

Artificial Intelligence in screening colonoscopy and error reduction

Inteligencia artificial en la colonoscopia de tamizaje y la disminución del error

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Abstract

Artificial Intelligence (AI) has the potential to change many aspects of healthcare practice. Image discrimination and classification has many applications within medicine. Machine learning algorithms and complicated neural networks have been developed to train a computer to differentiate between normal and abnormal areas. Machine learning is a form of AI that allows the platform to improve without being programmed. Computer Assisted Diagnosis (CAD) is based on latency, which is the time between the captured image and when it is displayed on the screen. AI-assisted endoscopy can increase the detection rate by identifying missed lesions. An AI CAD system must be responsive, specific, with easy-to-use interfaces, and provide fast results without substantially prolonging procedures. AI has the potential to help both, trained and trainee endoscopists. Rather than being a substitute for high-quality technique, it should serve as a complement to good practice. AI has been evaluated in three clinical scenarios in colonic neoplasms: the detection of polyps, their characterization (adenomatous vs non-adenomatous) and the prediction of invasive cancer within a polypoid lesion.

Keywords: Artificial Intelligence. Colonoscopy. Missed lesions. Colonic neoplasms.

Resumen

La inteligencia artificial (IA) tiene el potencial de cambiar muchos aspectos de la práctica sanitaria. La discriminación y la clasificación de imágenes tiene muchas aplicaciones dentro de la medicina. Se han desarrollado algoritmos de aprendizaje automático y redes neuronales complicadas para entrenar a una computadora a diferenciar las áreas normales de las anormales. El aprendizaje automático es una forma de IA que permite que la plataforma mejore sin ser programada. El diagnóstico asistido por computadora (CAD) se basa en latencia, que es el tiempo entre la imagen capturada y cuando es mostrada en la pantalla. La endoscopia asistida por IA puede incrementar la tasa de detección al identificar lesiones obviadas. Un sistema CAD de IA debe ser sensible, específico, con interfaces fáciles de usar, y proporcionar resultados rápidos sin prolongar sustancialmente los procedimientos. La IA tiene el potencial de ayudar tanto a endoscopistas entrenados como a los que están en entrenamiento. En vez de ser un sustituto para una técnica de alta calidad, deberá servir como un complemento de las buenas prácticas. La IA ha sido evaluada en tres escenarios clínicos en las neoplasias colónicas: la detección de pólipos, su caracterización (adenomatosos vs no adenomatosos) y la predicción de cáncer invasor dentro de una lesión polipoide.

Palabras clave: Inteligencia artificial. Colonoscopia. Neoplasias de colon.

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The three laws of robotics

A robot may not harm a human being, or, through inaction, allow a human being to come to harm. A robot must obey the orders given to it by human beings, except where such orders would conflict with the First Law.

A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

"I, Robot" by Isaac Asimov

The first video game I played was in the '90s: Super Mario Bros. Honestly, I don't remember what I saw or how I felt, I just know that I learned how to play after falling into the void several times, or crashing into some turtle, fish, or fireball. Over the years, and after many other games played, I intuitively know where and when to jump and how to avoid crashing into the game elements.

This is the typical example of a natural learning process where, through trial and error, one learns, through observation, the successes, and errors of movements, creating a relationship between observation and movement that eventually gives us a skill: hand-eye coordination.

Training in endoscopy

According to the American Society for Gastrointestinal Endoscopy (ASGE), before trainees can be certified, they must perform a minimum number of procedures to achieve endoscopic competence¹. However, training in a clinical setting has various medical and legal implications. The acquisition of skills will largely depend on shortening the learning curve. To achieve this, we need more realistic models.

Training on mechanical, digital, ex-vivo biological, and animal simulators allows for practice and tutorial teaching and increases the number of repetitions (n) to shorten the learning curve²⁻⁷. However, although these models try to recreate reality, they lack the necessary realism for training, competence, or certification⁵.

We need phantoms that recreate reality. Recently, a model with polyvinyl alcohol (PVA) hydrogels was published to reduce diagnostic errors through amplified repetition. Understanding the mechanical properties (elasticity/stiffness coefficient) of PVA allowed the model to simulate digestive organs and lesions that were visible under endoscopic ultrasound/elastography (EUS-E)⁸.

Diagnostic error

What are the consequences of making a diagnosis mistake? Decision-making has a space of consequences and is associated with errors (false positives, or false negatives), the risk associated with the test, "labeling," and the possibility of recommending a "harmful" treatment. Within the space of consequences, 2 decisions will be correct (appears sick and is sick; does not appear sick and is not sick), and 2 will be incorrect (appears sick and is not; does not appear sick and is). Imagine resecting a segment of the colon in a patient without a malignant lesion (false positive), or sending a patient home with a misdiagnosed lesion (false negative). Although both are errors, their severity differs.

Through a 2 x 2 table, we compare our clinical suspicion vs the reference standard and calculate sensitivity (Sn), specificity (Sp), positive predictive value (PPV), negative predictive value (NPV), positive likelihood ratio (LR+), negative likelihood ratio (LR-), diagnostic efficacy, and disease prevalence.

In the United States, in 2015, 6.1 million esophago-gastroduodenoscopies (EGDs) were performed. In the Western world, the rate of undetected gastric cancer (GC) during EGD ranged from 2.3% to 13.9% (Spain, 9.1%), a figure similar to post-polypectomy colorectal cancer (CRC) (2.5% to 7.7%)⁹⁻¹².

There are 3 levels of quality in health care systems: structure, process, and outcome. A quality indicator is identifying digestive lesions. Within a multidimensional model, we can measure effectiveness (complete examination from the oropharynx to the 2nd portion of the duodenum, or from the anal margin to the cecum and ileocecal valve), efficiency (every lesion should be identified), safety (adverse events), care (patient satisfaction), and accessibility (waiting time for scheduling the study)¹³.

In the Western world, endoscopic training aims to improve technical skills for the detection of conditions such as cancer, esophagitis, and peptic ulcers, so that procedures are only performed by qualified endoscopists^{14,15}.

Quality parameters in colonoscopy include a) photographic documentation of the cecum; b) withdrawal time from the cecum (minimum, 6 min); c) adenoma detection rate (25% overall: 30% in men and 20% in women); d) colon cleanliness (> 85%); e) taking biopsies (for chronic diarrhea and colitis); and f) resections based on the lesion size¹⁶. The cognitive process involves 2 stages: identification of the

suspicious lesion, and differentiation (pathology). However, ordinary diagnostic EGD is relegated to the less experienced, who are not trained to identify incipient lesions¹⁷.

How many procedures are necessary to achieve competence in endoscopy?

The number is a minimum requirement, as there is no evidence that it impacts competence. The “magic” number varies widely: 100 in the Western world and > 1000 in Asia. Additional training will impact higher diagnostic performance¹⁸⁻²⁰. Cognitive knowledge, repetitions (training), standardize systems, high definition, and mucosal inspection techniques increase lesion detection rates^{11,21}.

What is the effect of continuous education vs maintaining a minimum annual endoscopic volume? How can we maintain the ability to perform high-quality examinations? According to Gladwell in his book “Outliers,” to become an expert, one needs to dedicate about 10 000 hours to continuous education. He called these people successful, those whose achievements are beyond the norm.

An important indicator in EGD is mucosal inspection time (precision). If we spend > 7 min, the possibility of detecting high-risk lesions (intestinal metaplasia, atrophy, dysplasia, or cancer), and dysplasias, and/or GC will increase 2 to 3 times, respectively. The detection of adenomas was higher (0.25% vs 0.17%) in slow vs fast endoscopists (mean, 3.25 min vs 2.38 min)²²⁻²⁵.

Detection of gastric neoplasms has been correlated with procedure duration; 8 min to 10 min will ensure high quality in EGD. The measurement should include intubation, distension, cleansing with mucolytics, defoaming agents, and antispasmodics, and thorough mucosal examination⁹⁻²¹. However, the number of quality indicators continues to increase. How should we interpret this?²⁶ We need these indicators to be more objective and reproducible. The rate of unnoticed cancer is the only process measure that has proven to impact cancer-related mortality^{27,28}.

EGD and white light colonoscopy are the gold standard for detecting digestive lesions. However, subtle lesions can be easily missed. Once a lesion has been identified, we can characterize it with advanced imaging modalities such as acetic acid, Lugol's iodine, electronic chromoendoscopy (iScan, Fuji, NBI) to help delineate, or detect abnormalities^{17,20}.

Table 1. Factors associated with errors during screening endoscopy

Endoscopist error
Training
Continuing medical education
Training supervision
Sampling error
Multiple biopsies
Proper sampling
Endoscopic precision
Patient tolerance (sedation)
Recognition of lesions
Mucolytics (mucosal visibility)
Extended time
Photo documentation
Post-EGD errors
Follow-up
Patient notification
Pathologist error

EGD, esophagogastroduodenoscopy.
Adapted from Cho, 2016¹⁸.

Factors impacting the non-detection of cancer

There are factors that influence the omission of a malignant lesion during detection endoscopy. Table 1 shows limiting factors and suggestions to minimize the risk of missing cancer during everyday detection endoscopy¹⁷.

Lack of precision in mucosal examination has been associated with undetected GC (11.3%) 3 years before diagnosis¹¹, all due to: a) lack of contrast between lesions and normal tissue; b) sampling error (random biopsies); c) misinterpretation of histopathology (concordance), and d) inappropriate follow-up (diagnostic failure)²⁹.

Identifying an incipient cancer is really challenging even among expert endoscopists. Proper knowledge of endoluminal anatomy and photo documentation is necessary. Key elements include cognitive knowledge, the “endoscopic eye,” and systematic, standardized, and complete mucosal inspection^{30,31}.

Emura et al.³⁰ reported a GC detection rate in Colombia similar to that found in China in average-risk subjects (0.3% vs 0.37%) using systematic alphanumeric coded endoscopy (SACE). However, effectiveness was higher in ordinary EGD vs screening (92.4% vs 7.6%), which was explained by the quality of EGD^{32,33}. In Mexico, SACE increased the detection

rate of intestinal metaplasia, as the method ensures greater robustness by including photo documentation (28 overlapping images), which reduces blind spots during examination³⁴.

Incipient lesions present morphological and color changes (pallor or discoloration), making them imperceptible. “Endoscopists without knowledge of what incipient GC looks like will not be able to detect it, even with appropriate techniques”²⁹.

Cleansing the oropharyngeal, esophageal, gastric, and colonic mucosa improves the detection of incipient lesions by enhancing mucosal visibility and eliminating artifacts (foam, residual liquids, food). Monroy et al.³⁵ reported better endoscopic quality when combining an antifoaming agent (dimethicone 200 mg) with a mucolytic (N-acetylcysteine [NAC] 500 mg, or 1000 mg) vs dimethicone or NAC alone, or without intervention. We still face significant challenges in measuring quality, most of which are process measurements.

Artificial intelligence

Seth Bling, a programmer, created an artificial intelligence (AI) simulator designed to learn how to play video games. In 2018, it was programmed for Super Mario Bros. In the simulations, the program systematically selected a new action to progress and overcome obstacles. After 17 days, the simulator failed to complete the first level. This was due to “complex spatial movements required to jump over certain obstacles.”

Ironically, this was not Bling's first experiment with algorithms. Back in 2015, when he created the program, he used it in another video game, Super Mario World. In this programming, he fed the program with a set of more complex movements. Based on these movements, the program was able to run an ordered simulation of movements known as neuroEvolution of augmented topologies (NEAT), selecting and discarding movements to complete the level. After 34 iterations with 300 different combinations of each movement (around 24 hours), the simulator managed to complete the level.

Intelligence *per se* is not a quality of matter, not even of gray matter. Intelligence is a learned function. It is an information network capable of matching information and selecting a movement to achieve a certain goal.

Evolution has taken millions of years to shape our intelligence, with centuries of trials, errors, and obstacles. By creating these intelligent selection programs,

we are saving millions of years and violent spaces for rapid growth.

It takes a program 24 hours to learn how to make it from one video game level to another. It may have taken me more at the beginning because I had to help my mom with household chores, let my siblings watch TV, or simply eat or sleep before learning the final move. AI can grow much faster than us simply because it can be fed with existing information and has all the time in the world to learn new movements, or “appropriate selections” that we, by our own nature, simply cannot.

In the end, AI won't be our natural replacement because the natural world has complex spatial obstacles, and as in the case of the 2018 simulation, no matter how many combinations you have, human intelligence is required to “jump” those complex spaces.

Artificial intelligence in endoscopy

The main goal of AI is to improve the quality of computer-aided diagnosis (CAD), as well as the detection and classification of dysplastic and neoplastic lesions, which can be extremely challenging even for experienced physicians³⁶.

Technical aspects of artificial intelligence and machine learning

Software encodes a program based on an algorithm that generates specific input to a defined output. Machine learning (ML) will eventually change the paradigm. After encoding, input data and a training procedure are used to “learn” from them. The goal is for the model to work on new samples not included in the training, so the data can be processed correctly, and the computer will learn how to face new situations³⁶.

The term AI is used for procedures that include the learning component. The system involves pattern recognition. There are 3 different types of learning procedures³⁷: a) supervised, through which the machine learns from known patterns; b) unsupervised, through which the machine finds common features in unknown patterns, and c) reinforcement, where the machine learns through trial and error.

Applications of artificial intelligence in GI endoscopy

AI has the potential to change many aspects of the routine clinical practice. Imaging discrimination and

image have many applications in medicine. ML algorithms, and convolutional neural networks (CNN) have been developed to train machines how to differentiate between normal and abnormal areas. ML a form of AI that allows the platform to improve without being specifically programmed. CAD detection is based on latency, which is the time elapsed between image acquisition and the image being displayed on screen³⁸.

CNNs have been developed to assess whether the images/video frames acquired by the endoscopist are informative, and to improve the quality of the examination by evaluating blind spots and determining the amount of the mucosal surface area under examination.

ML refers to AI where the algorithm, based on raw input data, analyzes features in a separate dataset without being specifically programmed, and eventually provides a specific classification output³⁹.

The algorithm uses coordinate bounding boxes for lesion localization that can be tracked over time, extracting an appearance signature from each detected lesion, which, along with motion, speed, and direction information, are used to allocate an identifier to each lesion. This model could detect polyps with a 96.5% Sn rate. The multiple-object precision metric takes into account algorithm errors, and the 92.8% score tells us that most polyps were correctly detected and identified⁴⁰.

The improvement in AI system capabilities does not mean AI will eventually replace humans in making multiple decisions in the future. Machines will only do what they are trained to do. The system makes decisions based on training.

AI-assisted endoscopy can increase the detection rate by identifying overlooked lesions. An AI based CAD system should be sensitive, specific, have user-friendly interfaces, and provide quick results without substantially prolonging procedures⁴¹. AI has the potential to assist both trained endoscopists and trainees. Instead of being a substitute for high-quality technique, it should serve as a complement to good practices⁴¹.

Clinical applications of artificial intelligence

AI applications can be subdivided into tasks or assignments based on clinical challenges in daily practice and according to endoscopic methods. Table 2 shows reported applications of CAD and AI in various endoscopic procedures⁴¹.

Table 2. Reported applications of computer-aided diagnosis and AI in various endoscopic procedures

Procedure and applications
Colonoscopy Polyp detection (in real-time and in still images and videos)* Polyp classification (neoplastic vs hyperplastic)* Detection of malignancy within polyps (depth of invasion in endocytoscopic images)* Presence of inflammation in endocytoscopic images*
Wireless capsule endoscopy Detection and classification of lesions (bleeding, ulcers, polyps)* Assessment of intestinal motility Celiac disease (assessment of villous atrophy, intestinal motility) Improving image review efficacy Elimination of duplicate images and non-informative image frames (eg. images with debris)*
Upper endoscopy Anatomical location identification* Diagnosis of <i>Helicobacter pylori</i> infection status* Detection of gastric cancer and assessment of depth of invasion* Esophageal squamous dysplasia Detection and delineation of early dysplasia in Barrett's esophagus* Real-time image segmentation in volumetric laser endomicroscopy in Barrett's esophagus*
Endoscopic ultrasound Differentiation of pancreatic cancer from chronic pancreatitis and normal pancreas Differentiation of autoimmune pancreatitis from chronic pancreatitis Endoscopic ultrasound with elastography

*Applications where the use of deep learning has been reported.

Adapted from Pannala et al., 2020³⁹.

Colorectal lesions

The biggest progress in the endoscopic application of AI has been made in the colon, where AI has approached clinical implementation in real-life settings (Fig. 1)⁴².

Colorectal polyps: detection, classification, and cancer prediction

AI has been evaluated in 3 different clinical scenarios for colorectal neoplasms: polyp detection, characterization (adenomatous vs non-adenomatous), and the prediction of invasive cancer within a polypoid lesion. Studies on CAD for polyp computer-aided detection (CADE) and classification (CADx) are subject to a series of limitations: the selection of higher-quality images (selection bias), and the inclusion of sessile serrated lesions in a CADE model, as these polyps are precursors (30%) of CRC (Fig. 2).



Figure 1. Lateral growth lesion in the ascending colon next to the ileocecal valve: the blue box highlights the detection by AI. **A:** white light. **B:** narrow-band imaging. **C and D:** vital chromoendoscopy with indigo carmine.



Figure 2. Sessile polyps < 5 mm detected with AI. **A:** in an area prone to small polyp loss, a suspicious area is identified with AI. **B:** same lesion with chromoendoscopy and AI. **C:** sessile polyp identified with AI.

To date, only 2 real-time colonoscopy studies have been conducted. For clinical usefulness, AI platforms will require rapid image analysis with real-time information to accurately determine the presence and/or type of polyp present⁴³⁻⁴⁵.

A prospective, randomized, controlled trial reported the results of a validated deep learning model for

real-time colonoscopic polyp detection in 1038 patients (536 standard colonoscopies, and 522 CAD-assisted colonoscopies). The CAD system increased the adenoma detection rate (ADR) (29.1% vs 20.3%) and polyp detection rate (PDR) (45% vs 29%), no. of adenomas (53% vs 31%), and no. of polyps (95% vs 50%) per colonoscopy compared to unassisted colonoscopy.

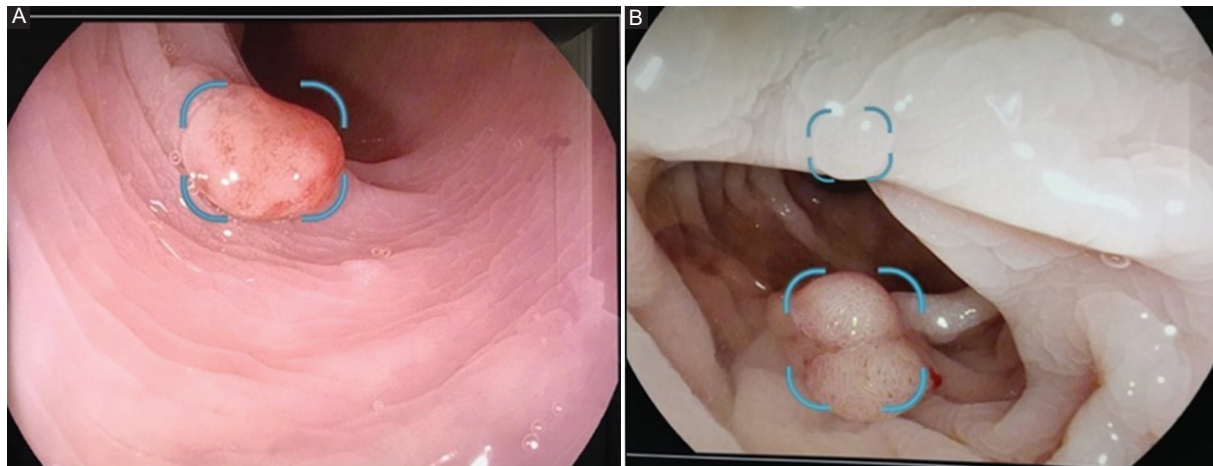


Figure 3. Sessile polyps detected with AI: 5 mm with central depression (A) and bilobulated (B).

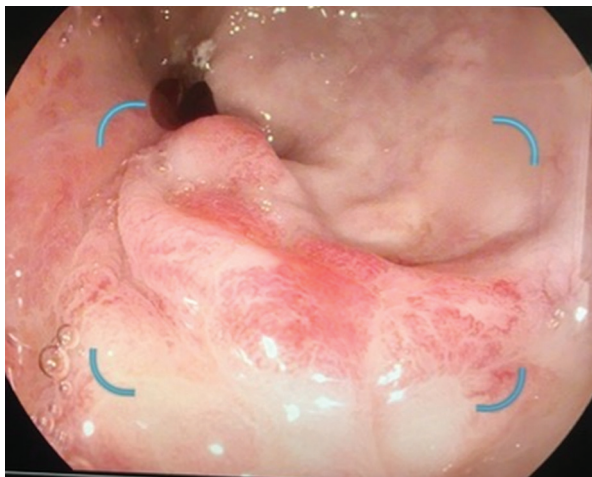


Figure 4. Infiltrating lateral growth lesion of the sigmoid colon detected with AI.

The system identified all polyps detected by endoscopists with a low false-positive rate (0.075 per colonoscopy). A higher rate of detection of diminutive lesions was reported, but the study did not quantify the rates of false positives, or false negatives⁴³.

The rate of missed polyps during colonoscopy has been reported at 26%⁴⁶. Subtle appearance, quality of bowel preparation, the endoscopist's mucosal inspection technique, adherent mucus, and even fatigue can contribute to undetected polyps³⁹.

The detection of neoplastic polyps can result in a greater reduction in interval colorectal cancers (ICRC). A 1% increase in ADR has been associated with a 3% decrease in the incidence of ICRC, meaning that it is associated with various factors, such as blind spots and

human errors. AI can reduce the rates of missed polyps, especially in endoscopists with low ADR (Figs. 3-5)⁴⁵.

A single-center study with a CNN system analyzed a total of 8641 images with 4088 single colonoscopy polyps (2000 patients). The diagnostic accuracy was 96.4%, with a false-positive rate of 7%. In an expert review with CNN overlay as the gold standard, the Sn and Sp rates for polyp detection were 93% and 93%, respectively ($p < 0.00001$). The false positives generated by CNN were related to collapsed mucosa (near-field), presence of artifacts, suction marks, narrow-band imaging (NBI) images, and polypectomy sites. Strategies have been proposed for managing diminutive polyps, including “resect and discard” or “leave in situ” paradigms. CADx can provide a support tool for endoscopists to improve recommended accuracy thresholds. Potential benefits include better cost-effectiveness, shorter procedural times, and fewer adverse events resulting from unnecessary polypectomies⁴⁶.

The diagnostic accuracy of CADx for classifying diminutive polyps was reported at 93.2% in a single-operator center of 118 colorectal neoplasms, with the pathological diagnosis of the resected polyp serving as the gold standard⁴⁷.

Four different studies used CNN to categorize diminutive polyps as adenomatous or hyperplastic after inspection with conventional NBI^{48,49}, magnifying NBI⁵⁰, or near-focus NBI⁵¹, using histopathology as the gold standard. In validation sets of 106 to 300 polyps, CNNs identified adenomatous polyps in real-time (50-millisecond delay in 1 study) with diagnostic accuracy rates ranging from 88.5% to 94% and a NPV from 91.5% to 97%.

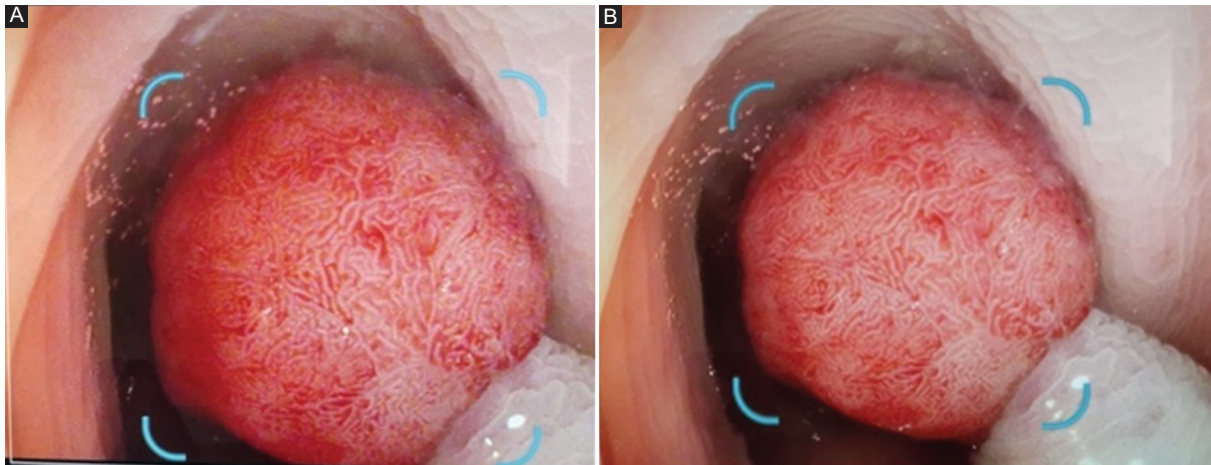


Figure 5. A and B: pedunculated lesion of the sigmoid colon detected with AI: a pedunculated lesion with a broad base, irregular velvety surface pattern, and irregular vessels can be observed.

Deep learning with CNN has the potential to differentiate adenomas from hyperplastic polyps with high Sn and Sp (98% and 83%, respectively), histological prediction of 94%, and PPVs of 90% and NPVs of 97% using video frames with NBI. However, its utility in real-time in both expert and non-expert centers is yet to be elucidated⁵².

Another randomized trial for polyp detection (real-time colonoscopy) included 685 participants who were randomized on a 1:1 ratio to CADe (GI-Genius, Medtronic, Dublin, Ireland) with white-light and high-definition colonoscopy plus CAD or colonoscopy alone. The CADe system improved the ADR up to 54.8% (187 out of 341) from 40.4% (139 out of 344) in the control group (relative risk, 1.30; 95% confidence interval [CI], 1.14-1.45). The rate of detected adenomas was higher in the CADe group (mean, 1.07 ± 1.54) vs the control group (mean, 0.71 ± 1.20) (incidence rate, 1.46; 95%CI, 1.15-1.86). The incidence rate increase was observed in polyps < 5 mm and 5 mm to 9 mm in diameter, without increasing with withdrawal time⁵³.

Another AI-assisted study based on NBI with non-magnified optical images predicted the histopathology of solitary colonic lesions. The Sn for hyperplastic/serrated polyps was 96.6%, with a NPV of 99.6%. However, it was lower for tubular adenoma/cancer lesions. The AI image classifier had high accuracy, at 88.2%, in predicting deeply invasive carcinoma. The correlation of surveillance colonoscopy interval using an AI image classifier and histology was 97.7%⁵⁴.

In a prospective study of 791 consecutive patients, real-time CADx characterized 466 diminutive rectosigmoid polyps with the deep learning system, showing

performance necessary for employing the “diagnose and leave in situ” strategy for non-neoplastic polyps. The system distinguished between adenomas and hyperplastic polyps with an accuracy of 94% and an NPV of 96%. However, CAD was not useful in distinguishing neoplastic from non-neoplastic polyps in segments proximal to the sigmoid colon (NPV, 60.0%)⁴⁴.

Hotta et al.⁵⁵ reported the validity of CAD endocytoscopy in diagnosing neoplastic or non-neoplastic colorectal lesions, comparing the diagnostic ability of non-expert endoscopists with stained endocytoscopic images, diagnostic accuracy, and the Sn of EB-01 (Cybernet Corp, Tokyo, Japan) (98.0%, 69.0%, 96.9%, and 70.8%, respectively). When using images, the EB-01 diagnostic accuracy was 96% vs 70.4% for non-experts. The Sn rate was higher in the EB-01 group (96.9%) vs non-experts (62.1%). Stained endocytoscopic evaluation with images showed greater accuracy in the EB-01 group (98%) vs the expert group (93.3%). However, the accuracy was similar in both groups when using NBI endocytoscopic images (96.0% in the EB-01 group vs 94.6% in the expert group).

Accurate optical diagnosis of T1 CRC and the depth of submucosal invasion will determine the optimal treatment approach. T1 lesions confined to SM1 (< 1000 μ m) may be considered for endoscopic resection using en bloc techniques, with endoscopic resection of the mucosa (lesion diameter = 2 cm), or submucosal endoscopic dissection. When the lesion invades deep submucosa (1000 μ m or more, T2), surgery is required due to the higher risk involved of lymph node metastasis⁵⁶.

A randomized study evaluated 5543 endocytoscopy images (2506 non-neoplastic, 2667 adenomas, and 370 invasive cancers) from 238 lesions (100 non-neoplastic, 112 adenomas, and 26 invasive cancers) from a database using a CAD system based on endocytoscopy to differentiate invasive cancer from non-malignant adenomas. Sessile serrated lesions were excluded. The algorithm achieved an accuracy of 94.1% (95% confidence interval [CI], 89.7-97.0) for invasive malignancy⁵⁷.

A study that included 190 images of 41 lesions (cTis = 14, cT1a = 14, and cT1b = 13) evaluated the depth of invasion of malignant polyps using CNN. The Sn, Sp, and diagnostic accuracy for deep invasion (cT1b) were 67.5%, 89.0%, and 81.2%, respectively⁵⁸.

Inflammatory bowel disease

The diagnostic accuracy of the CAD system was reported at 91% (83% to 95%) for evaluating the persistence of inflammation (histopathology) in endocytoscopic images obtained during colonoscopy in patients with ulcerative colitis⁵⁹.

A different study evaluated the ability of a CAD system (CNN) to accurately identify patients with ulcerative colitis (accuracy, 90.1%; 95%CI, 89.2-90.9%) and histopathological remission (accuracy, 92.9%; 95%CI, 92.1-93.7%) based on computerized analysis of mucosal appearance during endoscopy⁶⁰.

To date, there are no studies with CAD systems for the detection and classification of dysplasia in the surveillance colonoscopy setting for patients with chronic colitis.

Conclusions

Technological advancements have a fundamental goal, which is to identify and reduce the source of human error. New tools should undergo rigorous examinations to evaluate their efficacy and safety profile in different study populations through randomized clinical trials. However, these tools do not replace endoscopic training, which aims to develop skills and abilities. They should be used as additional resources or support tools to achieve better endoscopic diagnoses and reduce the possibility of missing a malignant neoplasm during a screening colonoscopy.

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Conflicts of interest

None declared.

Ethical disclosures

Protection of human and animal subjects. The authors declare that the procedures followed were in accordance with the regulations of the relevant clinical research ethics committee and with those of the Code of Ethics of the World Medical Association (Declaration of Helsinki).

Confidentiality of data. The authors declare that they have followed the protocols of their work center on the publication of patient data.

Right to privacy and informed consent. The authors have obtained the written informed consent of the patients or subjects mentioned in the article. The corresponding author is in possession of this document.

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