Best Practice & Research Clinical Gastroenterology 52-53 (2021) 101745

Contents lists available at ScienceDirect

Best Practice & Research Clinical Gastroenterology

journal homepage: https://ees.elsevier.com/ybega/default.asp

# Detection of flat colorectal neoplasia by artificial intelligence: A systematic review

Masayoshi Yamada [a, b, c], Yutaka Saito [a, *], Shigemi Yamada [c, d], Hiroko Kondo [c, d], Ryuji Hamamoto [c, d]

[a] Endoscopy Division, National Cancer Center Hospital, Tokyo, Japan
[b] Division of Science and Technology for Endoscopy, National Cancer Center Exploratory Oncology Research & Clinical Trial Center, Tokyo, Japan
[c] Division of Medical AI Research and Development, National Cancer Center Research Institute, Tokyo, Japan
[d] Advanced Intelligence Project Center, RIKEN, Tokyo, Japan

ARTICLE INFO

*Article history:*
Received 29 March 2021
Accepted 14 April 2021

*Keywords:*
Endoscopy
Artificial interagency
Deep learning
Endoscopic submucosal dissection
Colorectal cancer

ABSTRACT

*Objectives:* This study review focuses on a deep learning method for the detection of colorectal lesions in colonoscopy and AI support for detecting colorectal neoplasia, especially in flat lesions.
*Data sources:* We performed a systematic electric search with PubMed by using "colonoscopy", "artificial intelligence", and "detection". Finally, nine articles about development and validation study and eight clinical trials met the review criteria.
*Results:* Development and validation studies showed that trained AI models had high accuracy—approximately 90% or more for detecting lesions. Performance was better in elevated lesions than in superficial lesions in the two studies. Among the eight clinical trials, all but one trial showed a significantly high adenoma detection rate in the CADe group than in the control group. Interestingly, the CADe group detected significantly high flat lesions than the control group in the seven studies.
*Conclusion:* Flat colorectal neoplasia can be detected by endoscopists who use AI.


## Introduction

With remarkable advances in endoscopy and endoscopic diagnostics, even small lesions – as small as several millimeters, can be detected during endoscopy. The process from detection to treatment can now be performed with an endoscopy. Endoscopy is the most useful examination for the early detection of gastrointestinal cancer, and the effect of endoscopic screening has been reported to reduce the mortality caused by gastric cancer and colorectal cancer. It was reported that the mortality rate of those who underwent endoscopy for gastric cancer screening was 67% lower than that of those who underwent endoscopy for upper gastrointestinal series. Endoscopy for gastric cancer screening has also been reported to reduce mortality by 47% compared with those who have not undergone endoscopy for gastric cancer screening between the ages of 40 and 74 [1,2]. Regarding colorectal cancer, it has been reported that the detection and resection of neoplastic lesions (adenomatous polyps) during colonoscopy decreased the incident rate from 76% to 90%, and the mortality rate by 53% based on the results of the National polyp study and its cohort study conducted in the United States [3,4]. In other words, early detection and treatment of cancer are possible in the area of the gastrointestinal tract that can be observed by endoscopy. It is thought that this progress in both endoscopic diagnostics and technology has been established by a 1-on-1 detailed comparison between endoscopic findings and histopathological images, and now, lesions that could not be diagnosed earlier can also be diagnosed.

However, so-called "interval cancer", in which cancer is found even though the patient has undergone endoscopy, has become an important issue of endoscopy in recent years. In the differential diagnosis after lesion detection, there is a problem such as an experience difference in which the diagnostic accuracy differs between experts and beginners who perform endoscopy. In endoscopy examination, an endoscope is inserted into the living body through the mouth or anus, and the luminal surface of the target organ is visualized on a monitor with a high-definition image. The workflow of endoscopy for early detection and treatment of cancer mainly consists of four processes: 1) lesion detection, 2)

* Corresponding author. Endoscopy Division, National Cancer Center Hospital 5-1-1 Tsukiji, Chuo-ku, Tokyo 104-0045, Japan.
*E-mail address:* ytsaito@ncc.go.jp (Y. Saito).

https://doi.org/10.1016/j.bpg.2021.101745
1521-6918/

differential/depth diagnosis, 3) treatment, and 4) surveillance [5–7]. In all these processes, the doctor makes a real-time clinical decision, by observing the captured endoscopic image on the monitor. For example, a missed lesion is the main cause of the above-mentioned "interval cancer" in which no lesion is expected to be found during the endoscopy, and it is reported that one of the causes is an experience gap between doctors [8]. This experience gap is a heavy burden for patients and is an issue that needs to be solved. This experience gap affects all the aforementioned processes, especially when a lesion is found, but the neoplastic lesion is mistakenly diagnosed endoscopically as a nonneoplastic lesion and the lesion is left in vivo. The accuracy of differential diagnosis and the detection of lesions is important, as it will otherwise provide the patient with wrong surveillance endoscopy intervals.

In the endoscopic image diagnosis support system using AI technology, in the field of gastrointestinal endoscopy, the AI system automatically analyzes the image displayed on the monitor of the endoscope and predicts the suspected lesion location, the differential diagnosis, the tumor depth of invasion, and the presence or absence of metastasis [9,10]. Because AI prediction is judged by setting an arbitrary threshold, endoscopic diagnosis becomes more objective, and it has been attracting attention in recent years from the viewpoint of improving the diagnostic ability of doctors, reducing human mistakes, and eliminating the experience gap of doctors. In a colonoscopy, six AI systems are now regulatory approved in the EU and/or Japan; WISE VISION (NEC), CAD-EYE (Fujifilm medical), EndoBRAIN-EYE (Olympus), GI-Genius, Discovery AI (Pentax), and Endoscreener (Wision AI). In the present review, we focus on this deep learning method and the detection of colorectal neoplasms, particularly in flat lesions.

### Data source and study flow

We performed a systematic electric search with PubMed for articles using the search terms "colonoscopy", "artificial intelligence", and "detection" (final access on 03/2021). The search was limited to fully published original articles described in "development and validation study" with testing on independent image sets, or "clinical trials" of the AI system by using deep learning technology for detecting lesions in colonoscopy, and written in English – published between 2016 and 2021 (Fig. 1). Literature search, study selection, and data extraction were independently performed by two authors (M.Y. and S.Y.), and disagreements were resolved through discussion with a third author (H.K.).

### Application of deep learning technology for colonoscopy

AI is defined as " the science and engineering of making intelligent machines, especially intelligent computer programs" by John McCarthy, and intelligent learning is to find information that can be

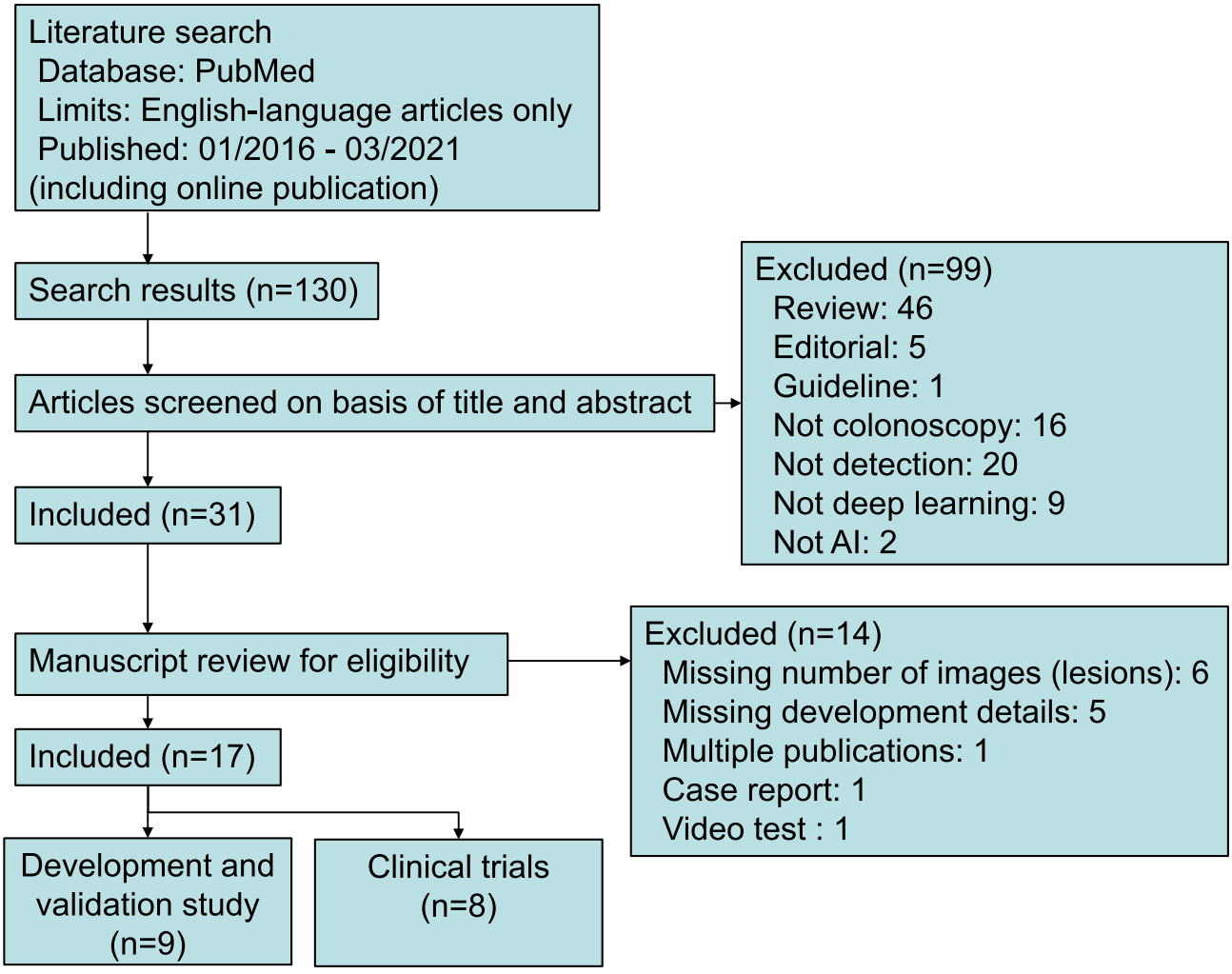


**Fig. 1.** Flow diagram of study selection.

used for inference from input data and to get a new conclusion based on that information [11]. Thus far, methods such as neocognitron, support vector machine, and deep learning have been developed as part of this intelligence program. AI has been booming in the 1960s and 1980s; however, its performance has been limited and it has not reached a breakthrough [12]. The current third AI boom was because of the Deep Belief Network reported by Geoffrey Hinton et al., in 2006 [13]. Now, it has developed into a convolutional neural network, which controls overfitting as exhibited in machine learning, and the learning performance has improved dramatically. This deep learning method is particularly suitable for extracting image features and is known to exert extremely high capabilities in detection, classification, and identification. Combined with recent improvements in computer performance such as GPUs, we are entering the third AI boom represented by "Deep Blue" in chess and autonomous driving [14]. The high performance of deep learning has been exhibited in global image recognition contests, and it is said to have already surpassed human ability [15]. It is expected that deep learning technology that makes this intellectual inference will be used in the medical field. From 2016 to 2017, studies regarding deep learning of skin cancer images, fundus photographs of diabetic retinopathy, and HE specimen images of breast cancer reported that diseases can be detected by AI with accuracy in comparison to expert doctors [16–20].

## Utilization of deep learning technology for lesion detection in colonoscopy

Until recent years, a traditional machine learning technology has been used for automatic lesion detection in colonoscopy. However, the recent development of deep learning technology has helped in lesion detection. There has been a debate about the unclear process of deep learning judgment, the so-called "black box" problem, and overfitting that the AI system can fit for the training and validation data, but cannot fit for independent test data. However, based on the findings of the deep learning, high-performance data for lesion detection in colonoscopy obtained from independent pure-test studies (Table 1) —conducted in Japan and Europe, South Korea, and China, six AI systems are now regulatory approved in the EU and Japan as described in the introduction.

The nine studies listed in Table 1 are development and validation studies of AI systems using deep learning technology for lesion detection in colonoscopy [9,21–28]. Each study includes an independent test set in addition to training and validation to evaluate the performance of the trained AI model. Although the performance of the trained AI model cannot be compared directly, because the test sets are all different, the sensitivities and specificities in the independent pure test sets are high – approximately 90% or more in each model. Regarding the images used for training, many images are needed for development and validation; around 1000 to 4000 still images or video frames can be used for supervised training.

The accuracy of the trained AI model is better in elevated lesions than in superficial lesions in the 2 studies (Table 1). AI shows the same behavior as humans, and it is considered that AI may be weak against images that have never been learned. Certainly, it can be seen that the model trained only with the video frames seems to be strong in the pure-test set of the video frames, and the model trained only with the still image is strong in the pure-test set using the still image. It is to be noted that values in the table are calculated per frame. In other words, considering that the video is composed of 30 frames per second, detection itself is possible only if the sensitivity is above 70%. Indeed, the AI detection image of the flat lesion is depicted in Fig. 2. The flat-type lesions are detected by AI. Furthermore, AI could also detect missed lesions (Fig. 3). Therefore, this lesion may have been detected if the doctor used AI.

**Table 1**
Development and validation study of a deep learning model for the detection of the colorectal neoplasms during colonoscopy.

| Author | Year of Publication | Country | AI system, company | Trained | | | Pure test sets: still images | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | lesions, total, n | still images, n | video frames, n | images, n | Sensitivity, overall | Sensitivity, superficial lesions | Specificity, overall |
| Yamada M et al. | 2019 | Japan | WISE VISION, NEC | 2116 | 4087 | 891 | 4840 | 97.3% (95.9–98.4) | 92.9% (86.4–96.9) | 92.9% (88.5–92.9) |
| Hassan C et al. | 2020 | Italy | GI-Genius, Medtronic | 2684 | NA | NA | NA | NA | NA | NA |
| Wang P et al. | 2018 | China | EndoScreener, Wision AI | | | | 27133 | 94.38% | NA | 95.92% |
| Urban G et al. | 2018 | USA | AI_for_GI | NA | 8641 | 44947 | 8641 | 90% | NA | 99.5% |
| Misawa M et al. | 2021 | Japan | EndoBRAIN-EYE, Olympus | NA | NA | 56668 | NA | NA | NA | NA |
| Lee JY et al. | 2020 | Korea | | NA | NA | 8075 | 1338 | 96.7% | 89.8% | NA |
| Ozawa T et al. | 2020 | Japan | AI Medical Service Inc. | 4752 | 16418 | NA | 7077 | 92% | | NA |
| Jheng YC et al. | 2021 | Taiwan | GUTAID | NA | 7838 | NA | 1273 | 89.8% | NA | 96.8% |
| Weigt J et al. | 2021 | Italy | CAD-EYE,Fujifilm | 1132 | NA | >200000 | 680 | 92.9% (88.7–95.9) | NA | 90.6% (86.1–94) |

| Pure test sets: video frames | | | |
|---|---|---|---|
| video (examination), n | Sensitivity, overall | Specificity, overall | Sensitivity, superficial lesions |
| 77 | 75% (47.0–85.1) | 95% (89.4–98.1) | NA |
| 338 | 99.7% (per lesion) | NA | NA |
| 192 | 92% | 95% | NA |
| 9 | 93% | 93% | NA |
| 113 | 91% | 94% | 97% (84.7–99.9) (per lesion) |
| 15 | 89% | NA | NA |
| NA | NA | NA | NA |
| NA | NA | NA | NA |
| NA | NA | NA | NA |

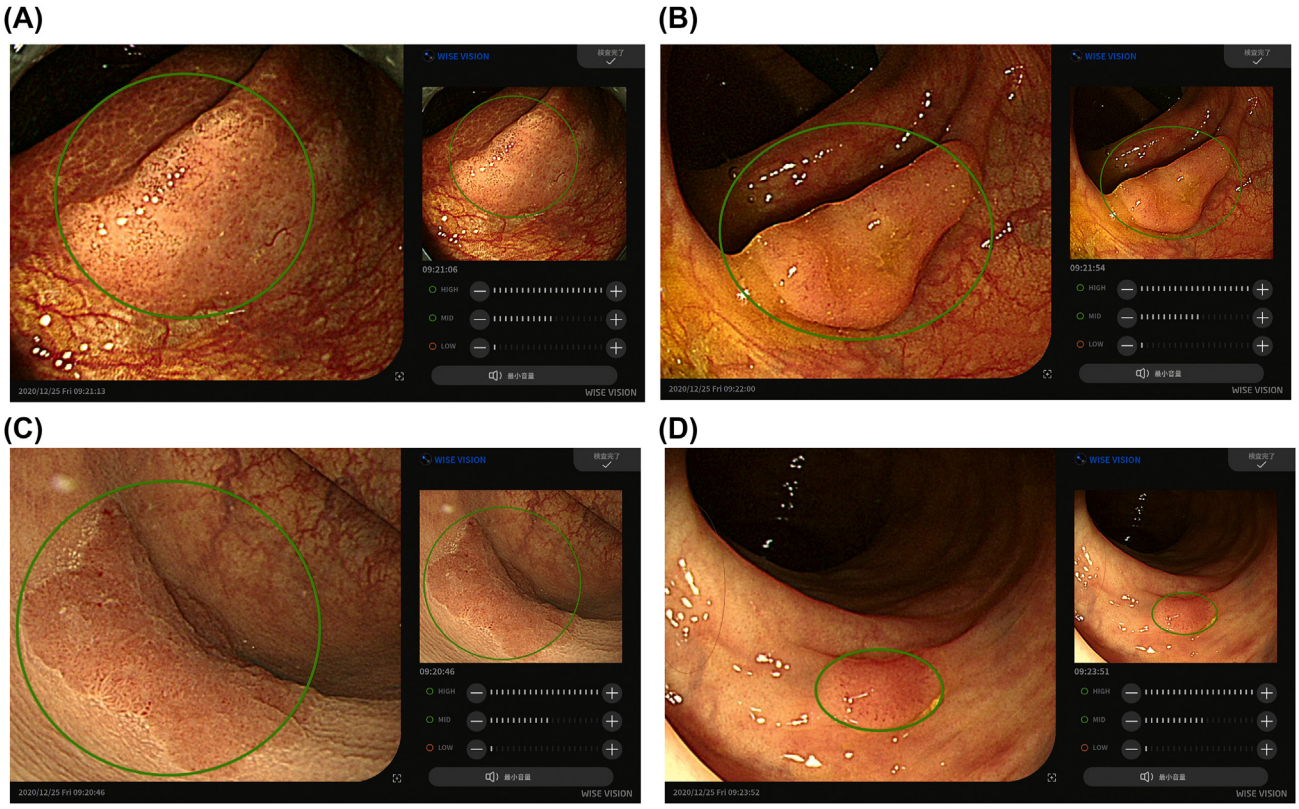


**Fig. 2.** Representative images of AI detection of flat and depressed lesions. A, B) sessile serrated lesion, C) laterally spreading tumor – nongranular type, D) superficial depressed lesion (0-IIc).

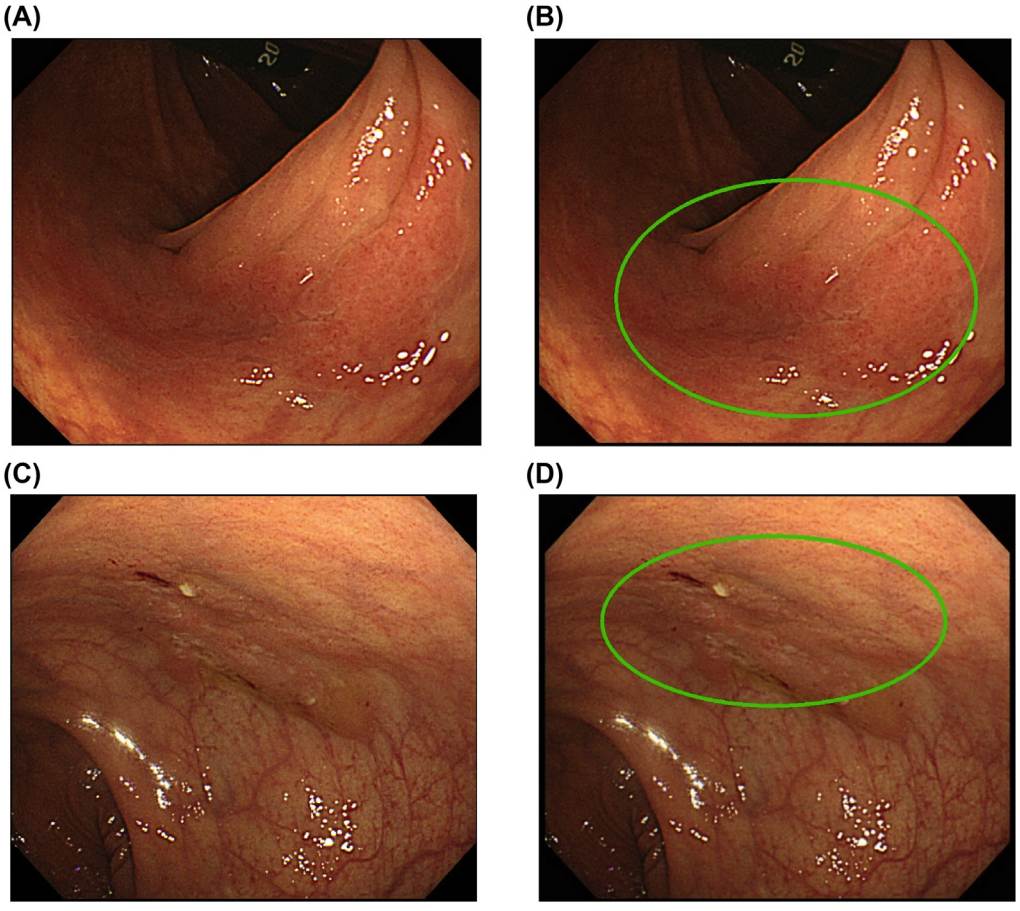


**Fig. 3.** AI detection for images of missed lesions. AI can detect these missed lesions. Therefore, this lesion may have been detected if the doctor used AI. A) missed laterally spreading tumor, nongranular type (high-grade dysplasia), B) A on AI, C) missed laterally spreading tumor, nongranular type (intramucosal cancer with signet ring cell carcinoma), D) C with AI.

**Table 2**
Clinical trials using a deep learning model for the detection of the colorectal neoplasm during colonoscopy.

| Author | Year of Publication | Country | AI system | Study Design | Indication of colonoscopy | number | | ADR | | PDR | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Control | CAD | Control | CAD | Control | CAD |
| Luo Y et al. | 2020 | China | Xiamen Innovision | back-to-back | NA | 150 | 150 | NA | NA | 34% (51/150) | 38.7% (58/150) |
| Wang P et al. | 2020 | China | EndoScreener | RCT | Screening 158 (16%)<br>Symptomatic 804 (84%) | 478 | 484 | 28% | 34%* | 37% | 52%* |
| Wang P et al. | 2019 | China | Shanghai Wision AI | RCT | Screening 84 (8%)<br>Symptomatic 974 (92%) | 536 | 522 | 20% | 29%* | 29% | 45%* |
| Wang P et al. | 2020 | China | NA | back-to-back | Screening 113 (31%)<br>Symptomatic 224 (61%)<br>Surveillance 32 (9%) | 369 | 369 | 26% | 35% | 38% | 56%* |
| Repici A et al. | 2020 | Italy | GI-Genius | RCT | FIT 207(30%)<br>Screening 153 (22%)<br>Surveillance 164 (24%)<br>Symptomatic 161 (24%) | 344 | 341 | 40% | 55%* | NA | NA |
| Gong D et al. | 2020 | China | ENDOANGEL | RCT | Screening 123 (18%)<br>Symptomatic 545 (77%)<br>Surveillance 36 (5%) | 349 | 355 | 8% | 16%* | 34% | 47%* |
| Liu P et al. | 2020 | China | EndoScreener | RCT | Screening 182 (23%)<br>Symptomatic 608 (77%) | 397 | 393 | 21% | 29%* | 33% | 47%* |
| Su JR et al. | 2020 | China | AQCS | RCT | Screening/surveillance 216 (35%)<br>Symptomatic 407 (65%) | 315 | 308 | 17% | 29%* | 25% | 38%* |

| Detected flat polyps | | Withdrawal time | |
|---|---|---|---|
| Control | CAD | Control | CAD |
| 76% (61/80) | 83%* (87/105) | 370.15 ± 31.44 | 373.17 ± 33.37 |
| 91% (279/308) (sessile) | 94%* (473/501) (sessile) | 6.99 (1.57) | 7.46* (2.02) |
| 49% (133/269) | 55%* (273/498) | 6.39 (1.21) | 6.89* (1.79) |
| AMR of non-peduncurated 42% (33–52) | 14%* (8–20) | 7.14 (5.5–8.8) | 7.85* (5.5–10) |
| Nonpolypoid lesion detected rate 18% | 27%* | 435 ± 149 | 417* ±101 |
| NA | NA | 4.76 (2.54) | 6.38* (2.48) |
| 89% (182/204) (sessile) | 95%* (398/421) (sessile) | 6.94 (1.53) | 7.29 (1.98) |
| 49% (47/96) | 47%* (84/177) | 5.68 ± 1.26 | 7.03* ±1.01 |

AMR, adenoma miss rate; *, $P < 0.05$.

In clinical practice, elevated lesions, particularly pedunculated lesions, can be detected easily even by novice colonoscopists. Therefore, it will be important and expected that AI can accurately detect flat lesions that are characteristic of interval cancer [29–31]. Adenoma detection rate (ADR) and flat lesion detection rate are well-known quality indicators of colonoscopy, and AI needs to accurately detect flat lesions and we need to update the AI performance so that we can provide safe and high-quality colonoscopies in the world.

## Clinical trials of deep learning technology in colonoscopy

AI system is used by humans; therefore, it is necessary to compare the difference in diagnostic ability between endoscopists those who use AI, and those who do not, rather than AI vs. doctor. Regarding the clinical trials of deep learning models for colorectal lesion detection, many clinical trials have been reported recently, and the representative ones are introduced here (Table 2). There were 8 reported clinical trials and the median difference of ADR between the CADe group and control group was 14% (13%–18%) [32–39]. All but one clinical trial showed significantly high ADR than the control group. PDRs are all significantly high in the CADe group than in the control group. Interestingly, the CADe group detected significantly high flat lesions than the control group in all seven studies. Therefore, it is considered that the detection of flat lesions is improved by using AI support as demonstrated by the data. However, withdrawal time excluding biopsy time was significantly longer than that for the control group in the six studies.

## Future view

Because of the deep learning research conducted thus far, a large amount of high-quality supervised data are still required. In deep learning, it is important to balance the amount of training data between each category and to improve the performance of the learning model. It is necessary to prepare images not only similar to lesions with low accuracy, but also those similar to lesions with high accuracy as further training data. Therefore, it is difficult to improve the diagnostic accuracy of AI for rare lesions. A new learning method that enables the reduction of supervised data is demanding. Independent pure-test sets are also very important in this research field.

In April 2018, the Food and Drug Administration (FDA) approved AI medical devices using deep learning to diagnose diabetic retinopathy – for the first time. Approval was based on the fact that diabetic retinopathy could be diagnosed with a sensitivity of 87.4% and a specialty of 89.5% in a clinical trial, and it went beyond the "support" of human diagnosis. This is the first product approved and permitted by the FDA to provide examination results even if the doctor did not interpret the image results. It is considered that discussions on whether to approve an AI system beyond the diagnostic "support" and necessary data will continue across the world.

**Practice points**

1) Flat colorectal lesions are likely to account for the majority of post-colonoscopy interval cancer.
2) Inexperienced endoscopists are less sensitive in detecting flat colorectal neoplasia.
3) Artificial intelligence shows a preliminary high accuracy for flat colorectal neoplasia in artificial studies, and it seems to increase its detection in comparative studies.

**Research agenda**

1) The benefit of AI in the additional detection of flat lesions with advanced neoplasia.
2) The accuracy of AI in the characterization of flat neoplasia, especially with regard to submucosal invasion.
3) The value of AI in addressing the choice between en bloc and piecemeal endoscopic resection or surgery for large or advanced flat lesions.

## Declaration of competing interest

None.

## Acknowledgment

This paper is partially funded by JST CREST Grant Number JPMJCR1689, Japan, AMED under Grant Number JP16ck0106028, and The National Cancer Center Research and Development Fund (30-A-9).

## References

[1] Hamashima C, Shabana M, Okada K, Okamoto M, Osaki Y. Mortality reduction from gastric cancer by endoscopic and radiographic screening. Canc Sci 2015;106:1744–9.
[2] Jun JK, Choi KS, Lee HY, Suh M, Park B, Song SH, et al. Effectiveness of the Korean national cancer screening program in reducing gastric cancer mortality. Gastroenterology 2017;152:1319–13128 e7.
[3] Winawer SJ, Zauber AG, Ho MN, O'Brien MJ, Gottlieb LS, Sternberg SS, et al. Prevention of colorectal cancer by colonoscopic polypectomy. The national polyp study workgroup. N Engl J Med 1993;329:1977–81.
[4] Zauber AG, Winawer SJ, O'Brien MJ, Lansdorp-Vogelaar I, van Ballegooijen M, Hankey BF, et al. Colonoscopic polypectomy and long-term prevention of colorectal-cancer deaths. N Engl J Med 2012;366:687–96.
[5] Yamada M, Sakamoto T, Otake Y, Nakajima T, Kuchiba A, Taniguchi H, et al. Investigating endoscopic features of sessile serrated adenomas/polyps by using narrow-band imaging with optical magnification. Gastrointest Endosc 2015;82:108–17.
[6] Yamada M, Saito Y, Sakamoto T, Nakajima T, Kushima R, Parra-Blanco A, et al. Endoscopic predictors of deep submucosal invasion in colorectal laterally spreading tumors. Endoscopy 2016;48:456–64.
[7] Yamada M, Saito Y, Takamaru H, Sasaki H, Yokota T, Matsuyama Y, et al. Long-term clinical outcomes of endoscopic submucosal dissection for colorectal neoplasms in 423 cases: a retrospective study. Endoscopy 2017;49:233–42.
[8] Rex DK, Cutler CS, Lemmel GT, Rahmani EY, Clark DW, Helper DJ, et al. Colonoscopic miss rates of adenomas determined by back-to-back colonoscopies. Gastroenterology 1997;112:24–8.
[9] Yamada M, Saito Y, Imaoka H, Saiko M, Yamada S, Kondo H, et al. Development of a real-time endoscopic image diagnosis support system using deep learning technology in colonoscopy. Sci Rep 2019;9:14465.
[10] Kudo SE, Ichimasa K, Villard B, Mori Y, Misawa M, Saito S, et al. Artificial intelligence system to determine risk of T1 colorectal cancer metastasis to lymph node. Gastroenterology 2021;160:1075–10784 e2.
[11] McCarthy JF, Marx KA, Hoffman PE, Gee AG, O'Neil P, Ujwal ML, et al. Applications of machine learning and high-dimensional visualization in cancer detection, diagnosis, and management. Ann N Y Acad Sci 2004;1020:239–62.
[12] Hamamoto R, Suvarna K, Yamada M, Kobayashi K, Shinkai N, Miyake M, et al. Application of artificial intelligence technology in oncology: towards the establishment of precision medicine. Cancers 2020;12.
[13] Hinton GE, Osindero S, Teh YW. A fast learning algorithm for deep belief nets. Neural Comput 2006;18:1527–54.
[14] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521:436–44.
[15] Zaid Alyafeai LG. A fully-automated deep learning pipeline for cervical cancer classification. Expert Syst Appl 2020;141:112951.
[16] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017;542:115–8.
[17] Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. J Am Med Assoc 2016;316:2402–10.
[18] Jinnai S, Yamazaki N, Hirano Y, Sugawara Y, Ohe Y, Hamamoto R. The development of a skin cancer classification system for pigmented skin lesions using deep learning. Biomolecules 2020;10.
[19] Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60–88.
[20] Ehteshami Bejnordi B, Veta M, Johannes van Diest P, van Ginneken B, Karssemeijer N, Litjens G, et al. Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer. J Am Med Assoc 2017;318:2199–210.
[21] Hassan C, Wallace MB, Sharma P, Maselli R, Craviotto V, Spadaccini M, et al. New artificial intelligence system: first validation study versus experienced endoscopists for colorectal polyp detection. Gut 2020;69:799–800.
[22] Urban G, Tripathi P, Alkayali T, Mittal M, Jalali F, Karnes W, et al. Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy. Gastroenterology 2018;155:1069–10678 e8.
[23] Misawa M, Kudo SE, Mori Y, Hotta K, Ohtsuka K, Matsuda T, et al. Development of a computer-aided detection system for colonoscopy and a publicly accessible large colonoscopy video database (with video). Gastrointest Endosc 2021;93:960–967 e3.
[24] Lee JY, Jeong J, Song EM, Ha C, Lee HJ, Koo JE, et al. Real-time detection of colon polyps during colonoscopy using deep learning: systematic validation with four independent datasets. Sci Rep 2020;10:8379.
[25] Ozawa T, Ishihara S, Fujishiro M, Kumagai Y, Shichijo S, Tada T. Automated endoscopic detection and classification of colorectal polyps using convolutional neural networks. Therap Adv Gastroenterol 2020;13. 1756284820910659.
[26] Jheng YC, Wang YP, Lin HE, Sung KY, Chu YC, Wang HS, et al. A novel machine learning-based algorithm to identify and classify lesions and anatomical landmarks in colonoscopy images. Surg Endosc 2021.
[27] Weigt J, Repici A, Antonelli G, Afifi A, Kliegis L, Correale L, et al. Performance of a new integrated CADe/CADx system for detection and characterization of colorectal neoplasia. Endoscopy 2021.
[28] Wang P, Xiao X, Glissen Brown JR, Berzin TM, Tu M, Xiong F, et al. Development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy. Nat Biomed Eng 2018;2:741–8.
[29] le Clercq CM, Sanduleanu S. Interval colorectal cancers: what and why. Curr Gastroenterol Rep 2014;16:375.
[30] Samadder NJ, Curtin K, Tuohy TM, Pappas L, Boucher K, Provenzale D, et al. Characteristics of missed or interval colorectal cancer and patient survival: a population-based study. Gastroenterology 2014;146:950–60.
[31] Kaminski MF, Regula J, Kraszewska E, Polkowski M, Wojciechowska U, Didkowska J, et al. Quality indicators for colonoscopy and the risk of interval cancer. N Engl J Med 2010;362:1795–803.
[32] Luo Y, Zhang Y, Liu M, Lai Y, Liu P, Wang Z, et al. Artificial intelligence-assisted colonoscopy for detection of colon polyps: a prospective, randomized cohort study. J Gastrointest Surg 2020.
[33] Wang P, Liu X, Berzin TM, Glissen Brown JR, Liu P, Zhou C, et al. Effect of a deep-learning computer-aided detection system on adenoma detection during colonoscopy (CADe-DB trial): a double-blind randomised study. Lancet Gastroenterol Hepatol 2020;5:343–51.
[34] Wang P, Berzin TM, Glissen Brown JR, Bharadwaj S, Becq A, Xiao X, et al. Real-time automatic detection system increases colonoscopic polyp and adenoma detection rates: a prospective randomised controlled study. Gut 2019;68:1813–9.
[35] Wang P, Liu P, Glissen Brown JR, Berzin TM, Zhou G, Lei S, et al. Lower adenoma miss rate of computer-aided detection-assisted colonoscopy vs routine white-light colonoscopy in a prospective tandem study. Gastroenterology 2020;159:1252–12561 e5.
[36] Repici A, Badalamenti M, Maselli R, Correale L, Radaelli F, Rondonotti E, et al. Efficacy of real-time computer-aided detection of colorectal neoplasia in a randomized trial. Gastroenterology 2020;159:512–520 e7.
[37] Gong D, Wu L, Zhang J, Mu G, Shen L, Liu J, et al. Detection of colorectal

adenomas with a real-time computer-aided system (ENDOANGEL): a randomised controlled study. Lancet Gastroenterol Hepatol 2020;5:352–61.
[38] Liu P, Wang P, Glissen Brown JR, Berzin TM, Zhou G, Liu W, et al. The single-monitor trial: an embedded CADe system increased adenoma detection during colonoscopy: a prospective randomized study. Therap Adv Gastroenterol 2020;13. 1756284820979165.
[39] Su JR, Li Z, Shao XJ, Ji CR, Ji R, Zhou RC, et al. Impact of a real-time automatic quality control system on colorectal polyp and adenoma detection: a prospective randomized controlled study (with videos). Gastrointest Endosc 2020;91:415–424 e4.