Editorial

Higher rate of colon polyp detection aided by an artificial intelligent software

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Colorectal cancer (CRC) is one of the most common malignancies in the United States and Europe (1,2). Detection and removal of colon polyps or early cancer is associated with a reduction in mortality from CRC (3). The adenoma detection rate (ADR) during screening colonoscopy is recommended as a measure of the quality of colonoscopic examination. Corley *et al.* reveled that a 1% increase in the ADR was associated with a 3% decrease in interval CRC incidence (4). More recently, a prospective study from Poland *et al.* showed 1% increase in the ADR was associated with a 6% reduced risk of interval CRC (5). However, the ADR varies widely, largely depending on the ability of gastroenterologist, time spent, and preparation quality. Unfortunately, adenoma miss rate remains high (6–27%) (6), despite of novel technologies, devises, and interpretation. It is partly because of well recognized blind spots on colonoscopies.

To resolve these issues, artificial intelligence (AI) has been applied to the field of gastrointestinal endoscopy. Since 1990s, the method for computer-aided detection (CADe) for colorectal polyps has been investigated combining texture, color or mixed analysis. Finally, CADe method with higher sensitivity is firstly reported by Karkanis *et al.*, which achieved >90% detection rate (7). However, these systems have not been widely prevalent in the clinical setting because these systems were established base on the static endoscopic image. Therefore, focus of research in this field shifted to the real-time imaging analysis. In 2016, real-time colonic polyp detection systems were developed, which have the challenge of having low sensitivity due to traditional machine learning methods (8). These problems were dramatically overcome through the deep learning method into CADe system. Recently, Misawa *et al.* developed a CADe system for colorectal polyps based on deep learning method (9). This system was trained by a total 546 short videos including 155 polyp-positive and 391 polyp-negative short videos. These videos were randomly divided into 2 groups: learning group (105 positive and 306 negative) and test group (50 positive and 85 negative polyp). This CADe system detected 94% (47 of 50) of the test group with 60% false-positive detection (51 of 85).

Most recently, Urban *et al.* built a novel CADe system in real time with 96% accuracy reported in the journal *Gastroenterology* (10). They designed CAD system using convolutional neural networks (CNN called "Deep Learning") in a set of 8,641 hand-labeled images containing 4,008 unique polyps collected from more than 2,000 patients. To achieve widespread clinical use, accuracy, portability, and rapid processing speed are desired. Therefore, this study was carefully designated by following several datasets, which were used to train and evaluate the deep learning model, separately polyp-detection and localization. (I) The ImageNet challenge dataset (1.2 million natural images); (II) 8,641 hand-selected colonoscopy images (4,088 unique polyps and 4,553 images without polyps), including white light and

NBI images; (III) a separate 1,330 colonoscopy images collected from different patients (672 unique polyp and 658 non-polyp images); (IV) and 9 colonoscopy videos; (V) a combined dataset consisting original 8,641 images and additional 44,947 images were extracted from 9 videos; (VI) additionally, 11 "challenging" colonoscopy videos performed by highly skilled endoscopists (ADR ≥50%) were used. For polyp detection, a test of accuracy of the CNN trained on the 8,641 images was 96.4% and the ROC-AUC of 0.794 in the independent 1,330 images dataset. In the analysis of colonoscopy video, 36 polyps were identified by 3 endoscopy experts and 45 polyps were identified by the CNN system (false-positive rate; 7%).

In this study, some interesting additional experiments were performed. First question was: can CNN classify all polyps in spite of its morphology? Nonpolypoid lesion (flat and depressed) were often not recognized by even skilled endoscopists compared with polypoid lesion. The CNN system missed 12% (84 of 678) polypoid polyps (Ip and Is) and 11% (41 of 381) nonpolypoid polyps (IIa, IIb and IIc). Therefore, polyp morphology does not impact on the performance of CNN system. Second question asked was: can CNN detect polyps under conditions of hurried withdrawal or poor inspection? With the use of purposefully difficult 11 colonoscopy videos, featuring "flyby" scenarios without closing to previously found polyps during withdrawal, missed polyps were located in "flyby" segments of the video. Therefore, CNN is less attuned to quick movement by endoscopists at this stage. Third question asked was: is it beneficial to train the CNN on NBI plus white light images? Recently, a CNN system trained by white light and NBI endoscopy images was developed, which achieved a 94% accuracy in differentiating diminutive adenomas from hyperplastic polyps (11). Although NBI or chromoendoscopy is very useful modality to characterize small polyps during screening or surveillance colonoscopy, inter- or intra-observer variability are unavoidable problems, depending on endoscopist's ability. Such computer-aided diagnosis (CADx) may decrease variance among endoscopists.

The works by Urban *et al.* has a number of prospective applications on the screening or surveillance colonoscopy. We congratulate them on their fabulous effort to move this field forward. Their willingness to loan the technology without asking for royalties and to benefit the population in general rather than subscribe to profit taking mentality.

In the future, more integration of the CADe and CADx systems may enable us to detect polyps more precisely and speedily in the clinical setting. However, transportability and acceptance of this technology waits for now…

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Footnote

Conflicts of Interest: The authors have no conflicts of interest to declare.

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