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Application of artificial intelligence in colorectal cancer screening by colonoscopy: Future prospects (Review)

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Abstract. Colorectal cancer (CRC) has become a severe global health concern, with the third-high incidence and second-high mortality rate of all cancers. The burden of CRC is expected to surge to 60% by 2030. Fortunately, effective early evidence-based screening could significantly reduce the incidence and mortality of CRC. Colonoscopy is the core screening method for CRC with high popularity and accuracy. Yet, the accuracy of colonoscopy in CRC screening is related to the experience and state of operating physicians. It is challenging to maintain the high CRC diagnostic rate of colonoscopy. Artificial intelligence (AI)-assisted colonoscopy will compensate for the above shortcomings and improve the accuracy, efficiency, and quality of colonoscopy screening. The unique advantages of AI, such as the continuous advancement of high-performance computing capabilities and innovative deep-learning architectures, which hugely impact the control of colorectal cancer morbidity and mortality expectancy, highlight its role in colonoscopy screening.

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Abbreviations: CRC, colorectal cancer; USPSTF, U.S. Preventive Services Taskforce; AI, artificial intelligence; ADR, adenoma detection rate; ML, machine learning; DL, deep learning; CADe, computer-aided detection

Key words: colorectal cancer, artificial intelligence, colonoscopy, CADe, CADx, prospect

Contents

1. Introduction

Colorectal cancer (CRC) has become a worldwide public health problem with a high incidence and mortality (1). By 2030, an extra 2.2 million new cases of CRC and 1.1 million cancer-related deaths are expected, representing a 60% increased burden of CRC.

The early symptoms of CRC are not obvious. Notably, >85% of patients with CRC are diagnosed at an advanced stage. However, when the optimal treatment window is missed, the survival time and quality of life for patients with advanced CRC are significantly reduced, resulting in a 5-year survival rate of <40% (2). By contrast, the 5-year survival rate of patients with CRC with early-stage disease after treatment is as high as 95%.

The prognosis of patients with CRC largely depends on the stage of the disease at first diagnosis. In most cases, CRC cases are sporadic and transform from adenomas (3), and the transition from adenoma to CRC typically spans several years. Detecting and removing adenomas at an early stage can effectively impede their progression to CRC, thus reducing the incidence of the disease (4,5). Moreover, accurate, evidence-based screening could significantly decrease the morbidity and mortality of CRC. Furthermore, early screening can improve the clinical outcomes of patients, avoid treatment delays, and reduce CRC mortality (6).

The U.S. Preventive Services Task Force (USPSTF) strongly advocates for CRC screening for precise diagnosis (7). Among the available methods, colonoscopy stands out as the primary screening approach due to its widespread use and high accuracy. In addition, the USPSTF recommends that colonoscopy be performed promptly, as colonoscopy can significantly reduce the incidence and mortality of CRC (8). However, it is imperative to acknowledge that colonoscopy does have certain limitations. One such limitation is the reliance on the skill level of the endoscopic physicians for diagnostic accuracy, which can vary among practitioners. Ensuring that each patient undergoes an examination by a highly skilled endoscopist can be challenging.

Artificial intelligence (AI) refers to the ability of machines to imitate human cognitive functions and perform tasks at or above the human level using a clever combination of computer science, algorithms, machine learning (ML), and data science. In recent years, advances in AI have permeated medicine, rapidly changing the way cancer research is conducted. Research has shown that AI-aided colonoscopy can enhance screening accuracy, efficiency, and quality (9). The availability of high-dimensional datasets, continuous advances in high-performance computing power, and innovative deep-learning architectures have all led to a rapidly emerging role for AI in CRC screening.

The combination of AI technology and colonoscopy holds great promise for controlling the morbidity and mortality of CRC. Therefore, the aim of the present review was to examine the advantages and limitations of colonoscopy while focusing on the application of AI-aided colonoscopy, providing a theoretical foundation for developing precise CRC screening.

2. Premalignant lesions of CRC and screening modalities

Colorectal polyps are protrusions occurring in the colorectal lumen, which can be divided into neoplastic and non-neoplastic polyps (Table I). Pathologically, neoplastic polyps can be classified as adenomatous and serrated polyps, and non-neoplastic polyps include inflammatory-associated polyps, hamartomatous polyps and hyperplastic polyps (10,11). Adenomatous polyps include three histological types: Tubular, tubulovillous, and villous (11). Conversely, serrated class lesions are a heterogeneous group of lesions that can be further classified into three categories: Hyperplastic polyps (HPs), sessile serrated lesions (SSPs), and traditional serrated adenomas (TSAs) (Table I). The carcinogenesis process of CRC involves four pathways: Adenoma-carcinoma, serrated neoplastic, inflammatory, and *de novo* (12,13). The first two pathways account for the vast majority of cases and arise from colorectal polyps. The conventional adenoma-carcinoma pathway leads to 70% of sporadic CRC cases (14), whereas the serrated neoplastic pathway accounts for 15-30% of CRC cases.

High-sensitivity Guaiac fecal occult blood test, fecal immunochemical test, multi-target fecal DNA, computed tomography colonography (CTC), colonoscopy, and other methods are currently the CRC screening methods recommended by the USPSTF (7,8,15). The diagnostic accuracy and effectiveness of visual screening (CTC, flexible sigmoidoscopy, and colonoscopy) are far higher than those of stool-based screening due to their ability to directly observe lesions (6,16-25). Compared to stool-based CRC screening, a colonoscopy may have lower in-patient compliance and frequency, yet it remains significantly more accurate in detecting colorectal lesions (26). This procedure allows for direct detection, biopsy, and removal of polyps during visual assessment of the entire colon. Colonoscopy has several benefits, including high sensitivity and specificity, and enables direct biopsy or excision of suspected polyps. As a result, the USPSTF has indicated that colonoscopy has the highest validity and popularity among CRC screening methods (8).

3. Colonoscopy in CRC screening

Colonoscopy is the most reliable form of CRC screening. According to a large, prospective observational study that included nearly 89,000 nurses and other health professionals, the CRC mortality rate was lower in people who self-reported at least one screening colonoscopy than in those who had never undergone a colonoscopy (27). Furthermore, the USPSTF included four studies (n=4,821) evaluating the accuracy of colonoscopy in 2021, demonstrating that for adenomas ≥10 mm, colonoscopy had a sensitivity of 89-95% and a specificity of 89%. Additionally, for adenomas ≥6 mm, colonoscopy had a sensitivity of 75-93% and a specificity of 94% (8). These results further support the high accuracy and specificity of colonoscopy.

Although colonoscopy is considered the 'gold standard' screening test, it does have its limitations (28). The challenge of endoscopic procedures lies in the real-time interpretation of endoscopic imagery, which is complex and sensitive to human error. Consequently, subtle, and early premalignant lesions in the colon and rectum can easily be missed by endoscopists. A systematic review (29) showed that the rate of missed adenomas on colonoscopy was 26%, and this was 9% for advanced adenomas and up to 27% for serrated polyps. A prospective study of individuals who underwent screening colonoscopy within a National Colorectal Cancer Screening Program associated an increased adenoma detection rate (ADR) with a reduced risk of post-colonoscopy colorectal cancer and colorectal cancer death. Notably, ADRs are negatively associated with CRC incidence, with each 1% increase in ADR associated with a 3-6% reduction in the risk of colorectal cancer (30). By contrast, a higher rate of missed adenoma detection inevitably increases the risk of colorectal cancer.

It is important to acknowledge that colonoscopy does not always detect colorectal cancer, and some patients may develop CRC even after receiving a negative examination result. When this occurs before the next recommended screening or surveillance examination, it is called interval cancer. However, the term 'interval cancer' is considered too restrictive to encompass all aspects necessary for colonoscopy quality assurance purposes. To address this, Rabeneck and Paszat introduced the term 'post-colonoscopy colorectal cancer' (PCCRC) in 2010 (31), defined as colorectal cancer not detected by screening or surveillance examinations and occurring before the recommended next examination date (32).

Colonoscopy, despite being a valuable screening tool, is not infallible and can potentially miss early or advanced non-characteristic lesions, leading to the risk of PCCRC (32). Studies have indicated a prevalence of PCCRC ranging from 3.7 to 8.6% following colonoscopy screening (33,34). However, failure to detect colorectal neoplasia remains the most relevant cause of PCCRC (35). It can be observed from research that an improvement in the ADR during screening colonoscopy, achieved through a comprehensive quality assurance program, translates into reduced risks of post-colonoscopy colorectal cancer. Specifically, an ADR of a suboptimal endoscopist

Table I. Colorectal polyps.

Neoplastic polyps	Adenomatous polyps	Tubular adenoma
		Tubulovillous adenoma
		Villous adenoma
	Serrated class lesions	Hyperplastic polyp
		Sessile serrated lesions
		Traditional serrated adenomas
Non-neoplastic polyps	Inflammatory-associated polyps	Inflammatory polyps
		Lymphoid polyps
		Schistosoma polyps
	Hamartomatous polyp	Juvenile polyps
		Peutz-Jeghers polyps
		Cowden syndrome-associated polyps
		Canada-Cronkhite syndrome-associated polyps
	Hyperplastic polyps	N/A

has been associated with a substantial increase in the risk of post-colonoscopy colorectal cancer incidence, whereas an ADR increase was effective in reversing this detrimental effect (36). Undoubtedly, high-quality colonoscopy will improve the diagnostic accuracy of adenoma and CRC lesions, which is crucial for re-sectioning precancerous lesions and preventing CRC (37).

AI has the potential to identify colorectal polyps or CRC lesions that have gone undetected due to perceptual errors. A multicenter and multi-county randomized crossover trial showed that AI resulted in an ~50% reduction in the miss rate of colorectal neoplasia. This finding highlights the potential of AI in mitigating perceptual errors associated with small and subtle lesions during standard colonoscopy (38). Consequently, combining colonoscopy and AI may be a potential future development direction.

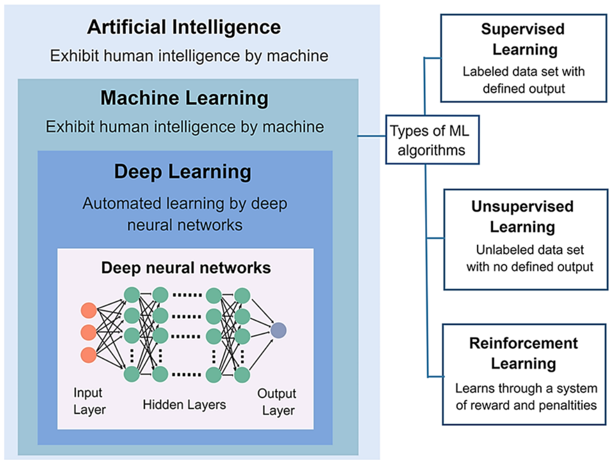

Figure 1. Relationship between artificial intelligence, machine learning and deep learning and commonly used algorithms as examples. ML, machine learning.

4. Artificial intelligence applications in colonoscopy screening

AI is a generic term broadly referring to utilizing computers to model intelligent behavior with minimal human intervention (39). ML is a subfield of AI that is capable of analyzing data through algorithms to take particular actions in response to specific inputs and improve ('learn') themselves as more data becomes available, i.e., 'train' (40). Supervised, unsupervised, and reinforcement learning are three machine-learning algorithm categories. Deep learning (DL) is an essential subfield of ML that 'learns' from large data sets of raw images, leading to higher accuracy and faster processing speeds when performing image recognition, as this process does not require 'instructions' to find specific image features (Fig. 1). Convolutional neural networks (CNNs), a classical branch of DL, are frequently employed in medical image analysis (41). Thus far, these methods have gradually penetrated the medical field with substantial success (42).

Numerous studies combining clinical and DL have emerged in oncology screening in recent years. These studies have utilized detection images and videos of colonoscopies or pathological images of tumor tissues as input data to train models with the help of ML (43). The aim was to assist in the diagnosis and efficacy determination of clinical tumors with the assistance of models to achieve efficient precision medicine (Fig. 2) (44). The combination of colonoscopy and AI has also been realized using computer algorithms.

Colonoscopy has established itself as the preferred diagnostic modality for CRC due to its promising clinical results and wide range. Unfortunately, due to challenges such as inter-observer variability in lesion detection, time-consuming biopsy protocols, and biopsy sampling errors (45), a substantial fluctuation in the ADR remains present (7-53%) (46), and the adenoma miss rate may be as high as 26% (29). Numerous studies have indicated that endoscopists may achieve improved discrimination between premalignant lesions and hyperplastic polyps through a combination of AI and colonoscopy. The integration of both has contributed to an elevated ADR (9) and markedly reduced CRC morbidity and mortality (47-50). Therefore, this review focuses on AI-aided colonoscopy,

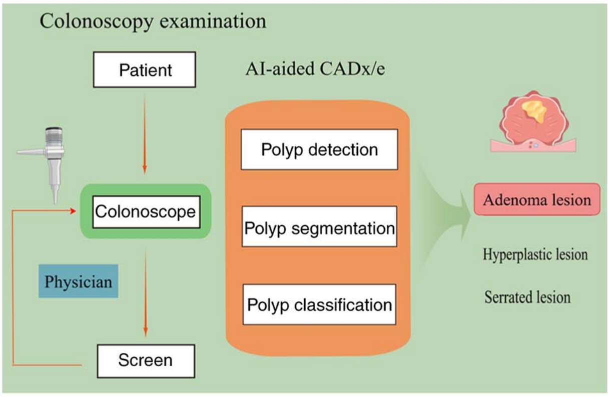

Figure 2. AI-aided CADx/e applications in a colonoscopy examination. AI, artificial intelligence; CADx/e, computer-aided detection/diagnosis.

the most promising and efficient CRC screening method in clinical settings.

Computer-aided detection (CADe) model. The concept of a CADe model was established in 2003 (51). This system supports the diagnosis of CRC and detection of premalignant polyps by processing endoscopic images or video frame sequences obtained during colonoscopy (52-58) (Table II). Karkanis *et al* (52) designed a CADe model based on color and texture analysis of the intestinal mucosal surface. This model had excellent sensitivity up to 99.3±0.3%, and specificity up to 93.6±0.8% in detecting abnormal colon regions associated with adenomas. However, the CADe model identifies polyps based on static colonoscopy images rather than real-time analysis of each image frame in the colonoscopy video, limiting its clinical practicality. To address this, AI models for automatically detecting polyps using a series of different imaging feature quantities (such as edge detection, texture analysis, and energy mapping) have been under investigation (52). Nevertheless, none of these methods have achieved a reliable detection rate of ≥90%, and real-time diagnosis has been hindered by computational power limitations (59). It was not until the advent of neural networks (NNs) that significant improvements in this situation began to unfold.

NN algorithms have emerged and been proven to detect and localize polyps automatically (60), thus improving the accuracy and sensitivity of the CADe model for diagnosing polyps and CRC lesions. In 2018, Misawa *et al* (53) developed a convolutional 3D NN algorithm based on the CADe model, reporting that the model had a sensitivity of 90.0% and a specificity of 63.3% for screening polyps. In 2019, Yamada *et al* (54) developed a CADe model based on deep neural networks (DNNs) and validated it using 705 static images containing cancerous lesions and 4,135 static images of normal tissues from 752 patients with CRC. The results were highly promising, with the CADe model exhibiting exceptional diagnostic accuracy for CRC, with a sensitivity of 97.3% and a specificity of 99.0%.

Previous prospective studies focusing on the real-time performance of CADe models have been limited. However, in 2019, Wang *et al* conducted the first prospective unblinded randomized controlled trial to investigate the impact of DL-based CADe models on the accuracy of colorectal screening for polyps and adenomas (55). A statistically significant increase in the ADR was observed with the aid of CADe compared to colorectal screening alone (29.1 vs. 20.3%; P<0.001). Furthermore, colonoscopy detected more diminutive adenomas using the CADe model than using colonoscopy alone (185 vs. 102; P<0.001). However, the study was unable to control the subjective bias of the operating physicians since they were not blinded to the CADe system. This could have influenced their vigilance or reliance on the CADe system, potentially overestimating or underestimating its effectiveness. To address this issue, Wang *et al* conducted a double-blind, randomized controlled trial (56) in 2020, using a 'dummy system' that completely mimicked the false alarm of the AI system without suggesting true polyps. The operating physicians were double-blinded, allowing for a more rigorous assessment of the effectiveness of the CADe system in improving the detection rate of colonic adenomas and polyps. This study demonstrated a significant increase of 23.4% in the ADR, from 27.6 to 34.1%, and a considerable increase in polyp detection rate (PDR) in the CADe group compared to the control group. The study also confirmed that a high-performance, real-time CADe model could effectively enhance the detection rate of adenomas and colorectal polyps, which may contribute to a lower prevalence of CRC. In addition, the present study revealed a marked improvement in the number of hyperplastic polyps detected in the CADe group compared with the control group (114 vs. 52; P<0.001). This finding may contribute to clinically reducing unnecessary polyp removal, thus avoiding additional treatment risks such as perforation and massive bleeding (61).

Negligence by endoscopists is responsible for a significant percentage (71-86%) of interstitial colorectal cancers (7,62). One of the main contributing factors to this negligence is the challenge faced by physicians in maintaining a standardized withdrawal time during long procedures under high work pressure. In order to address this issue, Gong *et al* (57) developed a CADe system based on DNNs and perceptual hashing algorithms. By performing real-time monitoring of the withdrawal speed, recording of the withdrawal time, and alerting when the colonoscope slips, the system provided normative feedback to the endoscopist. However, in contrast to other AI-assisted systems, this system does not improve the ADR by automatically examining polyps; instead, its primary objective is to enhance technical elements of the procedure to achieve improvement. The results revealed that the CADe group had a prolonged mean negative withdrawal time (6.38 vs. 4.76 min) and an ~100% enhancement in the ADR (16.34 vs. 7.74%) compared to the colonoscopy-only group. These findings surpass previous reports and indicate the practicality of improving the PDR and ADR by standardizing endoscopist practices through the implementation of the CADe system.

An AI-aided polyp detection system has shown a significant increase in the detection rate of lesions, and the ability of AI to detect lesions is not significantly affected by factors such as size, location, and shape (63). Real-time AI-aided colonoscopy has the potential to improved ADR even for experienced endoscopists (64). Therefore, high-quality clinical data are urgently required to demonstrate the effectiveness and accuracy of AI-assisted endoscopy.

Table II. Summary of studies on colonoscopy combined with CADe.

Authors, year	Study design	CADe model	Image type	Conclusion	(Refs.)
Karkanis *et al*, 2003	Retrospective study	CADe model for color and texture analysis of mucosal surfaces based on CWC features	Static images	Sensitivity, 99.3±0.3%	(52)
Misawa *et al*, 2018	Retrospective study	CNN-based CADe model	Colonoscopy video	Sensitivity, 90.0%	(53)
Urban *et al*, 2018	Retrospective study	CNN-based CADe model	Colonoscopy video	Sensitivity, 93.0%	(58)
Yamada *et al*, 2019	Retrospective study	DNN-based CADe model	Colonoscopy video	Sensitivity, 97.3%	(54)
Wang *et al*, 2019	Unblinded prospective randomized controlled trial	DL-based CADe model	Colonoscopy video	ADR in CADe group vs. standard colonoscopy group: 29.1 vs. 20.3f	(55)
Wang *et al*, 2020	Double-blind prospective randomized controlled trial	DL-based CADe model	Colonoscopy video	ADR in CADe group vs. control group: 34.1 vs. 28%	(56)
Gong *et al*, 2020	Single-blind prospective randomized controlled trial	ENDOANGEL system based on DNN and perceptual hash algorithm	Colonoscopy video	ADR in ENDOANGEL group vs. standard colonoscopy group: 16.34 vs. 7.74%	(57)

CADe, computer-assisted detection system; CWC, color wavelet covariance; CNN, convolutional neural network; DNN, deep learning neural network; DL, deep learning; ADR, adenoma detection rate.

Recently, a review highlighted the approval of the first AI-guided polyp detection system by the U.S. Food and Drug Administration (65). The GI Genius™ (Medtronic, Ltd.) system is a CADe system that integrates existing endoscopy systems and improves adenoma detection during colonoscopy. However, while the system shows promise in improving adenoma detection, it is essential to assess its actual impact on colorectal cancer prevention through large-scale population-based studies. A study called COLO-DETECT will be the first multi-center randomized controlled trial evaluting the GI Genius™ in real-world colonoscopy practice and will be unique in evaluating its clinical and cost effectiveness (66). The results will significantly impact the future adoption of this novel technology.

Computer-aided diagnosis (CADx) model. Recently, the European Society of Gastrointestinal Endoscopy (ESGE) published an official position statement aiming to define simple, safe, and easy-to-measure competence standards for endoscopists and AI systems performing optical diagnosis of diminutive colorectal polyps (67). In this regard, CADx has shown great potential in improving the accuracy of colorectal polyp characterization (61,68-74) (Table III). CADx systems may improve the accuracy of colorectal polyp optical diagnosis, leading to a reduction in the unnecessary removal of hyperplastic polyps. Moreover, CADx could help implement cost-saving strategies in colonoscopy by reducing the burden of polypectomy and pathology. In other words, its application facilitates the implementation of resect-and-discard (when polyps are resected and discarded without histological evaluation) and 'leave-in-situ' (when non-neoplastic lesions located in the rectum and sigmoid are left *in situ* without resection, as they have no malignant potential) strategies (75,76). Furthermore, the study conducted by Hassan *et al* confirmed that a real-time CADx system has the potential to reduce all polypectomies and related costs by 44.4% in the study population (77), highlighting the significant cost-saving benefits of this technology.

In contrast to CADe, in which only observation under normal white light is possible, CADx is available not only with white-light endoscopy (77,78) but also in combination with a variety of other optical imaging techniques, including magnifying narrow-band imaging (NBI) (68), linked-color imaging (LCI) (69), blue-light imaging (BLI) (79), and autofluorescence imaging (AFI) (70). Among these, studies on CADx and NBI are the most extensive. As an advanced endoscopic imaging method, NBI provides excellent visualization, can evaluate mucosal surfaces and microvascular structures, and is an excellent tool that can differentiate between neoplastic and non-neoplastic lesions (80). In 2010, Tischendorf *et al* (71) developed a CADx model that applied NBI and was capable of aiding the classification of colorectal polyps based on three

Table III. Summary of studies on colonoscopy combined with CADx.

Authors, year	Study design	Research objectives	Imaging modality	CADx model	CADx model performance	(Refs.)
Tischendorf *et al*, 2010	Prospective pilot study	Differentiation of neoplastic and non-neoplastic colorectal polyps	Magnifying NBI	SVM-based CADx	CADx: Sensitivity, 90%; Specificity, 70%; Accuracy, 85.3%	(71)
Gross *et al*, 2011	Prospective study	Differentiation between neoplastic and non-neoplastic colorectal polyps (≤10 mm)	Magnifying NBI	SVM-based CADx	-CADx group: Sensitivity, 93.4%; Specificity, 91.8%; Accuracy; 92.7% -Expert panel: Sensitivity, 93.8%; Specificity, 85.7%; Accuracy, 91.9% -Non-expert group: Sensitivity, 86%; Specificity, 87.8%; Accuracy, 86.8%	(72)
Aihara *et al*, 2013	Prospective study	Differentiation of neoplastic and non-neoplastic colorectal polyps	AFI	CADx based on AFE numerical olor analysis	Sensitivity, 83.3%; Specificity, 70.1%; PPV, 78.4%; NPV, 82.6%	(70)
Mori *et al*, 2018	Prospective study	Differentiation of small (≤5 mm) neoplastic and non-neoplastic colorectal polyps	Magnifying NBI	SVM-based CADx	Sensitivity, 92.7%; Specificity, 89.8%; PPV, 93.7%; NPV, 88.3%	(73)
Chen *et al*, 2018	Prospective study	Differentiation of small (≤5 mm) neoplastic and non-neoplastic colorectal polyps	Magnifying NBI	DL-based CADx	Sensitivity, 96.3%; Specificity, 78.1%; Accuracy, 90.1%; PPV, 89.6%; NPV, 91.5%	(61)
Min *et al*, 2019	Prospective study	Differentiation of adenomatous and non-adenomatous polyps	LCI	GMM-based CADx	Sensitivity, 83.3%; Specificity, 70.1%; Accuracy, 78.4%; PPV, 82.6%; NPV, 71.2%	(69)
Byrne *et al*, 2019	Retrospective study	Differentiation of small (≤5 mm) neoplastic and non-neoplastic colorectal polyps	Magnifying NBI	DCNN-based CADx	Sensitivity, 98%; Specificity, 83%; Accuracy, 94%; PPV, 90%; NPV, 97%	(68)

CADx, computer-aided diagnosis; NBI, narrow-band imaging; SVM, support vector machine; AFI, autofluorescence imaging; PPV, positive predictive value; NPV, negative predictive value; AFE, autofluorescence endoscope; LCI, linked-color imaging; DL, deep learning; GMM, Gaussian mixture model; DCNN, deep learning convolutional neural network.

vascular structural features: Mean vessel length, vessel circumference, and mean brightness as observed using NBI. However, the diagnostic accuracy of this model (85.3%) was markedly lower than that of endoscopic experts and barely meets the clinical needs of experts. In 2011, Gross *et al* (72) developed a CADx model to assist in classifying colorectal polyps through the analytical categorization of nine vessel characteristics (e.g., circumference and brightness). With this model, the sensitivity, specificity, and accuracy were 95, 90.3 and 93.1%, respectively. In addition, the diagnostic performance of this model was comparable to that of an endoscopic expert panel (93.4, 91.8 and 92.7% for sensitivity, specificity, and accuracy, respectively) and significantly better than that of a non-expert panel (86, 87.8 and 86.8% for sensitivity, specificity, and accuracy, respectively). However, these models lacked real-time diagnostic capabilities, highlighting the importance of incorporating real-time diagnosis into CADx technology for its practical application in clinical settings.

By constructing the CADx algorithm using real-time decision outputs from a support vector machine (SVM), the CADx algorithm has made significant progress in achieving real-time diagnosis capabilities (81-83). In 2018, Mori *et al* (73) provided further evidence supporting the use of an SVM-based CADx model for real-time assisted diagnosis in the NBI mode of diminutive colorectal polyps. Low- and high-grade adenomas are classified as neoplastic polyps; hyperplastic polyps, inflammatory polyps, juvenile polyps, and benign lymphoid polyps are considered non-neoplastic polyps (11). Therefore, with a sensitivity of 92.7% and specificity of 89.8%, this CADx model has sufficient potential to help endoscopists differentiate between neoplastic and non-neoplastic polyps during colonoscopy and to achieve the level of performance required for a 'leave-in-situ' strategy for patients with non-neoplastic polyps.

A CADx model has the capability to assist the endoscopist in differentiating between neoplastic and non-neoplastic polyps, allowing for the implementation of a 'leave-in-situ' strategy for non-neoplastic polyps. Additionally, it provides support in accurately grading neoplastic polyps for a 'resect-and-discard' approach. Min *et al* (68) designed a CADx model for predicting the pathological outcome (adenomatous vs. non-adenomatous) of colorectal polyps based on the results of image color assessments performed using LCI. Subsequently, it assisted the endoscopist in the selective resection of neoplastic colorectal polyps. The model exhibited a sensitivity of 83.3%, specificity of 70.1%, and accuracy of 78.4% in efficiently differentiating adenomatous from non-adenomatous polyps. These results are comparable to the accuracy achieved by endoscopic specialists (78.4 vs. 79.6%).

As a result of their technical shortcomings, traditional ML methods (such as SVMs) perform poorly when converting endoscopic images and video features into numerical data, leading to severe limitations in the development of CADx. However, the advent of DL has simplified the numerical conversion process of these features and substantially reduced their developmental hindrance. In 2018, Chen *et al* (61) developed a CADx model based on a DL algorithm that accurately classified small colorectal polyps (tumors or hyperplastic lesions). A total of 284 magnified NBI image samples of small colorectal polyps obtained from 193 patients were used to assess the diagnostic accuracy of this CADx model. The results showed that the model had a disease sensitivity of 96.3%, specificity of 78.1%, and accuracy of 90.1%. In addition, the algorithm enabled the discrimination between tumor and hyperplastic lesions in a shorter time than the time required by endoscopists and trainee endoscopists (0.45±0.07 vs. 1.54±1.30 vs. 1.77±1.37 sec), demonstrating its feasibility in clinical practice.

The CADx companion diagnostic results offer standardized and objective assessments independent of the expertise and experience of the endoscopist, reducing variations between beginners and experts. By utilizing CADx, the endoscopist can more easily make a qualitative diagnosis of the lesion and assess disease activity while maintaining a higher level of accuracy. However, the available data for most commercially available AI tools for lesion characterization remain inconclusive rather than definitive. The performance of CADx systems should be further evaluated in prospective randomized controlled trials conducted among both expert endoscopists and trainees to establish reliable data and evidence (84).

5. Future prospects

AI has garnered significant interest in healthcare, and its potential applications extend to various areas, including endoscopy. AI-aided colonoscopy has demonstrated promising accuracy in laboratory settings, and the performance of AI-aided diagnostic systems has been validated in prospective randomized controlled trials conducted in diverse healthcare settings, involving endoscopists with varying levels of experience (75,85). While the success of AI has been evident in small-sample trials, the challenge lies in its widespread implementation in clinical practice. Several issues need addressing before AI can be effectively integrated into daily practice.

Although several computer-aided colorectal polyp detection and diagnosis systems have been proposed for clinical applications, numerous remain susceptible to interference problems such as low image clarity, unevenness, and low accuracy in the analysis of dynamic images. These drawbacks affect the robustness and practicality of these systems (86). In this regard, an intraprocedural AI alert system for colonoscopy examination has been proposed using feature extraction and classification alongside a CNN model (87). This system can identify blurred images, instances of inadequate bowel cleansing, and instances of insufficient air insufflation during colonoscopy. Nevertheless, further clinical trials are required to verify whether this system can improve the detection rate of colorectal adenomas. Considering that the data of the study only comes from a single medical center (87), a large-scale prospective multicenter clinical trial is required to validate the efficacy of the proposed system in increasing the colon polyp detection rate.

In addition to the aforementioned challenges, the development, integration, and widespread implementation of AI models in clinical practice require significant investments in terms of time, resources, and expertise (88,89). Future studies should carefully consider the potential effects of these factors. For instance, constructing AI models requires entering numerous training and validation samples. Nevertheless, high-quality labeled samples are difficult to obtain in clinical settings, as these samples often contain numerous labeling errors, referred to as labeling noise or 'noisy labels' (90), which markedly decreases the accuracy of the model. In addition, AI training involves powerful computer configurations and long training times, and post-maintenance can be cumbersome. Clinicians, who are mostly non-specialists, can only assist in diagnosis based on predefined functions during clinical work. Therefore, it becomes difficult for doctors to update the database and algorithm when encountering new cases in clinics. These factors have greatly hindered the popularity and optimization of AI systems. Fortunately, these restrictions are gradually being overcome as a result of advances in computing power, increases in the number of digitally-stored medical images, and improvements in deep network (DPN) architecture. Future research should consider establishing an open data-sharing platform across multiple institutions to overcome these barriers. Appropriate data sharing would not only reduce competition among agencies but also alleviate the difficulties and costs associated with data access while enhancing data quality (91).

The current laws and regulations for newly developed AI tools by regulatory agencies are inadequate at this stage. Nonetheless, the situation is changing rapidly. In January 2021, the U.S. FDA released the first AI/ML-Based Software as a Medical Device (SaMD) Action Plan of the agency, which details several guidelines for AI implementation (92). However, refining the original legislation may not be sufficient to regulate AI in healthcare. It is crucial for lawmakers to engage in a collaborative process with computer scientists, clinicians, patients, professional associations, and health technology companies to establish a robust regulatory and legal framework for AI-based tools. This collaborative effort aims to ensure that AI tools meet acceptable standards of quality and safety.

From a clinical perspective, establishing trust in the clinical system is of utmost importance in AI-assisted decision-making (93). One crucial aspect in this regard is the stability of AI models. For clinical application, the AI model must withstand multiple fluctuations in the input data, such as operator-operator and laboratory-laboratory differences in data quality, resolution, intensity, and disease characteristics. However, most AI models have not demonstrated sufficient stability in the face of such fluctuations, which makes rigorous quality control necessary. Both the passage of time and changes in the patient population may lead to deviations in AI model performance; therefore, AI models applied in clinical settings must undergo regular quality monitoring and maintenance to maintain a stable clinical performance (88). The development of standards and guidelines for testing AI models could systematically assess the performance of AI-based tools and obtain precise and uniform measurements. This is the key component in future attempts to overcome distrust in the clinical system.

The combination of AI and colonoscopy holds practical and feasible potential, offering promising prospects for the future (94). Genetic testing and immune typing, coupled with AI technologies such as DL, have shown promise in CRC research, providing insights into tumor pathogenesis at the molecular level and offering theoretical support for CRC diagnosis and treatment. Numerous studies have supported that using AI to detect genetic mutations in CRC is a reliable method to offer a new treatment option for targeted therapy (94,95). Mutations in KRAS and BRAF genes are the main predictive biomarkers for the response to anti-EGFR monoclonal antibody-targeted therapy in metastatic colorectal cancer (96). Some scholars have used the DL method based on a residual NN and ML-based CT texture analysis to achieve the noninvasive prediction of the KRAS mutation status in CRC (97,98), while others have used a random forest classifier (RFC) model to predict the V600E mutation in the BRAF (97). This integration of AI with genetic testing and immune typing has the potential to enhance the accuracy and effectiveness of colonoscopy screening and diagnosis. However, relevant literature was reviewed and it was determined that there is no research currently on their use in colonoscopy.

To summarize, the combination of AI and colonoscopy is practical and feasible, and the future is bright; however, further exploration and innovation are still expected.

6. Conclusion

CRC is one of the most common tumors worldwide, accounting for 10% of all tumors. It is estimated that 608,000 people succumb to CRC annually (~8% of all cancer-related deaths). In addition, CRC incidence and mortality rates among adults under 50 years of age have been consistently increasing at an annual rate of 1.5% (2014-2018) and 1.2% (2005-2019), in recent years. Moreover, the global CRC disease burden is continuously increasing, with a trend toward younger incidence (1,99).

Although colonoscopy is valuable in decreasing the mortality or morbidity of CRC, its diagnostic accuracy still falls short of clinical needs, particularly for premalignant lesions or early-stage CRC. The introduction of AI in colonoscopy may potentially improve these deficiencies. For instance, various studies have shown that AI-based high-level auxiliary diagnostic systems can significantly improve the readability of medical images and help clinicians make accurate diagnostic and therapeutic decisions. In addition, CNNs can aid in the interpretation of histopathological tissue images, reducing inter-observer variability among doctors. Furthermore, CADe systems can significantly improve polyp and ADRs during early colonoscopy screenings, enhancing the differential diagnosis of non-neoplastic vs. neoplastic polyps and adenomatous vs. non-adenomatous polyps, thereby decreasing the possibility of mutating into CRC. Additionally, AI has the potential to contribute to cost-saving strategies by minimizing the need for unnecessary polypectomies and pathology examinations. Overall, the key findings of this review are that AI-aided colonoscopy could facilitate the efficiency and accuracy of CRC screening and diagnosis and ameliorate patient clinical outcomes and prognosis.

Preliminary data on AI-assisted systems are promising; however, the lack of high-quality clinical studies prevents reliable conclusions. It is essential to conduct higher-quality research using modern trial designs to improve the understanding of this field. Special attention should be given to utilizing larger datasets and prospectively validating AI systems in clinical settings. Moreover, these systems must provide quality assurance within a robust ethical and legal framework before clinicians and patients fully embrace them.

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Authors' contributions

SZ and GC conceived and designed the review. MD and JY collected and reviewed the literature as well as drafted the manuscript. SZ, MD and JY edited and revised the manuscript. All authors read and approved the final manuscript. Data authentication is not applicable.

Ethics approval and consent to participate

Not applicable.

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Competing interests

The authors declare that they have no competing interests.

References

1. Sung H, Ferlay J, Siegel RL, Laversanne M, Soerjomataram I, Jemal A and Bray F: Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J Clin 71: 209-249, 2021.
2. Trepanier M, Minnella EM, Paradis T, Awasthi R, Kaneva P, Schwartzman K, Carli F, Fried GM, Feldman LS and Lee L: Improved Disease-free survival after prehabilitation for colorectal cancer surgery. Ann Surg 270: 493-501, 2019.
3. Brenner H, Kloor M and Pox CP: Colorectal cancer. Lancet 383: 1490-1502, 2014.
4. Click B, Pinsky PF, Hickey T, Doroudi M and Schoen RE: Association of colonoscopy adenoma findings with Long-term colorectal cancer incidence. JAMA 319: 2021-2031, 2018.
5. Shinya H and Wolff WI: Morphology, anatomic distribution and cancer potential of colonic polyps. Ann Surg 190: 679-683, 1979.
6. Ladabaum U, Dominitz JA, Kahi C and Schoen RE: Strategies for colorectal cancer screening. Gastroenterology 158: 418-432, 2020.
7. US Preventive Services Task Force; Davidson KW, Barry MJ, Mangione CM, Cabana M, Caughey AB, Davis EM, Donahue KE, Doubeni CA, Krist AH, *et al*: Screening for colorectal cancer: US Preventive services task force recommendation statement. JAMA 325: 1965-1977, 2021.
8. Lin JS, Perdue LA, Henrikson NB, Bean SI and Blasi PR: Screening for colorectal cancer: Updated evidence report and systematic review for the US preventive services task force. JAMA 325: 1978-1998, 2021.
9. Barua I, Vinsard DG, Jodal HC, Loberg M, Kalager M, Holme O, Holme Ø, Misawa M, Bretthauer M and Mori Y: Artificial intelligence for polyp detection during colonoscopy: A systematic review and meta-analysis. Endoscopy 53: 277-284, 2021.
10. Gao P, Zhou K, Su W, Yu J and Zhou P: Endoscopic management of colorectal polyps. Gastroenterol Rep (Oxf) 11: goad027, 2023.
11. Meseeha M and Attia M: Colon Polyps. StatPearls. Treasure Island (FL) ineligible companies. Disclosure: Maximos Attia declares no relevant financial relationships with ineligible companies, 2023.
12. Kamaradova K: Non-conventional types of dysplastic changes in gastrointestinal tract mucosa-review of morphological features of individual subtypes. Cesk Patol 58: 38-51, 2022.
13. Keum N and Giovannucci E: Global burden of colorectal cancer: Emerging trends, risk factors and prevention strategies. Nat Rev Gastroenterol Hepatol 16: 713-732, 2019.
14. Crockett SD and Nagtegaal ID: Terminology, molecular features, epidemiology, and management of serrated colorectal neoplasia. Gastroenterology 157: 949-66.e4, 2019.
15. Haghighat S, Sussman DA and Deshpande A: US preventive services task force recommendation statement on screening for colorectal cancer. JAMA 326: 1328, 2021.
16. Carethers JM: Fecal DNA testing for colorectal cancer screening. Annu Rev Med 71: 59-69, 2020.
17. Mandel JS, Church TR, Bond JH, Ederer F, Geisser MS, Mongin SJ, Snover DC and Schuman LM: The effect of fecal occult-blood screening on the incidence of colorectal cancer. N Engl J Med 343: 1603-1607, 2000.
18. Faivre J, Dancourt V, Lejeune C, Tazi MA, Lamour J, Gerard D, Dassonville F and Bonithon-Kopp C: Reduction in colorectal cancer mortality by fecal occult blood screening in a French controlled study. Gastroenterology 126: 1674-1680, 2004.
19. Kronborg O, Jorgensen OD, Fenger C and Rasmussen M: Randomized study of biennial screening with a faecal occult blood test: Results after nine screening rounds. Scand J Gastroenterol 39: 846-851, 2004.
20. Scholefield JH, Moss SM, Mangham CM, Whynes DK and Hardcastle JD: Nottingham trial of faecal occult blood testing for colorectal cancer: A 20-year follow-up. Gut 61: 1036-1040, 2012.
21. Shaukat A, Mongin SJ, Geisser MS, Lederle FA, Bond JH, Mandel JS and Church TR: Long-term mortality after screening for colorectal cancer. N Engl J Med 369: 1106-1114, 2013.
22. Chiu HM, Chen SL, Yen AM, Chiu SY, Fann JC, Lee YC, Pan SL, Wu MS, Liao CS, Chen HH, *et al*: Effectiveness of fecal immunochemical testing in reducing colorectal cancer mortality from the One Million Taiwanese Screening Program. Cancer 121: 3221-3229, 2015.
23. Zorzi M, Fedeli U, Schievano E, Bovo E, Guzzinati S, Baracco S, Fedato C, Saugo M and Dei Tos AP: Impact on colorectal cancer mortality of screening programmes based on the faecal immunochemical test. Gut 64: 784-790, 2015.
24. Redwood DG, Dinh TA, Kisiel JB, Borah BJ, Moriarty JP, Provost EM, Sacco FD, Tiesinga JJ and Ahlquist DA: Cost-Effectiveness of multitarget stool DNA testing vs colonoscopy or fecal immunochemical testing for colorectal cancer screening in alaska native people. Mayo Clin Proc 96: 1203-1217, 2021.
25. Atkin W, Wooldrage K, Parkin DM, Kralj-Hans I, MacRae E, Shah U, Duffy S and Cross AJ: Long term effects of once-only flexible sigmoidoscopy screening after 17 years of follow-up: The UK Flexible Sigmoidoscopy Screening randomised controlled trial. Lancet 389: 1299-1311, 2017.
26. Wolf AMD, Fontham ETH, Church TR, Flowers CR, Guerra CE, LaMonte SJ, Etzioni R, McKenna MT, Oeffinger KC and Shih YT: Colorectal cancer screening for average-risk adults: 2018 guideline update from the American Cancer Society. CA Cancer J Clin 68: 250-281, 2018.
27. Nishihara R, Wu K, Lochhead P, Morikawa T, Liao X, Qian ZR, Inamura K, Kim SA, Kuchiba A, Yamauchi M, *et al*: Long-term colorectal-cancer incidence and mortality after lower endoscopy. N Engl J Med 369: 1095-1105, 2013.
28. Calderwood AH and Jacobson BC: Colonoscopy quality: Metrics and implementation. Gastroenterol Clin North Am 42: 599-618, 2013.
29. Zhao S, Wang S, Pan P, Xia T, Chang X, Yang X, Guo L, Meng Q, Yang F, Qian W, *et al*: Magnitude, risk factors, and factors associated with adenoma miss rate of tandem colonoscopy: A Systematic review and meta-analysis. Gastroenterology 156: 1661-1674.e11, 2019.
30. Kaminski MF, Wieszczy P, Rupinski M, Wojciechowska U, Didkowska J, Kraszewska E, Kobiela J, Franczyk R, Rupinska M, Kocot B, *et al*: Increased rate of adenoma detection associates with reduced risk of colorectal cancer and death. Gastroenterology 153: 98-105, 2017.
31. Rabeneck L and Paszat LF: Circumstances in which colonoscopy misses cancer. Frontline Gastroenterol 1: 52-58, 2010.
32. Rutter MD, Beintaris I, Valori R, Chiu HM, Corley DA, Cuatrecasas M, Dekker E, Forsberg A, Gore-Booth J, Haug U, *et al*: World endoscopy organization consensus statements on Post-Colonoscopy and Post-Imaging colorectal cancer. Gastroenterology 155: 909-25.e3, 2018.
33. Kyu HH, Bachman VF, Alexander LT, Mumford JE, Afshin A, Estep K, Veerman JL, Delwiche K, Iannarone ML, Moyer ML, *et al*: Physical activity and risk of breast cancer, colon cancer, diabetes, ischemic heart disease, and ischemic stroke events: Systematic review and dose-response meta-analysis for the Global Burden of Disease Study 2013. BMJ 354: i3857, 2016.

34. Morris EJ, Rutter MD, Finan PJ, Thomas JD and Valori R: Post-colonoscopy colorectal cancer (PCCRC) rates vary considerably depending on the method used to calculate them: A retrospective observational population-based study of PCCRC in the English National Health Service. Gut 64: 1248-1256, 2015.
35. Anderson R, Burr NE and Valori R: Causes of Post-colonoscopy colorectal cancers based on world endoscopy organization system of analysis. Gastroenterology 158: 1287-1299.e2, 2020.
36. Hassan C, Piovani D, Spadaccini M, Parigi T, Khalaf K, Facciorusso A, Fugazza A, Rösch T, Bretthauer M, Mori Y, *et al*: Variability in adenoma detection rate in control groups of randomized colonoscopy trials: A systematic review and meta-analysis. Gastrointest Endosc 97: 212-225.e7, 2023.
37. Burr N and Valori R: National post-colonoscopy colorectal cancer data challenge services to improve quality of colonoscopy. Endosc Int Open 7: E728-E729, 2019.
38. Wallace MB, Sharma P, Bhandari P, East J, Antonelli G, Lorenzetti R, Vieth M, Speranza I, Spadaccini M, Desai M, *et al*: Impact of artificial intelligence on miss rate of colorectal neoplasia. Gastroenterology 163: 295-304.e5, 2022.
39. Hamet P and Tremblay J: Artificial intelligence in medicine. Metabolism 69S: S36-S40, 2017.
40. Bishop C: Pattern Recognition and Machine Learning (Information Science and Statistics) Springer (April 6, 2011). ISBN-10: 03873107382011. 2011.
41. LeCun Y, Bengio Y and Hinton G: Deep learning. Nature 521: 436-444, 2015.
42. Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S and Dean J: A guide to deep learning in healthcare. Nat Med 25: 24-29, 2019.
43. Krenzer A, Makowski K, Hekalo A, Fitting D, Troya J, Zoller WG, Hann A and Puppe F: Fast machine learning annotation in the medical domain: A semi-automated video annotation tool for gastroenterologists. Biomed Eng Online 21: 33, 2022.
44. Bera K, Schalper KA, Rimm DL, Velcheti V and Madabhushi A: Artificial intelligence in digital pathology-new tools for diagnosis and precision oncology. Nat Rev Clin Oncol 16: 703-715, 2019.
45. Corley DA, Jensen CD, Marks AR, Zhao WK, Lee JK, Doubeni CA, Zauber AG, de Boer J, Fireman BH, Schottinger JE, *et al*: Adenoma detection rate and risk of colorectal cancer and death. N Engl J Med 370: 1298-1306, 2014.
46. Greenspan M, Rajan KB, Baig A, Beck T, Mobarhan S and Melson J: Advanced adenoma detection rate is independent of nonadvanced adenoma detection rate. Am J Gastroenterol 108: 1286-1292, 2013.
47. Singh H, Turner D, Xue L, Targownik LE and Bernstein CN: Risk of developing colorectal cancer following a negative colonoscopy examination: Evidence for a 10-year interval between colonoscopies. JAMA 295: 2366-2373, 2006.
48. Brenner H, Chang-Claude J, Seiler CM, Rickert A and Hoffmeister M: Protection from colorectal cancer after colonoscopy: A population-based, case-control study. Ann Intern Med 154: 22-30, 2011.
49. Baxter NN, Goldwasser MA, Paszat LF, Saskin R, Urbach DR and Rabeneck L: Association of colonoscopy and death from colorectal cancer. Ann Intern Med 150: 1-8, 2009.
50. Kahi CJ, Imperiale TF, Juliar BE and Rex DK: Effect of screening colonoscopy on colorectal cancer incidence and mortality. Clin Gastroenterol Hepatol 7: 770-775; quiz 11, 2009.
51. Maroulis DE, Iakovidis DK, Karkanis SA and Karras DA: CoLD: A versatile detection system for colorectal lesions in endoscopy video-frames. Comput Methods Programs Biomed 70: 151-166, 2003.
52. Karkanis SA, Iakovidis DK, Maroulis DE, Karras DA and Tzivras M: Computer-aided tumor detection in endoscopic video using color wavelet features. IEEE Trans Inf Technol Biomed 7: 141-152, 2003.
53. Misawa M, Kudo SE, Mori Y, Cho T, Kataoka S, Yamauchi A, Ogawa Y, Maeda Y, Takeda K, Ichimasa K, *et al*: Artificial Intelligence-Assisted polyp detection for colonoscopy: Initial experience. Gastroenterology 154: 2027-2029.e3, 2018.
54. Yamada M, Saito Y, Imaoka H, Saiko M, Yamada S, Kondo H, Takamaru H, Sakamoto T, Sese J, Kuchiba A, *et al*: Development of a real-time endoscopic image diagnosis support system using deep learning technology in colonoscopy. Sci Rep 9: 14465, 2019.
55. Wang P, Berzin TM, Glissen Brown JR, Bharadwaj S, Becq A, Xiao X, Liu P, Li L, Song Y, Zhang D, *et al*: Real-time automatic detection system increases colonoscopic polyp and adenoma detection rates: A prospective randomised controlled study. Gut 68: 1813-1819, 2019.
56. Wang P, Liu X, Berzin TM, Glissen Brown JR, Liu P, Zhou C, Lei L, Li L, Guo Z, Lei S, *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 5: 343-351, 2020.
57. Gong D, Wu L, Zhang J, Mu G, Shen L, Liu J, Wang Z, Zhou W, An P, Huang X, *et al*: Detection of colorectal adenomas with a real-time computer-aided system (ENDOANGEL): A randomised controlled study. Lancet Gastroenterol Hepatol 5: 352-361, 2020.
58. Urban G, Tripathi P, Alkayali T, Mittal M, Jalali F, Karnes W and Baldi P: Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy. Gastroenterology 155: 1069-1078.e8, 2018.
59. Kamitani Y, Nonaka K and Isomoto H: Current status and future perspectives of artificial intelligence in colonoscopy. J Clin Med 11: 2923, 2022.
60. Gonzalez-Bueno Puyal J, Brandao P, Ahmad OF, Bhatia KK, Toth D, Kader R, Lovat L, Mountney P and Stoyanov D: Polyp detection on video colonoscopy using a hybrid 2D/3D CNN. Med Image Anal 82: 102625, 2022.
61. Chen PJ, Lin MC, Lai MJ, Lin JC, Lu HH and Tseng VS: Accurate classification of diminutive colorectal polyps using computer-aided analysis. Gastroenterology 154: 568-575, 2018.
62. Ng K, May FP and Schrag D: US preventive services task force recommendations for colorectal cancer screening: Forty-five is the new fifty. JAMA 325: 1943-1945, 2021.
63. Huang D, Shen J, Hong J, Zhang Y, Dai S, Du N, Zhang M and Guo D: Effect of artificial intelligence-aided colonoscopy for adenoma and polyp detection: A meta-analysis of randomized clinical trials. Int J Colorectal Dis 37: 495-506, 2022.
64. Koh FH, Ladlad J, Centre SKHE, Teo EK, Lin CL and Foo FJ: Real-time artificial intelligence (AI)-aided endoscopy improves adenoma detection rates even in experienced endoscopists: A cohort study in Singapore. Surg Endosc 37: 165-171, 2023.
65. Spadaccini M, Marco A, Franchellucci G, Sharma P, Hassan C and Repici A: Discovering the first US FDA-approved computer-aided polyp detection system. Future Oncol 18: 1405-1412, 2022.
66. Seager A, Sharp L, Hampton JS, Neilson LJ, Lee TJW, Brand A, Evans R, Vale L, Whelpton J and Rees CJ: Trial protocol for COLO-DETECT: A randomized controlled trial of lesion detection comparing colonoscopy assisted by the GI Genius artificial intelligence endoscopy module with standard colonoscopy. Colorectal Dis 24: 1227-1237, 2022.
67. Houwen B, Hassan C, Coupe VMH, Greuter MJE, Hazewinkel Y, Vleugels JLA, Antonelli G, Bustamante-Balén M, Coron E, Cortas GA, *et al*: Definition of competence standards for optical diagnosis of diminutive colorectal polyps: European Society of Gastrointestinal Endoscopy (ESGE) Position Statement. Endoscopy 54: 88-99, 2022.
68. Byrne MF, Chapados N, Soudan F, Oertel C, Linares Perez M, Kelly R, Iqbal N, Chandelier F and Rex DK: Real-time differentiation of adenomatous and hyperplastic diminutive colorectal polyps during analysis of unaltered videos of standard colonoscopy using a deep learning model. Gut 68: 94-100, 2019.
69. Min M, Su S, He W, Bi Y, Ma Z and Liu Y: Computer-aided diagnosis of colorectal polyps using linked color imaging colonoscopy to predict histology. Sci Rep 9: 2881, 2019.
70. Aihara H, Saito S, Inomata H, Ide D, Tamai N, Ohya TR, Kato T, Amitani S and Tajiri H: Computer-aided diagnosis of neoplastic colorectal lesions using 'real-time' numerical color analysis during autofluorescence endoscopy. Eur J Gastroenterol Hepatol 25: 488-494, 2013.
71. Tischendorf JJ, Gross S, Winograd R, Hecker H, Auer R, Behrens A, Trautwein C, Aach T and Stehle T: Computer-aided classification of colorectal polyps based on vascular patterns: A pilot study. Endoscopy 42: 203-207, 2010.
72. Gross S, Trautwein C, Behrens A, Winograd R, Palm S, Lutz HH, Schirin-Sokhan R, Hecker H, Aach T and Tischendorf JJ: Computer-based classification of small colorectal polyps by using narrow-band imaging with optical magnification. Gastrointest Endosc 74: 1354-1359, 2011.
73. Mori Y, Kudo SE, Misawa M, Saito Y, Ikematsu H, Hotta K, Ohtsuka K, Urushibara F, Kataoka S, Ogawa Y, *et al*: Real-time use of artificial intelligence in identification of diminutive polyps during colonoscopy: A prospective study. Ann Intern Med 169: 357-366, 2018.
74. Vinsard DG, Mori Y, Misawa M, Kudo SE, Rastogi A, Bagci U, Rex DK and Wallace MB: Quality assurance of computer-aided detection and diagnosis in colonoscopy. Gastrointest Endosc 90: 55-63, 2019.

75. Spadaccini M, Massimi D, Mori Y, Alfarone L, Fugazza A, Maselli R, Sharma P, Facciorusso A, Hassan C and Repici A: Artificial intelligence-aided endoscopy and colorectal cancer screening. Diagnostics (Basel) 13: 1102, 2023.
76. Hassan C, Pickhardt PJ and Rex DK: A resect and discard strategy would improve cost-effectiveness of colorectal cancer screening. Clin Gastroenterol Hepatol 8: 865-869.e1-e3, 2010.
77. Hassan C, Balsamo G, Lorenzetti R, Zullo A and Antonelli G: Artificial intelligence allows leaving-in-situ colorectal polyps. Clin Gastroenterol Hepatol 20: 2505-2513.e4, 2022.
78. Sánchez-Montes C, Sánchez FJ, Bernal J, Córdova H, López-Cerón M, Cuatrecasas M, Rodríguez de Miguel C, García-Rodríguez A, Garcés-Durán R, Pellisé M, *et al*: Computer-aided prediction of polyp histology on white light colonoscopy using surface pattern analysis. Endoscopy 51: 261-265, 2019.
79. Yoshida N, Inoue K, Tomita Y, Kobayashi R, Hashimoto H, Sugino S, Hirose R, Dohi O, Yasuda H, Morinaga Y, *et al*: An analysis about the function of a new artificial intelligence, CAD EYE with the lesion recognition and diagnosis for colorectal polyps in clinical practice. Int J Colorectal Dis 36: 2237-2245, 2021.
80. Barbeiro S, Libanio D, Castro R, Dinis-Ribeiro M and Pimentel-Nunes P: Narrow-band imaging: Clinical application in gastrointestinal endoscopy. GE Port J Gastroenterol 26: 40-53, 2018.
81. Tamaki T, Yoshimuta J, Kawakami M, Raytchev B, Kaneda K, Yoshida S, Takemura Y, Onji K, Miyaki R and Tanaka S: Computer-aided colorectal tumor classification in NBI endoscopy using local features. Med Image Anal 17: 78-100, 2013.
82. Wimmer G, Tamaki T, Tischendorf JJ, Hafner M, Yoshida S, Tanaka S and Uhl A: Directional wavelet based features for colonic polyp classification. Med Image Anal 31: 16-36, 2016.
83. Hafner M, Tamaki T, Tanaka S, Uhl A, Wimmer G and Yoshida S: Local fractal dimension based approaches for colonic polyp classification. Med Image Anal 26: 92-107, 2015.
84. Mori Y, Neumann H, Misawa M, Kudo SE and Bretthauer M: Artificial intelligence in colonoscopy-Now on the market. What's next? J Gastroenterol Hepatol 36: 7-11, 2021.
85. Nazarian S, Glover B, Ashrafian H, Darzi A and Teare J: Diagnostic accuracy of artificial intelligence and computer-aided diagnosis for the detection and characterization of colorectal polyps: Systematic review and Meta-analysis. J Med Internet Res 23: e27370, 2021.
86. Hassan C, Badalamenti M, Maselli R, Correale L, Iannone A, Radaelli F, Rondonotti E, Ferrara E, Spadaccini M, Alkandari A, *et al*: Computer-aided detection-assisted colonoscopy: Classification and relevance of false positives. Gastrointest Endosc 92: 900-904.e4, 2020.
87. Hsu CM, Hsu CC, Hsu ZM, Chen TH and Kuo T: Intraprocedure artificial intelligence alert system for colonoscopy examination. Sensors (Basel) 23: 1211, 2023.
88. Elemento O, Leslie C, Lundin J and Tourassi G: Artificial intelligence in cancer research, diagnosis and therapy. Nat Rev Cancer 21: 747-752, 2021.
89. Wei JW, Suriawinata AA, Vaickus LJ, Ren B, Liu X, Lisovsky M, Tomita N, Abdollahi B, Kim AS, Snover DC, *et al*: Evaluation of a deep neural network for automated classification of colorectal polyps on histopathologic slides. JAMA Netw Open 3: e203398, 2020.
90. Karimi D, Dou H, Warfield SK and Gholipour A: Deep learning with noisy labels: Exploring techniques and remedies in medical image analysis. Med Image Anal 65: 101759, 2020.
91. Huang P, Feng Z, Shu X, Wu A, Wang Z, Hu T, Cao Y, Tu Y and Li Z: A bibliometric and visual analysis of publications on artificial intelligence in colorectal cancer (2002-2022). Front Oncol 13: 1077539, 2023.
92. Clark P, Kim J and Aphinyanaphongs Y: Marketing and US food and drug administration clearance of artificial intelligence and machine learning enabled software in and as medical devices: A systematic review. JAMA Netw Open 6: e2321792, 2023.
93. Bhinder B, Gilvary C, Madhukar NS and Elemento O: Artificial intelligence in cancer research and precision medicine. Cancer Discov 11: 900-915, 2021.
94. Yin Z, Yao C, Zhang L and Qi S: Application of artificial intelligence in diagnosis and treatment of colorectal cancer: A novel Prospect. Front Med (Lausanne) 10: 1128084, 2023.
95. Sorokin M, Zolotovskaia M, Nikitin D, Suntsova M, Poddubskaya E, Glusker A, Garazha A, Moisseev A, Li X, Sekacheva M, *et al*: Personalized targeted therapy prescription in colorectal cancer using algorithmic analysis of RNA sequencing data. BMC Cancer 22: 1113, 2022.
96. Sanchez-Ibarra HE, Jiang X, Gallegos-Gonzalez EY, Cavazos-Gonzalez AC, Chen Y, Morcos F and Barrera-Saldaña HA: KRAS, NRAS, and BRAF mutation prevalence, clinicopathological association, and their application in a predictive model in Mexican patients with metastatic colorectal cancer: A retrospective cohort study. PLoS One 15: e0235490, 2020.
97. He K, Liu X, Li M, Li X, Yang H and Zhang H: Noninvasive KRAS mutation estimation in colorectal cancer using a deep learning method based on CT imaging. BMC Med Imaging 20: 59, 2020.
98. Taguchi N, Oda S, Yokota Y, Yamamura S, Imuta M, Tsuchigame T, Nagayama Y, Kidoh M, Nakaura T, Shiraishi S, *et al*: CT texture analysis for the prediction of KRAS mutation status in colorectal cancer via a machine learning approach. Eur J Radiol 118: 38-43, 2019.
99. Spaander MCW, Zauber AG, Syngal S, Blaser MJ, Sung JJ, You YN and Kuipers EJ: Young-onset colorectal cancer. Nat Rev Dis Primers 9: 21, 2023.