Enhancing the Standard of Care in Gastroenterology: Artificial Intelligence Applications

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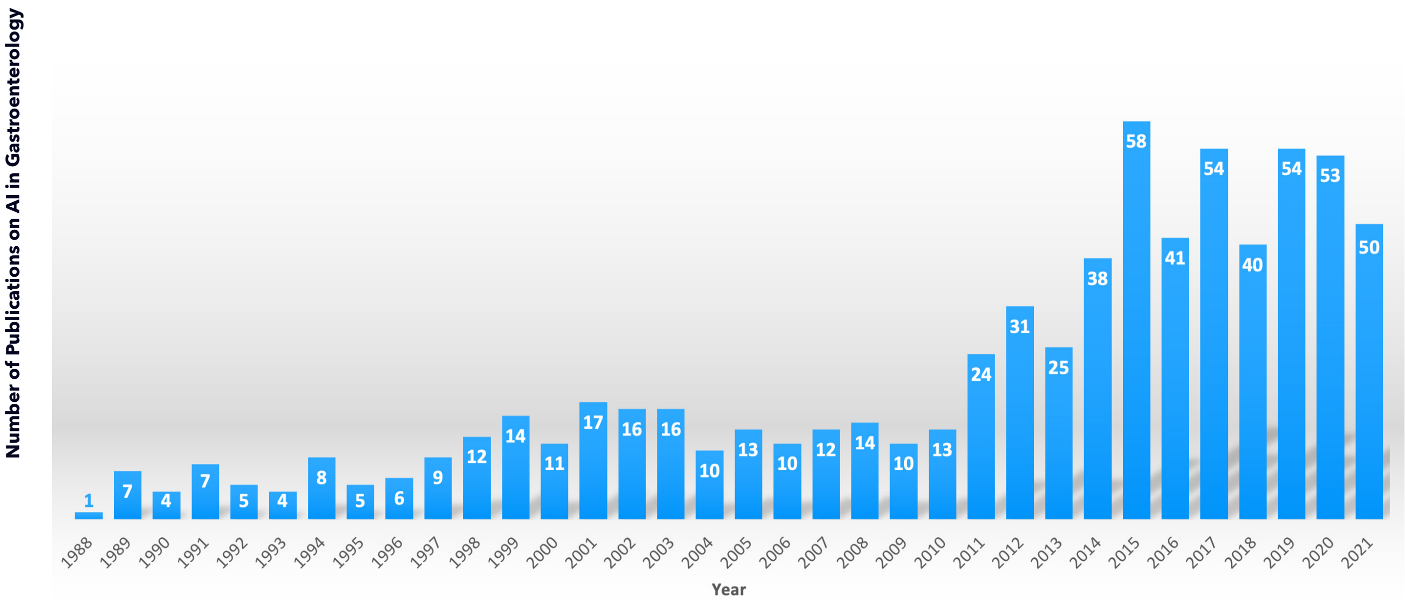
Introduction

Artificial intelligence (AI) is progressively disrupting the healthcare industry and rapidly making a meaningful impact on several medical fields. Gastroenterology has been leading the way by showcasing AI applications for the enhancement of patient care, life sciences, and clinical workflows. A subfield of AI, computer vision, interprets images and videos and is the focus of early applications of AI in gastroenterology, augmenting operator-dependent processes characteristic of endoscopy. Early applications include quality and efficiency of colonoscopies, diagnosis of endoscopic disease activity, and endoscopic data documentation. It is worth noting that computer vision technologies can integrate with other data modalities beyond image and video to create more complex medical AI applications. Similarly, clinical applications of an AI technology can integrate with existing technology infrastructure to enable its widespread adoption by gastroenterologists and the life sciences.

The past decade has seen a steep increase in peer-reviewed publications focused on AI in gastroenterology, which highlights the recent advancements in core technology paving the way for disruption (**Figure 1**).[1] With the increase in clinical research publications approaching clinical application development, identifying consistent methods by which the clinical applications of AI are assessed and validated can inform educated interpretations of such research. It can also mitigate current misconceptions of the role of AI in healthcare, specifically regarding its capabilities and safety profile. In this effort, the U.S. Food and Drug Administration has developed Good Machine Learning Practices, and AI-specific guidance documents have been published—such as the CONSORT-AI and SPIRIT-AI guidelines—that aim to improve transparency and completeness of reporting of clinical trials evaluating interventions that use AI.[2,3] The field of gastroenterology has championed the need for robust clinical validation of AI algorithms through design and execution of randomized clinical trials to assess safety and efficacy of interventions (**Supplementary Table 1**).[4-18] For AI applications to be introduced into the gastroenterology space in a responsible manner, collaboration between public and private entities must continue to be strengthened so that guidelines and standards can meet the demands of novel technologies.

Figure 1. Articles retrieved by a PubMed search of the term "AI in gastroenterology," limited to 1988-2021 and clinical trials only.[1]



There are varying unmet needs in the practice of gastroenterology and life science research and development that AI models may have the potential to address. Endoscopy, a highly skilled physician-dependent procedure, in which large amounts of information are generated and rigorously interpreted via close examination of mucosa, lends itself to a level of subjectivity.[19,20] Here AI algorithms could drive tools to increase consistency of interpretation and reporting of endoscopic assessments, potentially providing unprecedented insights into disease activity through precision diagnostics that can guide the management of gastrointestinal (GI) disease. Because the fields of AI and gastroenterology are broad, focusing this paper on a few specific areas of AI development may restrain overelaborations. The following content describes a few advancements in gastroenterology driven by computer vision, with a focus on early AI applications in screening for colorectal cancer (CRC) and inflammatory bowel disease (IBD).

AI-Enhanced Endoscopy

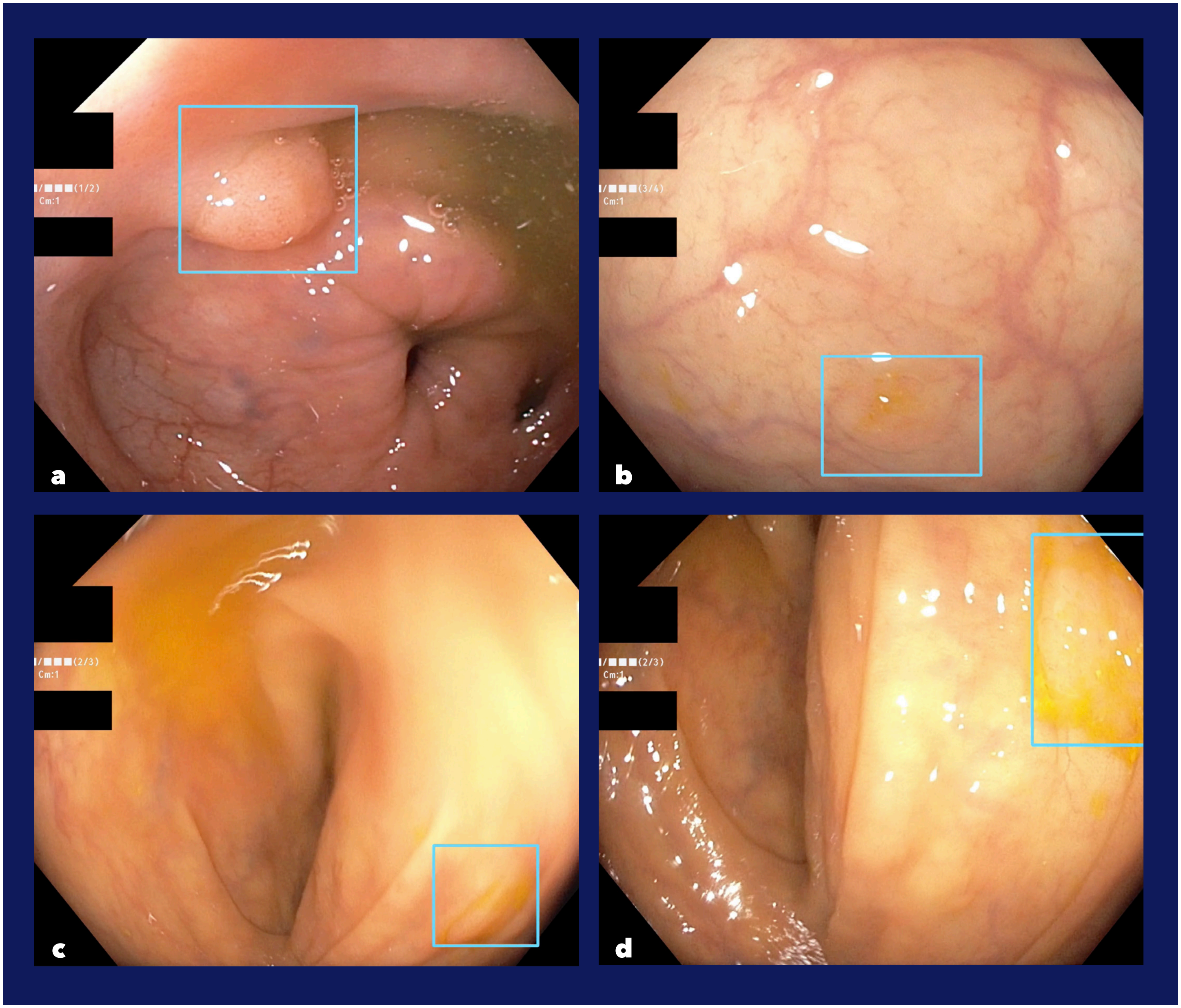
Considering that GI diseases are often diagnosed, assessed, and monitored endoscopically, AI and computer vision are well poised to address the unmet needs in the quality of endoscopy procedures.[21,22] In view of the fact that endoscopy is an invasive, operator-driven procedure that requires real-time examination and high-level expertise and analysis of mucosal features through a video-based review, it is an ideal space in which to apply computer vision and AI. A straightforward application for real-time visual examination in gastroenterology is that of computer-aided polyp detection technologies for CRC screening colonoscopies. More complex applications in chronic diseases go a step further and require multiple-feature video analysis, requiring more testing and experimentation. An example of a complicated application would be one to enhance diagnostic accuracy in scoring of IBD disease severity.

Colonoscopy in CRC Screening and Surveillance

CRC is the third most common malignancy and the second most deadly cancer.[23] The prevalence of CRC is considerable when compared with other well-known diseases that have a high population impact.[24,25] Colonoscopy is the most commonly used modality to screen for CRC in the United States and has been shown to reduce incidence and mortality through detection of early stage cancers and resection of preneoplastic polyps (ie, adenomas).[26,27] However, the efficacy of these colonoscopies is highly dependent on endoscopists' ability to visually detect and resect preneoplastic lesions.[28,29] Current literature reports that endoscopists miss up to 26% of these adenomas on average in screening exams, which highlights the need to improve procedure efficacy.

To measure efficacy, quality metrics have recently been implemented in endoscopy improvement programs. Conventionally, the detection of premalignant lesions has been measured through the adenoma detection rate (ADR), which is the proportion of an endoscopist's screening colonoscopies in which one adenoma is detected and resected.[20] But ADR as a quality metric has limitations. This methodological challenge can be addressed by the application of more accurate procedure quality metrics like the adenoma per colonoscopy (APC) rate, which accounts for all adenomas detected during a colonoscopy procedure.[6,30] By accounting for all potential precursors, APC may be the optimal predictor of CRC prevention. Recent efforts have focused on demonstrating the role of APC in reducing incidence of interval cancer after index colonoscopy. Arguably, APC should also be measured as part of colonoscopy quality improvement standards to characterize high-quality exams.

Figure 2. Polyp detection with SKOUT™ (Iterative Scopes, Cambridge, Massachusetts), indicated by the blue bounding box around the perimeter of the lesion.[31] **a.** Detection of a 10-mm tubular adenoma in the sigmoid colon. **b.** Detection of a 3-mm sessile serrated lesion in the rectum. **c, d.** Detection of a 5-mm sessile serrated lesion in the ascending colon, with images captured upon first detection and upon closer look, respectively. Reprinted with permission from Shaukat A, Colucci D, Erisson L, et al. Improvement in adenoma detection using a novel artificial intelligence-aided polyp detection device. *Endosc Int Open*. 2021;9(2):E263-E270. © Georg Thieme Verlag KG.



Straightforward real-time computer-vision applications can assist CRC screening quality, through computer-aided detection (CADe) technologies aimed at increasing overall adenoma detection (Figure 2).[21,22,31] In fact, recent studies have evaluated the impact that CADe technologies can have in improving overall adenoma detection rates, through different quality metrics.

A simple-feature application—like CADe—could be advanced to aid in identification and detection of the most difficult-to-detect lesions to diagnose through computer-aided diagnosis applications (CADx). Tools such as this have the potential to elevate the standard of care of routine colonoscopies across the community. Nonetheless, AI could also go beyond enhancing polyp detection and adenoma diagnosis, and into other procedure quality indicators including bowel preparation, cecal intubation rate, and withdrawal time. These indicators highlight unmet needs at the physician work-rate level because more measurement means more procedure documentation, which can be alleviated through computer-vision interpretation to drive automated documentation.

Solutions like this are poised to enter the clinic seamlessly through an integration infrastructure that is already in place through existing electronic health records and endowriter systems, which could enable the widespread distribution of polyp detection and automated procedure documentation technologies that can also support a progression of computer-vision capabilities onto more complex clinical applications.

IBD Endoscopic Severity Scoring

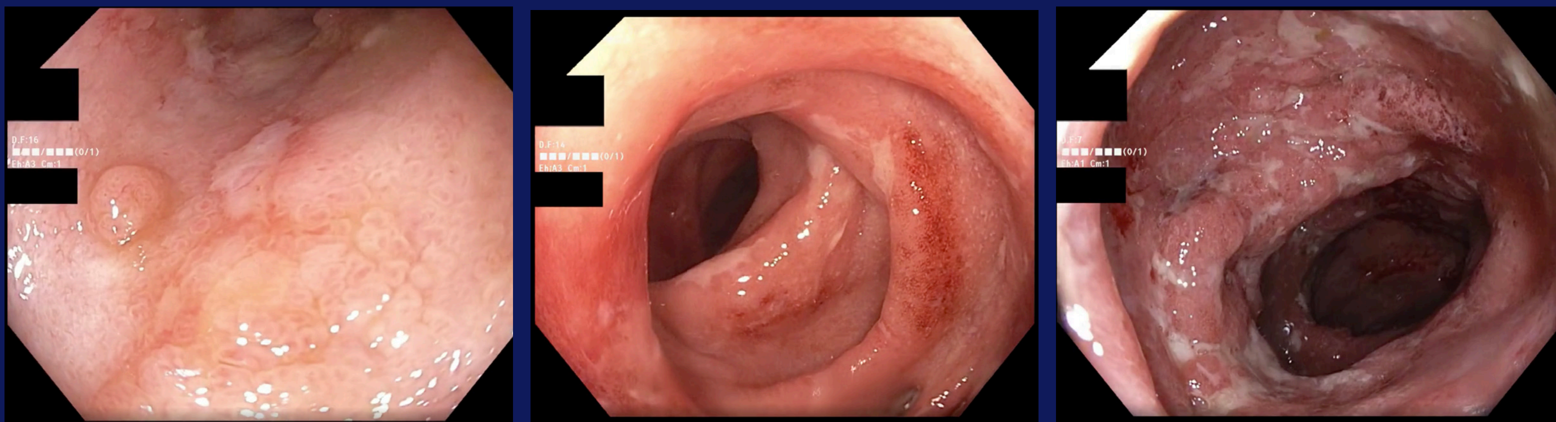
IBD is an umbrella term used to describe disorders that involve chronic inflammation of the digestive tract and are characterized by ulcerative colitis (UC) and Crohn's disease (CD). The burden of IBD is rising globally despite recent improvements in healthcare quality. Patients with IBD continue to struggle with suboptimal disease control, preventable complications, and failure to achieve lasting relief with current therapies. UC and CD are both diagnosed and assessed clinically and endoscopically,[32] with routine endoscopic assessment of disease activity and mucosal healing being fundamentally important as part of a treat-to-target strategy in clinical practice.[33] Recent evidence suggests that complete mucosal healing might be the ideal therapeutic goal, elevating the importance of endoscopic disease scoring to make diagnostic and treatment efficacy measures in routine practice (**Table 1**).[33,34]

Table 1. Mayo Endoscopic Score for Ulcerative Colitis

Score	Disease activity; endoscopic features
0	Normal or inactive; none
1	Mild; erythema, decreased vascular pattern, mild friability
2	Moderate; marked erythema, absent vascular pattern, friability, erosions
3	Severe; spontaneous bleeding, ulceration

The Mayo endoscopic score scale is a 4-point scoring system in which patients with normal or inactive, mild, moderate, or severe disease are given scores of 0, 1, 2, or 3, respectively.[34]

Figure 3. Patients scored with a severity score of 3 while having very different mucosal feature findings.



The use of recommended scales to assess endoscopic disease activity in UC and CD, such as the Mayo Endoscopic Score (eMS) for UC and Simple Endoscopic Score for CD (SES-CD), is not widespread across the gastroenterology community. The complexity of converting a patient's inflammatory burden to a score often takes on differences in interpretation and results in high rates of inter-reader variability, which restricts use of the endoscopic scale to IBD experts. These practicality limitations hinder interpretation consistency, report reproducibility, and widespread utility across healthcare practices and providers—resulting in a suboptimal diagnostic and treatment standard of care for patients with IBD. The application of AI algorithms that enable automated and consistent endoscopic severity scoring can help reduce discrepancies experienced by patients and providers, as well as elevate the standard of care across the community.

In clinical trials, where eMS and SES-CD are used as key trial endpoints to assess disease severity and response to therapy, the endoscopic assessment is made exclusively by IBD experts; however, these scales still lack appropriate granularity to match the range of endoscopic presentations of disease seen across patients. For example, endoscopic findings from 3 different patients with UC might show different mucosal features. In **Figure 3**, by definition the eMS would apply the same severity score to all 3 images (an eMS of 3, as each contains an ulceration), despite clear differences in their inflammatory burden.

Moreover, correlation between existing endoscopic scores and clinical assessment scales (overall Mayo Score/Disease Activity Index) may result in an imperfect mapping of symptoms and prognosis, highlighting an unmet need that may be addressed if AI models can enhance endoscopic disease assessment to enable more granular severity scoring and to uncover relationships to prognosis and outcomes.

The implementation of these AI applications may provide unprecedented insights that could drive improvements in diagnostic accuracy, prognosis, and treatment decision assignment. These advancements may also surface novel methods of quantifying endoscopic disease activity, resulting in better understanding of its relationship to patient symptoms and overall risk profile. At some point, AI models may achieve differentiation of endoscopic remission and symptom response, potentially enabling the proposal of novel clinical trial endpoints. Furthermore, improvements to endoscopic disease activity assessment can enable optimization of eligible patient identification and enrollment into clinical trials, resulting in an increase of access to new therapeutics.

AI algorithms that **enable automated and consistent endoscopic severity scoring** can help reduce discrepancies

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Given the complexity of IBD, the GI field is ripe with the potential to introduce multiple clinical applications in the coming years—starting with AI tools for endoscopic severity scoring, at the community and clinical trial level, to enhance the standard of care and improve drug development success.

Conclusion

For readability this paper did not elaborate on important methodology, regulatory, and clinical landscapes. Still, it is important that gastroenterologists and life science professionals are introduced to the topic of AI in gastroenterology and remain up to date on current AI technology developments and potential clinical applications, because they are key stakeholders in the conversation about the impact of AI technologies in the healthcare landscape and may become leading end-users of AI tools. According to surveys in the United States, gastroenterologists generally have a strong interest in AI tools.[35] Perhaps this is due to the promise that AI could enhance the standard of care and reduce discrepancies across the community.

AI technologies seem capable of enhancing gastroenterology and healthcare through different clinical application entry points; in fact, AI is already enhancing CRC screening and surveillance colonoscopy and will soon be positioned to address more complex gastroenterology challenges. As collaboration increases between healthcare providers and AI experts, so too will the design of more complex AI models and technology applications. Furthermore, as the adoption of currently developed technologies increases, the development of broader capabilities will be supported by in-place infrastructure. In a union of human and machine learning, gastroenterology is a medical field on the cusp of realizing significant improvements to clinical practice, life sciences, clinical workflows, and ultimately patient outcomes.

Supplementary Table 1. Applications of AI in Gastroenterology Research

Study	Use in medicine	AI subfield	Technical details
Colorectal cancer			
Misawa et al, 2016[4]	Characterization of colorectal lesions	Machine learning	• Machine learning trained 979 images from endocytoscopy with narrow-band imaging • Assessed diagnostic accuracy for adenomatous lesion
Mori et al, 2018[5]	Diagnosis of colorectal polyps	Real-time CAD	• CAD used to assess 466 diminutive polyps from 325 patients • Evaluated negative predictive value for identifying diminutive rectosigmoid adenomas
Wang et al, 2019[6]	Detection of colorectal cancer	Deep learning	• Real-time automatic polyp detection system developed on a deep learning architecture • Randomized controlled study evaluating ADR
Gastric and esophageal cancer			
Iizuka et al, 2020[7]	Classification of gastric and colonic epithelial tumors	Deep learning	• CNNs and RNNs trained on biopsy histopathology whole-slide images of stomach and colon
Horie et al, 2019[8]	Diagnosing esophageal cancer	Deep learning	• CNN trained on 8428 images of esophageal cancer • Evaluated sensitivity and diagnosis accuracy
Shiroma et al, 2021[9]	Detecting ESCC	Deep neural network architecture	• Deep CNN trained on 8428 images of esophageal lesions of histologically confirmed ESCC • Evaluated diagnostic accuracy to detect ESCC from recorded esophagogastroduodenoscopy videos
IBS and IBD			
Tap et al, 2017[10]	Severity of IBS	Machine learning	• Machine learning procedure to identify a microbial signature for IBS severity • Analyzed fecal and mucosal samples
Waljee et al, 2017[11]	Prediction of IBD	Machine learning	• Development of machine learning models to predict corticosteroid use and hospitalization as surrogates for clinically meaningful flares in patients with IBD • Analyzed longitudinal data from electronic medical records of 30,456 patients with an IBD diagnosis
Maeda et al, 2019[12]	Identify histologic inflammation in ulcerative colitis	Machine learning	• Validation of CAD model to differentiate histologically active versus histologically healing UC-induced inflammation • Machine learning based on 12,900 endoscopy images • Validation based on 9935 endoscopy images
Takenaka et al, 2021[13]	Ulcerative colitis	Deep neural networks	• Development and validation of deep neural network trained on 40,758 colonoscopy images and 6885 biopsy results from patients with a confirmed diagnosis of UC • Evaluated prediction of endoscopic remission and histologic remission
Other conditions			
Jovanovic et al, 2014[14]	Selecting patients with choledocholithiasis for therapeutic ERCP	Artificial neural network	• Evaluated discriminant ability and accuracy of ANN model
Itoh et al, 2018[15]	Early detection of *Helicobacter pylori*	Deep learning	• Development of a CNN system trained on 149 endoscopic images of the lesser curvature of the stomach
Ding et al, 2019[16]	Identification of small bowel diseases	Deep learning	• Validation of CNN-based algorithm trained on 158,235 small bowel capsule endoscopy images
Marya et al, 2020[17]	Diagnosis of autoimmune pancreatitis	Deep learning	• Development of a CNN based on endoscopic ultrasound images • Used 1,174,461 images from 583 patients
Seo et al, 2020[18]	Prediction of adverse events in gastrointestinal bleeding	Machine learning	• Evaluated 4 machine learning algorithms: logistic regression with regularization, random forest classifier, gradient boosting classifier, and voting classifier

ADR, adenoma detection rate; AI, artificial intelligence; ANN, artificial neural network; CAD, computer-aided diagnosis; CNN, convolutional neural network; ERCP, endoscopic retrograde cholangiopancreatography; ESCC, esophageal squamous cell carcinoma; IBD, inflammatory bowel disease; IBS, irritable bowel syndrome; RNN, recurrent neural network; UC, ulcerative colitis.

GLOSSARY

Algorithm: a set of rules or step-by-step instructions for a computer to complete a task[36]

Artificial intelligence (AI): the development of computer systems that can perform tasks or "make decisions" that have historically required human intelligence[36]

CADe: computer-aided detection algorithms for the automatic detection of polyps during colonoscopy[37]

CADx: computer-aided applications used in the characterization and diagnosis of polyps during colonoscopy[37]

Computer vision: a field of artificial intelligence that allows computers to derive meaningful information from photographs and videos and take actions or make recommendations based on that information (eg, identifying lesions or making diagnoses)[38]

Convolutional neural network (CNN): a type of neural network used in image recognition designed to function similarly to the receptive fields in the human brain[39]

Deep learning (DL): deep learning systems represent machine-learning algorithms with multiple layers, allowing the analysis of large data sets and more complex outputs[38]

Endowriter: software used to document medical procedures, including image-based endoscopy[40]

Machine learning (ML): the use and development of computer systems that are able to learn and adapt without following explicit instructions.[36] These systems use algorithms and models to analyze and draw inferences from patterns in data that they are "trained" on[38]

Neural network: A class of machine learning algorithm modeled on the human brain and composed of multiple interconnected units organized into layers that can combine multiple inputs to produce a single output[41]

Recurrent neural network (RNN): a type of neural network in which network activity is propagated in cycles to enable more complex computations[41]

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