these movements facilitating complete polyp removal. Current video capsule endoscopy does not allow steering of the capsule, obtaining samples or remove lesions; all of this in theory can be addressed, and DL is expected to play a major role in this. With miniaturization and better battery technology any hardware can be located inside the body whereas the software driving a robotic capsule able to change position or remove lesions is residing outside the patient. Indeed, it is likely that

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predominantly hybrid robots will be applied in the colon where the tools are inside and the operating system outside the patient, either connected via a wire, also allowing power transmission, such as via the anus, or a wireless solution, requiring a battery-operated robot [

## VI. CONCLUSION

We summarize the research of the past few years and the near future development of real-time AI-assisted colonoscopy. Recent scientific trials show that some late feedback in vivo techniques improve first-class patient care by detecting more polyps. Further work will be carried out as described in future research directions. Data privacy complicates matters, as certain medical imaging data are not always permitted to be shared. Finally, implementing all the tools in clinical practice does not mean the problem is solved. Perfect AI grading for colon cleansing and peripheral inspection is not the same as careful inspection of the entire mucosa. All in all, endoscopists have met the expectations of AI-based classifiers. Finally, required trials demonstrate that AI-based strategies applied during colonoscopy reduce CRC incidence, morbidity, and mortality. These have been and will continue to be the latest indicators of the success of CRC prevention. Therefore, AI-assisted systems must demonstrate that their implementations meet these CRC benchmarks.

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