Review Article

Artificial intelligence and computer-aided diagnosis for colonoscopy: where do we stand now?

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Abstract: Computer-aided diagnosis (CAD) for colonoscopy with use of artificial intelligence (AI) is catching increased attention of endoscopists. CAD allows automated detection and pathological prediction, namely optical biopsy, of colorectal polyps during real-time endoscopy, which help endoscopists avoid missing and/or misdiagnosing colorectal lesions. With the increased number of publications in this field and emergence of the AI medical device that have already secured regulatory approval, CAD in colonoscopy is now being implemented into clinical practice. On the other side, drawbacks and weak points of CAD in colonoscopy have not been thoroughly discussed. In this review, we provide an overview of CAD for optical biopsy of colorectal lesions with a particular focus on its clinical applications and limitations.

Keywords: Computer-aided diagnosis (CAD); colon cancer; polyp

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Introduction

Colorectal cancer (CRC) is the third most common cancer and the fourth leading cause of death from cancer worldwide (1). With the early detection and removal of neoplastic lesions, CRC is considered to be efficacy prevented (2). However, a meta-analysis including six studies on patients undergoing two same-day colonoscopies showed a pooled miss rate of 22% for colorectal polyps (3) and post-colonoscopy CRC is reported to account for about 8.6% of all the CRC (4) Low adenoma detection rates (ADRs) and incompletely resected are recognized as main causes of this kind of CRC (5,6). To overcome this situation, numerous attempts have been adopted to improve ADR including educational interventions, enhanced imaging techniques and mechanical devices to improve mucosal exposure. Computer-aided diagnosis (CAD) systems using AI have been expected to be a new modality that can improve ADR (7). The major roles of CAD in colonoscopy include automated detection (*Figure 1*) and pathological prediction (i.e., optical biopsy) of colorectal polyps during real-time endoscope (8).

Definition of AI

Figure 2 illustrates the general concept of AI, machine learning, and deep learning (DL). AI has been basically designed to imitate human's thinking way and show intelligence similar to that of human beings. The concept of AI was firstly presented at the Dartmouth Conference held in 1956 by McCarthy *et al.* (9) Machine learning is a type of AI, which allows automated learning on data sets without the need for explicit programming of prediction

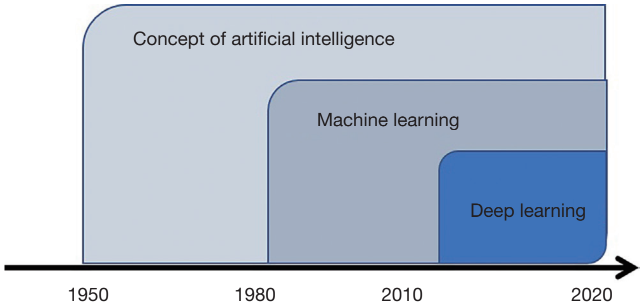

Figure 1 Automated detection of a colonic polyp. The presence of a polyps is highlighted with yellow color outside the endoscopic monitor, showing 74% possibility of its presence.

rules (10). DL approaches, one of the advanced machine learning methods, have been revolutionizing the area by applying artificial neural networks (11). The DL algorithm was inspired by the concept of neurons and synapses in the human brain to discover image features that optimally represent the data for a specific task. DL is currently considered as one of the most prominent prediction methods in the AI field.

Computer-aided characterization of colorectal lesions

CAD for polyp characterization is generally designed to predict lesion pathology with help of machine learning based algorithm. Various imaging technologies are considered as the targets for CAD for polyp characterization such as white-light endoscopy (12,13), magnifying narrow band imaging (NBI) (14,15), magnifying chromoendoscopy (16), endocytoscopy (17-20), confocal laser endomicroscopy (21) and laser-induced fluorescence spectroscopy (22-25) (*Table 1*).

Magnifying NBI

The application of CAD to magnifying NBI was firstly reported by Tischendorf *et al.* (14) and Gross *et al.* (30) in 2010 and 2011, respectively. In their model, nine vessel features such as length, brightness, diameter, and others, were extracted from magnified NBI images and used for machine learning referring corresponding pathological diagnoses as ground truth. Their developed model provided an accuracy of 85.3% in differentiation between neoplastic and non-neoplastic polyps. However, these studies were based on off-site assessment of already captured images. Subsequently, Japanese research team (31,32) reported the differently designed model based on machine learning and validated it in a real-time clinical practice, succeeding *in vivo* classification of polyps during endoscopy with an accuracy of over 90%. However, generalization of the study result is still required because of the limited number of the included patients (i.e., 41 patients) of the validation study.

Endocytoscopy

Endocytoscopy (EC, CF-H290ECI; Olympus Corp, Tokyo, Japan) allows *in vivo* visualization of cellular imaging with ultra-magnifying power of 520-fold) has also been investigated as an attractive target for CAD in colonoscopy. EC is considered one of the ideal modalities for CAD, because it realizes focused, consistent images of fixed size that enable easier image analysis for AI. Several pilot studies including one large-scale prospective study demonstrated an approximately 90% accuracy of EC for identification of adenomas with only a 0.4-second latency after capturing an image (18-20,33,34) (*Figure 3*).

Laser-induced fluorescence spectroscopy

Rath *et al.* (23) prospectively investigated the performance of real-time running CAD for laser-induced fluorescence spectroscopy (WavSTAT4; Pentax Corp., Tokyo, Japan), reporting 100% sensitivity, 80.6% specificity for diminutive colorectal adenomas. On the other hand, Kuiper *et al.* (22) demonstrated less-impressive results, with 83.0% sensitivity, 59.7% specificity, 71.6% for diminutive adenomas, thus further assessment would be required to clarify the clinical usefulness of this modality.

White light endoscopy

CAD for white-light endoscopy has not been the hottest research topic though it is the most available endoscopic modality, because white-light endoscopy is considered to have limitation in its accuracy of optical diagnosis of colorectal lesions (8). Recently, Komeda *et al.* (12) developed a deep-learning model, providing 75.1% accuracy with a cross-validation method, while Sánchez-Montes *et al.* (13) developed a handcrafted, predictive model based on 3 measures (contrast, tubularity, and branching) of the polyp surface pattern, resulting in 95.0% sensitivity, 87.9% specificity, 82.6% PPV, and 96.7% NPV for diminutive rectosigmoid adenomas. However, there has been no

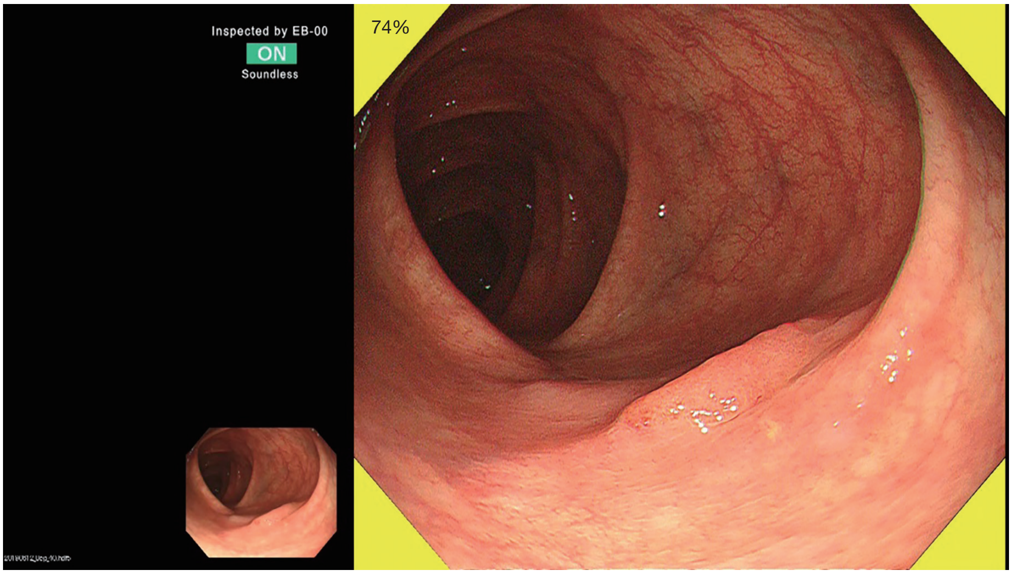

Figure 2 The concept of artificial intelligence was proposed in 1950s. Machine learning is a kind of artificial intelligence methods, comprising deep learning.

Table 1 Picked up publications regarding Automated polyp characterization (only physician-initiated studies are included)

Reference	Journal	Year	Endoscopic modality	Study design	Subjects	Outcomes
Chen *et al.* (15)	*Gastroenterology*	2018	Magnifying NBI	Retrospective study	284 lesions	96.3% sensitivity and 78.1% specificity for adenomas
Mori *et al.* (17)	*Ann Intern Med*	2018	Endocytoscopy	Prospective study	791 patients with 466 lesions	92.7% sensitivity and 89.8% specificity for adenomas
Renner *et al.* (26)	*Scand J Gastroenterol*	2018	White light endoscopy and non-magnifying NBI	Retrospective study	100 polyps	92.3% sensitivity and 62.5% specificity for adenomas
Ito *et al.* (27)	*Oncology*	2019	White light endoscopy	Retrospective study	190 images	67.5% sensitivity and 89.0% specificity for deeply invasive submucosal cancer (cross validation)
Byrne *et al.* (28)	*Gut*	2019	Magnifying NBI	Retrospective study	125 lesions	98% sensitivity and 83% specificity for adenomas
Horiuchi *et al.* (29)	*Scand J Gastroenterol*	2019	Autofluorescence imaging	Prospective study	95 patients with 258 lesions	80.0% sensitivity and 95.3% specificity for adenomas
Sánchez-Montes *et al.* (13)	*Endoscopy*	2019	White light endoscopy and non-magnifying NBI	Retrospective study	225 polyps	92.3% sensitivity and 89.2% specificity for adenomas

study evaluating the real-time use of CAD for white light endoscopy.

Advantages of AI

Some colorectal lesions including flat and depressed neoplasia are endoscopically subtle but sometimes harbor advanced histopathology (35). These lesions including sessile serrated lesions are sometime difficult to identify its histopathology even with experienced endoscopists' eyes (36). Therefore, the major goal of CAD for colonoscopy is to predict the histology of these kinds of "difficult"

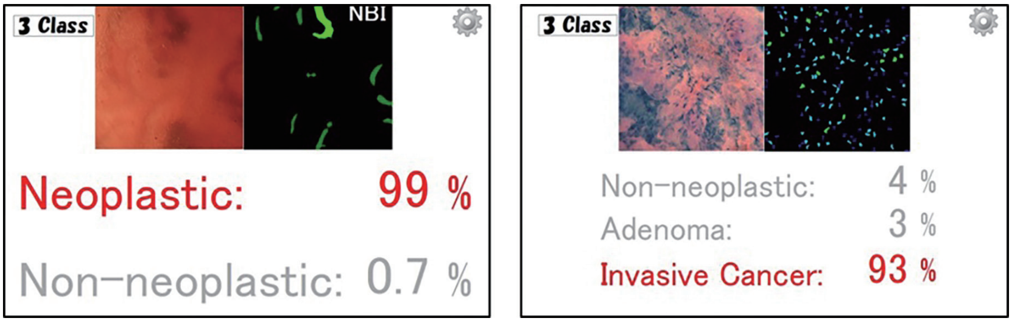

Figure 3 Endocytoscopic polyp characterization. With the narrow-band imaging mode, a lesion is characterized as either neoplastic or non-neoplastic (the left image), while a lesion is characterized as either non-neoplastic, adenoma, or invasive cancer with the staining mode.

polyps and help endoscopists perform appropriate treatment options during ongoing endoscopy. Given precise identification of polyp histology particularly for diminutive (≤5 mm) polyps is allowed with use of CAD, the resect-and-discard strategy can also be implemented, leading to significant reduction in costs related to unnecessary polypectomy and pathological assessment (37,38).

The optical biopsy of the lesions suspected of the early invasive cancers or the prediction of depth of invasion is another important research topic (*Figure 3*). CAD will be able to play significant role in differentiating "endoscopically curative" lesions; endoscopic treatments can be considered curative for lesions with superficial invasion into submucosal layer, while surgical resection is recommended for those with deeply invasive sub-mucosal cancers. Validated classification systems based on advanced imaging using magnifying chromoendoscopy and NBI have been developed to predict cancer invasion into deep submucosal layer, however these classification including the Kudo pit pattern classification, Sano capillary pattern classification, Hiroshima classification, and NBI International Colorectal Endoscopic Classification allow highly accurate prediction only in limited situations (e.g., effective only when used in tertiary care centers or with experts' hands) (39). Therefore, use of AI can be an attractive option for predicting such "difficult-to-diagnose" lesions in near future.

Disadvantages of CAD

Nowadays, AI is becoming one of the hottest research topics in medical fields, attracting the interest of many medical doctors, however, from the perspective of clinical application, we should not ignore the weak points and limitations which the AI potentially harbors.

Firstly, increased time required for endoscopy examination can be a limitation of practice. A prospective study investigating AI for endocytoscopy by Mori *et al.* (17) pointed out that additional 35–47 s will be required to assess a polyp. Secondly, AI's output displayed in the monitor might distract endoscopists attention, resulting in missing and/or misdiagnosis of the target/different lesions. Thirdly, misdiagnosis from CAD sometimes affects endoscopists decision in a bad way even if the initial diagnosis based on endoscopists' visual inspection is correct. Fourthly, dependence on such machine-aided diagnosis possibly makes the new generation of endoscopists less skillful.

To overcome these drawbacks of AI, some measures can be proposed. Firstly, education programs regarding how to use and interpret the outputs from AI would be mandatory. At least, endoscopists should understand how wrong predictions by AI can affect endoscopists' final diagnoses and decision. In addition, potential legal issues should be shared via these training program; legal responsibilities basically belong to the users rather than AI or companies developing AI. On the other hand, CAD can be a valuable tool for training of less experienced doctors as they are always able to compare their own optical diagnosis with outputs of CAD during ongoing colonoscopy.

Conclusions

Strong collaborations between clinicians and computer scientists has been contributing to overcome translational barriers that AI in colonoscopy harbors and it is now being implemented into clinical colonoscopy; actually, a couple of AI medical devices have already secured regulatory approval and are commercially available depending on the countries. Of course, clinician's acceptance of these newly developed devices is crucial for wider implementation, because it may change a bit clinical procedure workflow. At the same time, robust clinical trials will be required to demonstrate improvements in performance, because currently available clinical studies provide very limited evidence of AI in colonoscopy. However, with increasing industry involvement and governmental incentives, AI will be rapidly implemented into colonoscopy practice in the next few years.

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Footnote

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