Published online: 2020-10-08

Artificial Intelligence in Small Bowel Endoscopy: Current Perspectives and Future Directions

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J Digest Endosc

Abstract

Artificial intelligence (AI) is a computer system that is able to perform tasks which normally require human intelligence. The role of AI in the field of gastroenterology has been gradually evolving since its inception in the 1950s. Discovery of wireless capsule endoscopy (WCE) and balloon enteroscopy (BE) has revolutionized small gut imaging. While WCE is a relatively patient-friendly and noninvasive mode to examine the nonobstructed small gut, it is limited by a lengthy examination time and the need for expertise in reading images acquired by the capsule. Similarly, BE, despite having the advantage of therapeutic intervention, is costly, invasive, and requires general sedation. *Incorporation of concepts* like machine learning and deep learning has been used to handle large amounts of data and images in gastroenterology. Interestingly, in small gut imaging, the application of AI has been limited to WCE only. *This review was planned to examine and summarize available published data on various AI-based approaches applied to small bowel disease.*

We conducted an extensive literature search using Google search engine, Google Scholar, and PubMed database for published literature in *English on the* application of different AI techniques in small bowel endoscopy, and have summarized the outcome and benefits of *these applications* of AI in small bowel endoscopy. Incorporation of AI in WCE has resulted in significant advancements in the detection of various lesions starting from dysplastic mucosa, inflammatory and nonmalignant lesions to the detection of bleeding with increasing accuracy and has shortened the lengthy review time in image analysis. As most of the studies to evaluate AI are retrospective, the presence of inherent selection bias cannot be excluded. Besides, the interpretability (black-box nature) of AI models remains a *cause for concern*. Finally, issues related to medical ethics and AI need to be judiciously addressed to enable its seamless use in future.

Keywords
- artificial intelligence
- machine learning
- deep learning
- wireless capsule endoscopy
- balloon enteroscopy
- artificial neural network
- convolutional neural network

Introduction

Artificial intelligence (AI) involves computer programs that perform functions normally attributed to human intelligence, such as learning and problem solving.[1] AI has gradually evolved over the decades since its inception in the 1950s as a display of intelligent behavior indistinguishable from that of a human being and has come to incorporate concepts like machine learning (ML) and deep learning (DL). DL, a relatively new concept, has emerged as a revelation in the realm of computer technology. A substantial amount of research has been done using DL application in the domain of image analysis in various medical fields including gastroenterology and hepatology. AI has been applied in the endoscopic analysis of nonmalignant

DOI https://doi.org/10.1055/s-0040-1717824
ISSN 0976-5042.

lesions such as polyps, ulcers, lymphangiectasia, angiectasia, etc. In addition to cancer detection and analysis of inflammatory lesions or localizing the lesion in obscure bleeding during wireless capsule endoscopy (WCE), AI has been used to good effect in diagnosis making and prognostication. The application of AI has waxed and waned over the past six decades with seemingly little improvement but various ML-based models like support vector machine (SVM), artificial neural network (ANN), and convolutional neural network (CNN) have proven to be useful in different branches of medicine with outstanding performance in image recognition and analysis. However, the optimal performance of DL-based methods requires a huge amount of properly labeled training data. This issue has been addressed by combining DL methods with reinforcement learning principles.[2] A graphical summary of the concepts of AI, ML, and DL is depicted in ►**Fig. 1**.

Nevertheless, AI and its newer models are not fool-proof or free from errors. The major drawbacks with newer techniques are overfitting and a lack of explainability. While the DL-based models perform much better than other models, these are intrinsically dependent on the training dataset. The lack of diversity and the presence of unidentified bias in the training dataset may hinder generalization to real-life situations and may lead to problems in proper model validation. Moreover, lack of explainability (black-box nature) is a major concern in AI-based models.

Until now, most of the studies have stressed on improving the explainability of AI-based models.[3] In the field of luminal gastroenterology, most reviews related to AI have focused on AI-assisted endoscopy, either in the form of automatic polyp detection in a colonoscopy[4] or malignant lesion detection in the stomach and esophagus.[5] In contrast, studies on AI-assisted endoscopy in diagnosing or localizing inflammatory, malignant, or bleeding lesions in the small bowel have been sparse. Studies on WCE have dealt only with the technical improvements of AI models in lesion detection, classification, and characterization. Surprisingly, data on the use of AI on single/double-balloon enteroscopy (DBE) are lacking. Furthermore, real-time

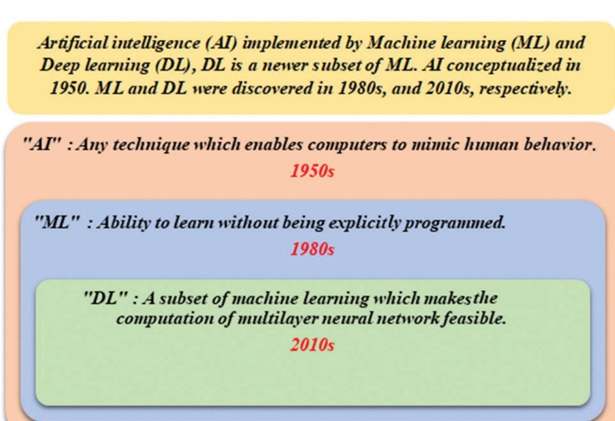

Fig. 1 Summary of the development of artificial intelligence, machine learning, and deep learning.

applications of AI on any form of small bowel enteroscopy are lacking.

We conducted an extensive search in the internet using Google Scholar, Google search engine, and PubMed database on most recent and relevant articles using keywords: AI and small bowel endoscopy, computer-aided diagnosis (CAD), and capsule endoscopy, computer-based diagnosis in small bowel diseases, ML in small bowel endoscopies, and application of AI techniques in small bowel endoscopy. No exclusions were made on study designs and all articles were in English. In this present review, we have tried to summarize the different modalities of application of various AI models in diagnosing small bowel diseases with special emphasis on WCE and have dwelt on the pros and cons of such applications including their prospects.

Small Bowel Endoscopy and AI Application

WCE and balloon (single or double) enteroscopy **have** revolutionized the field of small gut imaging. It is no secret that the invention of WCE by Gavriel Iddan et al[6] has brought in a sea change in the management of small-bowel diseases, including occult gastrointestinal (GI) bleeding, Crohn's disease, polyposis syndromes, malignancy, and celiac disease. Although its use is limited to the nonobstructed bowel, the advent of balloon enteroscopy (BE) to "chase" the findings of WCE has ushered in a new revolution in the realm of therapeutic interventions in the small bowel.

Advancements like suspected blood indicator,[7] adaptive frame rate technology,[8] and the quick-view algorithm[9] based on AI for CAD have been developed to reduce the long review time and increase the accuracy in diagnosis. However, it is important to keep a note of the fact that these have yielded mixed results in terms of diagnosis and have reported high missing rates too.[10]

Current Use of WCE in Practice

Analysis of Malignant and Premalignant Lesions

As mentioned above, there have been only a few studies that have focused on small gut malignancies in particular.[11-14] Technical variations on detection and characterization of polyps in WCE images have been tested in patients with suspected or previously known polyposis syndromes such as familial adenomatous polyposis and Peutz-Jeghers syndrome.[15,16] WCE has also been found to be beneficial in the detection of polyps in the jejunum and ileum.[15] WCE is found comparable to magnetic resonance enterography (MR enterography)[17] whereas computed tomography (CT) enterography and DBE have shown a superior sensitivity compared with WCE in the detection of small bowel tumors.[18,19]

Therefore, the presence of multiple constraints like lack of accuracy in image reading by an observer, lengthy capsule processing, and concerns regarding the image quality in WCE procedures coupled with the fact that the importance and applicability of AI have been steadily increasing led scientists to devise models that would be swift and would be less erroneous in detecting polyps and tumors in the small intestine. This, in turn, led researchers to focus primarily on domains like automatic polyp detection and characterization in the GI tract. Detection and characterization of a polyp are done using features (color, shape, edge, and texture) with various AI classifiers with a sensitivity of approximately 95% and accuracy varying from 91 to 98%. The different methods of AI to detect and characterize polyp in WCE images/videos are summarized in ►**Table 1**.

A few studies have also highlighted the methods of detecting polyp/malignant lesions in WCE images/videos concerning the small bowel using only various AI-based models, viz., ANN, KNN (K-nearest neighbors), multilayer perception network (MLP), and SVM[11-14] with a reported sensitivity of 92 to 98% and a diagnostic accuracy of 92 to 97%. The results of the AI studies involving small gut malignancies are summarized in ►**Table 1**.

Inflammatory and Other Nonmalignant Lesions

Crohn's Disease

WCE is useful in the evaluation of Crohn's disease in the small intestine in cases where there is a diagnostic dilemma. Many studies have established the role of WCE as a valuable adjunct to conventional endoscopy and colonoscopy with ileoscopy with a reported sensitivity and specificity of 89 to 93% and 84 to 100%, respectively.[20,21] WCE has also been shown to be superior to CT enteroclysis[22] and MR enterography,[23] especially in terminal ileal disease and proximal small-bowel disease.[22] Overall, most studies suggest a superior sensitivity of WCE with varying degrees of specificity over other radiological tests in the detection of small bowel Crohn's disease. It is, however, pertinent to remember that a lack of validated capsule criteria and the inability to obtain biopsy specimens for confirmation of diagnosis are significant limitations in the diagnosis of Crohn's disease.[24] While DBE was found to be superior to WCE,[25] false-positive results in a few asymptomatic patients raise concerns regarding accuracy in Crohn's disease.[26] Further, severity scales for Crohn's disease using WCE: the Lewis score and the capsule endoscopy Crohn's disease activity index have also been developed which are undergoing validation and these may prove useful in diagnosing Crohn's disease of the small bowel.[27,28]

To overcome the various limitations of WCE, researchers have tried to develop and modify AI-based models with considerable success. Various methods to determine features (color, edge, and texture), viz., mean shift algorithm[29] and local binary pattern[30] have been used to characterize inflammation in Crohn's disease. ML technique has also been used successfully in risk assessment of Crohn's disease and ulcerative colitis. Overall sensitivity and accuracy reported in the above studies are to the tune of 71 to 95% and 80 to 94%, respectively.[29-32] Studies showing the application of AI in patients of small gut IBD are summarized in ►**Table 2.**

Celiac Disease

Celiac disease (CD), with a worldwide incidence of 1%, manifests as loss/scalloping of duodenal folds with nonspecific mucosal lesions (fissures, crevices, grooves, micro nodules, or a mosaic pattern) in the small intestine.[33]

Duodenal biopsies using standard endoscopy together with serological testing have been the cornerstone of diagnosis in CD.[34] The invasiveness of endoscopic biopsy and the expense of serological tests have resulted in the search for alternative economical, feasible, and noninvasive methods. Duodenoscopy, despite being convenient for inspecting and assessing villous atrophy in the duodenum, has significant limitations that it cannot examine the extent and severity of the disease. In this context, WCE may well be a suitable noninvasive, patient-friendly, and feasible alternative, which could visualize the entire small bowel for a detailed evaluation of the mucosal villous architecture with sufficient resolution in patients of suspected CD.[35] Overall sensitivity and accuracy of 87 to 89% and 97%, respectively are reported for the diagnosis of CD using WCE.

Table 1 Summaries of studies on polyp detection (overall) and tumor localization/characterization (in small bowel) involving AI

Study	Disease/ localization	Design	Feature/ technique	Classifier	Image/ videos	Accuracy	Sensitivity
Nawarathna et al[14]	Polyp(LB)	RS	Texton histogram	KNN, SVM	400	95.27%	–
Zhao et al[20]	Polyp(LB)	RS	HMM	Boosted SVM	1,200	90%	–
Li et al[21]	Polyp(LB)	RS	Uniform LBP + wavelet transform	SVM	1,200	91.6%	–
Condessa et al[22]	Polyp(LB)	RS	Local polynomial approximation	SVM	3 videos	–	92.31%
Constantinescu et al[11]	Polyp (SB)	RS	WCE (SB)	ANN	54 videos/90 images	97.7%	93.8%
Li et al[12]	Tumor (SB)	RS	WCE (SB)	KNN, MLP	900/300 images	90.5%	92.3%
Dinevari et al[23]	Tumor (SB)	RS	WCE (SB)	SVM	600/200 images	93.5%	94.04%
Liu et al[13]	Tumor (SB)	RS	WCE (SB)	SVM	1,800 images	97.3%	97.8%

Abbreviations: AI, artificial intelligence; ANN, artificial neural network; CV, cross validation; HMM, hidden Markov model; KNN, k-nearest neighbors; LBP, local binary patterns; MLP, multilayer perception network; RS, retrospective study; SB, small bowel; SVM, support vector machine; WCE, wireless capsule endoscopy.

Table 2 Summaries of studies on Crohn's disease and Celiac disease in small bowel involving AI

Study	Disease/ localization	Design	Diagnostic modality	AI classifier	Videos/ Images in training/ testing	Accuracy	Sensitivity/ specificity
Girgis et al[29]	Crohn's disease	RS	WCE (SB)	SVM	467/277 images	87	80/93
Kumar et al[30]	Crohn's disease	RS	WCE (SB)	SVM	533 images	80.2	81.1/93.6
Wei et al[31]	Crohn's disease	RS	Genetics	SVM	53,279/22,442	AUROC-0.86	71/83
Charisis and Hadjileontiadis[32]	Crohn's disease	RS	WCE (SB)	SVM	800/102 images	93.8	95.2/92.4
Ciaccio et al[35]	Celiac disease	RS	WCE(SB)	SVM	8,600/10,000 images	76.7	88/80
Tenório et al[36]	Celiac disease	RS	EMR	BI, KNN	178/38 images	80	78.8/80
Gadermayr et al[37]	Celiac disease	RS	WL/NBI	SVM	2,835 images	99.6	NA
Zhou et al[38]	Celiac disease	RS	EMR	GoogLeNet	8,800/8000 images	NA	100/100
Chen and Lee[41]	Ulcer	RS	WCE(SB)	SVM	250/930 images	96.3	91.7/99.4
Charisis et al[40]	Ulcer	RS	WCE(SB)	SVM, MNN	156/18 images	95	96.6/93.5
Eid et al[42]	Ulcer	RS	WCE(SB)	SVM	260 images	86.5	84.5/88.6
Yuan et al[43]	Ulcer	RS	WCE(SB)	SVM	271/68 images	92.7	94.1/91.2

Abbreviations: AI, artificial intelligence; ANN, artificial neural network; BI, Bayesian inference; CD, Celiac disease; CV, cross-validation; EMR, electronic medical records; IBD, inflammatory bowel disease; KNN, K nearest neighbor; MNN, Multilayer neural network; NBI, narrow band imaging; RS, retrospective study; SB, small bowel; SVM, support vector machine; SVM, support vector machines; WCE, wireless capsule endoscopy; WL, white light.

Over the last decade, AI has been evolving in diagnosing and classifying disease severity in CD using WCE. The features (color, texture, and shape) of a lesion are being utilized for diagnosis and assessment of extent and severity of CD.[35] A web-based clinical decision support system that uses AI techniques to diagnose CD cases has also been reported.[36] A few researchers assessed a hybrid approach that incorporated expertise and technical knowledge into the computer-based classification, which showed a very high accuracy in diagnosing CD.[37] A 22-layered deep CNN named GoogLeNet achieved 100% sensitivity and specificity in diagnosing CD from WCE clips.[38] However, another group of researchers who built a series of predictive models to diagnose CD utilizing a variety of statistical approaches met with unsatisfactory results, yielding poor discriminatory performance with AUCs ranging from 0.49 to 0.53. Overall sensitivity and accuracy reported in the above studies are 78 to 100% and 76 to 99%, respectively.[35-38] ►**Table 3** summarizes the results of studies on CD using AI.

Ulcer

A vast majority of WCE-related literature is concerned with the reduction of the examination time of WCE data in the detection of certain disorders in the small gut. However, there have been very few studies that have dealt with the detection of ulcers (7%) and Crohn's lesions (2%).[39] Detection of such lesions is difficult owing to the inherent challenges like nonspecific characteristics of such lesions and the huge diversity in appearance. Time, expertise, and feasibility also remain a matter of concern for definitive identification and localization. Various methods have been utilized to extract the color and texture of ulcers while a few studies have focused on the salient region identification. Color-texture extraction using segmentation scheme,[40] ulcer salient map redefined with Gabor filter,[41] texture only extraction method based on discrete curvelet transform,[42] and saliency map using super-pixel region[43] are some of the techniques that have been successfully used. These methods have been reported to achieve a sensitivity of 84 to 97% while the overall diagnostic accuracy remains 86 to 96%. The results of the AI-based studies on ulcers are summarized in ►**Table 2.**

Other Non-Inflammatory and Nonmalignant Lesions

Lymphangiectasia

Lymphangiectasia is the pathologic dilation of lymphatic channels. When it occurs in the intestines, it is known as intestinal lymphangiectasia, also simply called lymphangiectasis. WCE is of use in the detection of these lesions in patients presenting with features of protein-losing enteropathy or chronic malnutrition.[44] Here again, the variability in color, shape, and textural characteristics of lymphangiectatic lesions often makes it extremely difficult to characterize the lesion using WCE or BE, thus making the role of AI even more important.[45] Algorithms using luminance information in hue, saturation, and intensity colors space and Commission Internationale de l'éclairage-Laboratory representation have reported a sensitivity and accuracy of approximately 48 and approximately 98%, respectively in the detection of lymphangiectatic lesions in the small bowel.

Hookworm Infestations

Intestinal hookworms are difficult to find with direct visualization because of their small tubular structures and semitransparent features, which make it tough to distinguish them from the intestinal mucosa. Moreover, the presence

Table 3 Summaries of studies on identification of non-inflammatory lesions and obscure gastrointestinal bleed in small bowel involving AI

Study	Disease/ localization	Design	Diagnostic modality	AI Classifier	Videos/Images in training/testing	Accuracy	Sensitivity/ specificity
Cui et al[45]	Lymphangiectasia	RS	WCE(SB)	Threshold SVM	7,218 images	97.9	48.8/NA
He et al[47]	Hookworm	RS	WCE(SB)	CNN	20,000–30,000	88.5	84.6/88.6
Wu et al[48]	Hookworm	RS	WCE(SB)	Rusboost SVM	401,476/40,148 images	78.2	77.2/77.9
Li and Meng[56]	Obscure GI bleed	RS	WCE(SB)	MLP	2,700/900	NA	87.8/88.6
Pan et al[57]	Obscure GI bleed	RS	WCE(SB)	PNN	14,630 images/150 videos	87.4	93.1/85.8
Lv et al[58]	Obscure GI bleed	RS	WCE(SB)	SVM	280/280	97.9	97.8/98
Fu et al[59]	Obscure GI bleed	RS	WCE(SB)	SVM	30,000/30,000 pixels	94	97/92
Sainju et al[60]	Obscure GI bleed	RS	WCE(SB)	MLP	100 images	93	96/90
Hassan and Haque[61]	Obscure GI Bleed	RS	WCE(SB)	SVM	1,200/1,720 images	99.2	99.4/99
Leenhardt et al[63]	Obscure GI bleed	RS	WCE(SB)	CNN	600/600 images	98	100/96
Tsuboi et al[64]	Obscure GI bleed	RS	WCE(SB)	CNN	2,237/10488 images	NA	98.8/98.4

Abbreviations: AI, artificial intelligence; CNN, convolutional neural network; GI, gastrointestinal; MLP, multilayer perceptron network; MNN, multilayer neural network; RS, retrospective study; SB, small bowel; SSMD, single shot multibox detector; SVM, support vector machines; WCE, wireless capsule endoscopy.

of intestinal secretions makes detection even more difficult. The role of WCE in detecting hookworms in the small intestine has been mentioned in the literature, albeit with highly variable detection rates.[46] Interestingly, AI methods have been utilized to detect hookworms in the small bowel with a sensitivity of 77 to 84% and accuracy of 78 to 88%. The flip side of this is the reportedly high missing rates of around 23%.[47,48] ►**Table 3** summarizes the results of the studies on noninflammatory lesions of the small gut using AI-based methods.

Obscure GI Bleed

Obscure gastrointestinal bleeding (OGIB) is defined as the bleeding from the digestive tract, which recurs or persists after a negative initial evaluation, using both upper and lower GI endoscopy and a negative result on radiologic imaging using small bowel follow-through or enteroclysis.[49] Accounting for approximately 5% of overall GI bleeding, OGIB bleed has been shown to arise from the small bowel distal to the Ampulla of Vater and proximal to the ileocecal valve in more than 80% of the cases, rendering it relatively inaccessible to traditional endoscopy.[49] While the efficacy and reliability of WCE have been tested over many years, the detection rate is variable ranging from 35 to 77%.[50,51]

Various studies comparing WCE to other methods in unraveling the causes of OGIB have shown it to be superior to the other investigations. WCE performed better than CT angiography,[52] CT-enteroclysis, intraoperative enteroscopy,[53] and push enteroscopy[54] in the detection of the lesion. However, the detection rate is comparable to DBE.[55]

Despite the obvious advantages of WCEs over the traditional techniques, issues like exhaustive evaluation of images and interobserver/intraobserver variability including subjective humane error have plagued this novel technique. In a bid to overcome these problems, the application of different AI methodologies has been tried with variable success rates. Combining color and spatial information of bleeding lesions, viz., chromaticity moment ([HIS Color space],[56] [RGB Color space][57]) and color descriptors (pyramid of color invariant histograms, pyramid of hue histograms , and pyramid of transformed color histograms),[58] researchers have applied AI models to detect and localize bleeding lesions in the small bowel. Besides, a few studies have also explored the use of textural features such as pixel segmentation and pixel grouping[59] while a few others have utilized statistical features like a color histogram.[60] A novel algorithm that operates on normalized gray level co-occurrence matrix using the frequency spectrum of WCE images has also successfully been used.[61] Further, AI methods like CNN, MLP, SVM, and PNN have also been used to classify the above image patterns for lesion detection and localization with a sensitivity of 87 to 100%, specificity of 85 to 99%, and a diagnostic accuracy ranging from 87 to 99%.

Small-bowel angiectasia comprises the majority of small-bowel vascular lesions and is diagnosed in 30 to 40% of OGIB cases.[62] Although detection of angiectasia using WCE is well established, computer-aided detection methods have not been validated as yet. CNN algorithm using still frames featuring annotated angiectasia[63] and CNN algorithm based on single shot multibox detector using WCE images of angiectasia[64] have been applied with a reported sensitivity of 98 to 100%, specificity of 96 to 98%, and accuracy of 98%. ►**Table 3** summarizes the results of AI-based studies on small gut for the evaluation of OGIB.

Challenges in AI and Future Directions

Soon, AI is envisaged to play a major role in helping establish diagnoses, devising treatment protocols, and in the prediction of treatment outcomes. Over the last seven decades, AI has been studied extensively and important developments have been made which show promising results. However, a major drawback of all these endeavors is the retrospective nature of most of these studies which have heavily banked upon data chosen from specific endoscopic modalities limited to a fewer number of institutions. In such a situation, there is a high likelihood of selection bias creeping in, therefore, it is crucial to validate the performance of AI using different population-based models in a "real world" setting. Overfitting and spectrum bias have also been observed to impact negatively on AI performance in terms of reproducibility. Overfitting occurs when the learning model is dependent too much on a training dataset, resulting in unsuitable generalization to newer dataset leading to overfitting.[65] There have indeed been attempts to find a way out to solve this problem but with limited success. Besides, datasets in case–control design studies are readily vulnerable to spectrum bias. Spectrum bias occurs when the training dataset does not adequately represent the target population.[66] Because overfitting and spectrum bias may overestimate the accuracy of a model, external validation of unused datasets is mandatory. Additionally, robust clinical verification, as well as properly designed multicenter prospective studies with adequate criteria (inclusion/exclusion) representing the target population, is required. Furthermore, a lack of interpretability or explainability (black box nature) is a major concern in AI technology where the decision-making mechanism of AI models may not be clearly understood and corrected if needed. Some techniques have been developed to address "black box" limitations such as the attention mapping and saliency region identification; these, however, require further studies regarding their applicability.[67] As the accuracy and efficiency of ML model is proportional to the input data, developing an efficient ML model is challenging due to the paucity of human-labeled data. Data augmentation strategies have been proposed to address this problem.[68] Of note Spiking neural networks, which closely mimic the biological mechanisms of neurons, can potentially replace the present ANN models, bringing in higher and more sophisticated computational ability.[69]

The diagnostic precision of AI does not always reflect the exact picture in real clinical practice. The actual benefit in terms of clinical outcome, viz., physician's satisfaction, cost-effectiveness, etc. must be proven by appropriate methods. AI-based models having either inaccuracies or those that deliver results divorced from clinical reality are likely to cause ethical issues owing to misdiagnosis or misclassification. Thus, the impact of AI application on the traditional doctor–patient relationship, which is the essence of the practice of medicine, should be looked into carefully. Ethical principles relevant to AI-based models (akin to Asimov's laws of robotics!) might need to be developed to tackle problems concerning medical ethics and AI. Finally, the formulation of reasonable regulatory guidelines and devising a proper reimbursement policy keeping in mind the economic aspects of health care are essential before integrating AI technology into the current health care structure. It is to be remembered that AI is not perfect and error-free. That is why the concept of "augmented intelligence" has emerged that emphasizes on improving and enhancing human intelligence rather than replacing it. The future challenges in the field of AI-based technology are described in ►**Table 4.**

Conclusion

AI remains an ever-widening field with vast opportunities. In the domain of small bowel diseases, WCE seems to be the only modality at present where ML has been successfully applied in the form of lesion detection and localization. Although the scope of therapeutic intervention is limited, it is hoped that the use of appropriate AI-based technology cannot only shorten the examination time in WCE but also reduce intra/inter observer's variations and eliminate human bias. There is still a lot to be explored in the field of AI including rigorous validation of ML/DL-based models. Therefore, in the present context, these cannot replace clinicians in making a diagnosis. Overfitting, spectrum bias, and lack of explainability remain the core concerns in the development of appropriate AI models. The ethical issues and the economic impact must be addressed judiciously as the day might not be far away when DL methods could be at the forefront among the scheme of modalities in diagnosis making. Real-time diagnosis using AI is a challenge and so also is the development of therapeutic options. To conclude, AI-based models, as of now, can only be used as an adjunct to the physician's clinical acumen and skills. However, the rapid pace at which AI is advancing promises exciting times in the field of endoscopic diagnosis and interventions in the GI tract, especially the small bowel.

Author Contributions

S.P.S. contributed toward conceptualization, methodology, data curation, writing, reviewing, and editing.

D.M., P.B., M.G., and P.A. contributed toward data curation and writing—original draft preparation.

All authors approved the final version of the article, including the authorship list.

Table 4 Future challenges in artificial intelligence

Variations in performance levels: • Great heterogeneity and lack of high-quality datasets. • Wide variety of performance metrics (sensitivity, specificity, and accuracy). • Lack of proper validation techniques in multiple studies.
Lack of randomized controlled trials (RCT) comparing AI vs. non-AI based approaches: • Only two published RCTs to date. Most evidence on AI-based approaches come from preclinical studies.
Limitations of AI techniques that require further investigation: • "Black-box models" barring physicians from finding potential confounding factors. • Ethical challenges • Spectrum bias • Overfitting.

Abbreviation: AI, artificial intelligence.

Conflict of Interest
None declared.

Acknowledgments
This work was partially supported by a grant from the Kalinga Gastroenterology Foundation, Cuttack, India.

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