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# Role of Artificial Intelligence in Endoscopic Intervention: A Clinical Review

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# Role of Artificial Intelligence in Endoscopic Intervention: A Clinical Review

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**Abstract**

**Gastrointestinal diseases are increasing in global prevalence. As a result, the contribution to both mortality and healthcare costs is increasing. While interventions utilizing scoping techniques or ultrasound are crucial to both the timely diagnosis and management of illness, a few limitations are associated with these techniques. Artificial intelligence, using computerized diagnoses, deep learning systems, or neural networks, is increasingly being employed in multiple aspects of medicine to improve the characteristics and outcomes of these tools. Therefore, this review aims to discuss applications of artificial intelligence in endoscopy, colonoscopy, and endoscopic ultrasound.**

*Keywords:* Artificial intelligence, Gastrointestinal disease, Capsule endoscopy, Colonoscopy, Esophagogastroduodenoscopy, Endoscopic ultrasound, Sensitivity, Specificity, Detection rate

## 1. Introduction

Gastrointestinal diseases are quite prevalent globally with estimates beginning from 40%.[1] In the US, about 60–70 million people are impacted by gastrointestinal diseases.[2] As a result, the healthcare cost is quite high. According to a study from 2015, annual health care expenditures for gastrointestinal diseases totaled $135.9 billion.[3] Among the common causes, gastrointestinal hemorrhage, cholelithiasis, cholecystitis, pancreatitis and liver diseases were most prevalent.[3] Apart from management, an important component of healthcare costs includes diagnosis and the diagnostic techniques. In this regard, a few critical diagnostic tools include endoscopy, colonoscopy, and endoscopic ultrasound. Endoscopy was first invented in 1853 and since then has been widely used in gastrointestinal diseases.[4,5] Endoscopy has a few pertinent features including direct visualization of the mucosa of the gastrointestinal (GI) tract, colour changes, abnormalities in vascular pattern that help in diagnosis.[6] Additionally, tissue can be biopsied at the same time.[6] However, endoscopy has certain limitations. The technique is associated with longer procedure times, need for advanced skills and fluoroscopy.[7] This led to invention of capsule endoscopy.[7] However, capsule endoscopy is also associated with a few limitations including delayed transition, uncontrolled air insufflation, limited battery life, and no biopsy capacity.[8] Similar applications for large intestine are performed using colonoscopy.[9] Major complications associated with colonoscopy include bleeding and perforation.[10] In case of pancreaticobiliary diseases, endoscopic ultrasound is a gold standard technique for establishing diagnosis and management.[11] However, based on imaging only, on endoscopic ultrasound, benign and malignant lesions cannot be differentiated. Additionally, endoscopic ultrasound is operator dependent.[12] Artificial intelligence is one of the solutions to the limitations of the gastrointestinal techniques. The aim of this review is to discuss artificial intelligence in endoscopy, colonoscopy, and endoscopic ultrasound.

## 2. Methodology

We did a narrative review from PubMed and Google Scholar on studies published on artificial

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intelligence and endoscopic intervention from 2004 to 2023. The keywords used were 'artificial intelligence, 'gastrointestinal diseases, 'esophagogastroduodenoscopy, 'capsule endoscopy, 'colonoscopy', and endoscopic ultrasound'. The study's eligibility criteria comprised two main aspects: 1) research related to artificial intelligence, **specifically deep learning methods, convolutional neural networks, artificial neural networks, algorithm data, pattern recognition, multilayered input/output models, computer-assisted recognition systems** and 2) investigations on gastrointestinal diseases. Excluded from consideration were studies lacking the specified outcomes or prerequisites, those not presented in English or lacking an English translation, and studies for which data retrieval proved unfeasible.

## 3. Discussion

A summary of the basic network for uses of artificial intelligence in endoscopic techniques is illustrated in Fig. 1.

### 3.1. Artificial intelligence in endoscopy

#### 3.1.1. Detection of blind spots

Deep Learning algorithms have been created to flag standard structures. These algorithms have been combined with neural networks to limit blind spots. In one such study investigating neural networks, the accuracy of imaging was 97%.[13] In another single-center study investigating WISE-NSE used in identifying areas of limited visibility during esophagogastroduodenoscopy (EGD) and establishing an automated photographic documentation system, the blind spot detection had increased significantly 5.86% (P < 00.001).[14] Similar findings were discussed in a randomized controlled trial.[15]

#### 3.1.2. Diagnosis of Helicobacter pylori infection

Utilizing artificial intelligence has the potential to enhance the diagnostic capabilities of physicians in identifying H pylori infection through pattern recognition in endoscopic images. In a particular investigation, a 22-layer neural network was employed on a collection of gastric images from upper endoscopy, and its performance was compared with that of gastroenterologists. The detection rate was comparable to expert endoscopists but notably superior to less experienced ones.[16,17] One challenge in endoscopic diagnosis involves distinguishing between active and eradicated infections, and in this context, algorithms are likely to be specific to particular populations.[16]

#### 3.1.3. Diagnosis of premalignant and malignant lesions

In a specific investigation, an algorithm employing a neural network was developed to diagnose gastric cancer through the analysis of endoscopic images. Within a brief duration of 47 s, the algorithm demonstrated a high accuracy in identifying lesions as malignant (sensitivity 92.2%).[18] However, a significant portion of benign lesions was erroneously classified as cancer, resulting in a reduced positive predictive value.[18] Additionally, the study noted that all well-differentiated gastric cancers were overlooked.[18] Another study focused on distinguishing lesions based on their depth using a neural network.[19] In this research, the system exhibited improved accuracy (by 17.25%; 95% CI, 11.63%–22.59%) and specificity (by 32.21%; 95% CI, 26.78–37.44%) in differentiating early gastric cancer from deeper submucosal invasion.[19]

#### 3.1.4. Evaluation of esophageal malignancy and dysplasia

An alternative algorithm was employed to improve the identification of esophageal dysplasia

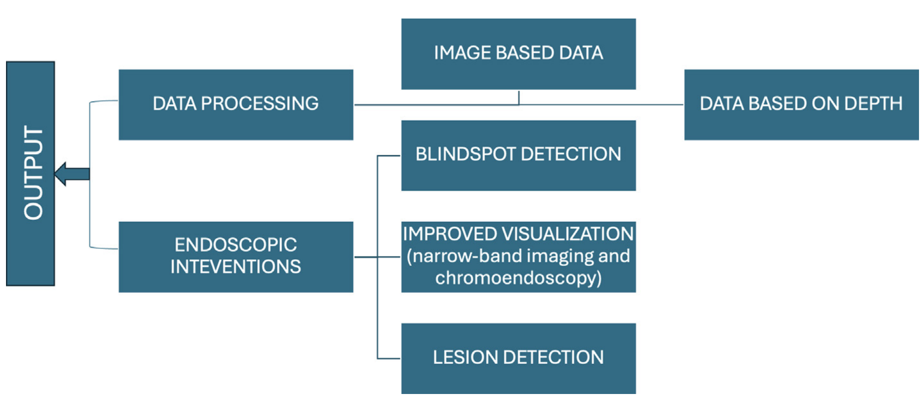


*Fig. 1. Proposed network for use of artificial intelligence in endoscopic techniques.*

and cancer by utilizing archived images.[20] The sensitivity of this technique ranged from 81% to 89%, while the positive predictive value was 40%, with a limitation related to shadows or anatomical impressions on the esophageal lumen.[20] Addressing dysplasia in Barrett's esophagus presents a challenge in endoscopy. A deep learning system validated high-resolution images from patients with Barrett's esophagus using two datasets.[21] The system demonstrated an accuracy of 89%, sensitivity of 90%, and specificity of 88% in precisely classifying dysplasia. Furthermore, it successfully pinpointed the optimal biopsy site for dysplastic Barrett's esophagus in 92%−97% of cases.[21]

### 3.2. *Artificial intelligence in capsule endoscopy*

#### 3.2.1. *Application in gastrointestinal hemorrhage*

Video capsule endoscopy has found application in detecting gastrointestinal hemorrhage, and artificial intelligence has played a crucial role in advancing its capabilities. In a study examining 400 frames of gastrointestinal hemorrhage, a support-vector machine model demonstrated a sensitivity exceeding 80% in identifying active bleeding.[22,23] Higher levels of accuracy, specificity, and sensitivity were achieved with a multilayer perceptron (MLP) model.[24] Charisis et al. utilized a dataset comparing images of normal mucosa to ulcers, successfully detecting cases with active bleeding; however, the model exhibited limitations in identifying cases of mild severity.[25] The evolution of imaging since the integration of artificial intelligence has shown improvement, with recent studies identifying optimal operator-dependent variables at a low computational cost.[26,27]

#### 3.2.2. *AI and protuberant lesions*

Artificial intelligence proves effective in precisely identifying structures within the mucosa of the small intestine. In 2008, an algorithm utilizing the MLP method was developed, achieving a sensitivity of 98.7% and specificity of 96.6% in detecting small intestine tumors.[28] In 2011, a color-oriented approach was employed, resulting in a sensitivity of 82.3% and specificity of 84.7% in identifying gastrointestinal tumors.[29] Zhao et al. explored a more dynamic approach by analyzing consecutive images of the same lesion. The study demonstrated that a polyp sequence could contain normal frames, and conversely, a normal mucosa sequence could include abnormal frames. This technique led to improved specificity and sensitivity in evaluating each frame.[30]

#### 3.2.3. *Artificial intelligence in inflammatory bowel disease*

Klang et al. formulated a deep-learning algorithm by employing endoscopic capsule images from individuals with Crohn's disease (CD) and those without the condition. The algorithm demonstrated an accuracy surpassing 95%, indicating the potential of this technology in predicting small-bowel findings through video capsule endoscopy in CD patients.[31] Subsequent studies in March 2020 further reinforced the principles under consideration.[32]

#### 3.2.4. *AI and hookworm*

Capsule endoscopy with artificial intelligence has been discussed in detecting parasites. The sensitivity and specificity were about 78%.[33] The major limitation of the technique was due to an inability to detect the parasite's structure from some bubbles and intestinal folds.[33]

### 3.3. *Artificial intelligence in colonoscopy*

Artificial intelligence has been employed in identifying both neoplastic and non-neoplastic lesions, with advancements such as high-definition white light (HDWL) endoscopy enhancing traditional techniques. Other improvements include narrow-band imaging and chromoendoscopy.[34-36] In a 2017 study, a convolutional neural network was explored to enhance WL endoscopy. Following training on pre-existing images, the system accurately differentiated between adenomatous and non-adenomatous polyps in 70% of newly presented cases.[37] Similar studies were able to correctly differentiate polyps from suspicious lesions.[38-40] Additionally, a deep learning model was examined for classifying colorectal lesions during WL endoscopy, achieving a sensitivity of 80.0% and specificity of 91.3% in identifying high-grade dysplasia, stages T1-T4 colorectal cancer, and non-advanced lesions.[40]

### 3.4. *Artificial intelligence in endoscopic ultrasound*

#### 3.4.1. *Pancreatic lesions*

Computer-aided diagnosis (CAD) utilizing artificial intelligence has proven valuable in image differentiation and enhanced diagnostic accuracy. In a previous investigation, artificial intelligence-assisted endoscopic ultrasound achieved a diagnostic accuracy of 95% for pancreatic diseases.[41,42] By employing a neural network, another study demonstrated a diagnostic capability of approximately 93% for distinguishing acute and chronic pancreatitis, improving to 94% with a vector system.[43,44] Another study introduced a deep-learning system to discern between high-grade dysplasia and malignancy, estimating an accuracy of 94%.[44] The use of occlusion heatmap analysis contributed to distinguishing autoimmune pancreatitis from pancreatic ductal adenocarcinoma, guiding early initiation of immunosuppressive or chemotherapy and reducing unnecessary resections.[45] Additionally, a study focused on analyzing cyst fluid to differentiate benign lesions from cystic pancreatic lesions. The diagnostic algorithm incorporated factors such as CEA, carbohydrate antigen 19-9, carbohydrate antigen 125, amylase in the cyst fluid, sex, cyst location, connection of the pancreatic duct and cyst, type of cyst, and cytology.[46] In terms of diagnostic ability for malignant cystic lesions, the area under the receiver-operating characteristics curves was 0.719 (CEA), 0.739 (cytology), and 0.966 (AI).[46] The sensitivity, specificity, and accuracy of AI in diagnosing malignant cystic lesions were 95.7%, 91.9%, and 92.9%, respectively.[46] AI sensitivity surpassed that of CEA (60.9%, $p = 0.021$) and cytology (47.8%, $p = 0.001$), while AI accuracy was also higher than CEA (71.8%, $p < 0.001$) and cytology (85.9%, $p = 0.210$).[46] However, limitations of artificial intelligence in this context include the black-box phenomenon, which may lead to judgment errors, and the absence of external validation despite internal validation of multiple operator-dependent characteristics.[47,48]

### *3.4.2. Gastrointestinal subepithelial lesions*

Computer-aided diagnosis systems have been applied to gastrointestinal subepithelial lesions, demonstrating superior performance compared to B-mode EUS in distinguishing between leiomyomas and GISTs, as well as in discerning the risk stratification of GISTs.[49] Image analysis techniques have been employed for the diagnosis of gastric stromal tumors.[50,51] Malignancy stratification in GISTs has also been conducted using artificial intelligence, with the overall accuracy of AI models predicting malignant potential ranging from 66.0% to 83.4%.[52-55] In the research by Nguyen et al., a neural network exhibited strong discriminatory capabilities for lipomas (AUC = 0.92), carcinoids (AUC = 0.86), and GISTs (AUC = 0.89).[56] However, the studies addressing artificial intelligence noted challenges related to heterogeneity, and due to the diverse nature of the samples, uniform validation could not be consistently performed.

### *3.4.3. Gallbladder lesions*

An artificial intelligence algorithm evaluated the diagnostic performance for gallbladder polyps. For the differential diagnosis of neoplastic and non-neoplastic GB polyps, these values for endoscopic ultrasound were 57.9%, 96.5%, 77.8%, 91.6%, and 89.8%, respectively. Estimates for accuracy using external validation ranged from 66.7% to 77.5%.[57] Further studies have also evaluated algorithms in diagnosing and screening for biliary malignancy.[58]

### *3.4.4. Limitations*

The use of AI tools in medicine presents both opportunities and challenges. While standardizing medical practices through AI may seem beneficial, a significant issue lies in the lack of transparency regarding how AI reaches its conclusions, known as the “black box problem.” Users of AI algorithms are often unaware of the factors considered or omitted in decision-making, making it difficult to detect and address biases.[59] Moreover, biases inherent in human-generated training data can perpetuate in AI outputs, potentially amplifying biases in clinical decision-making.[59] Even well-intentioned AI systems might unknowingly incorporate biases, as demonstrated by AI accurately predicting race from medical images, raising concerns about racial bias in decision-making processes.[60] Although AI can help identify implicit biases in physicians, overreliance on technology is cautioned against.[61] While AI holds promise for enhancing objectivity and reducing bias in various fields, without adequate attention to bias mitigation during development, it risks exacerbating and concealing biases instead.[61]

Furthermore, patient autonomy, allowing patients to make and have their decisions honored, even regarding AI-assisted treatment should be maintained.[62] Privacy and confidentiality are crucial aspects of respect for persons, ensuring that health information used to empower AI is protected against unauthorized use.[62] Integrity, emphasizing trust in both AI and healthcare professionals, is essential despite the challenges posed by the “black box problem” of AI decision-making.[59,62] Conflicts of interest must be addressed transparently to maintain integrity, particularly concerning patient data used for AI learning.[62]

Beneficence, focusing on improving diagnosis, prognosis, and treatment, underscores AI's aim to enhance individual lives and distribute benefits across populations equitably while minimizing waste.[62] Nonmaleficence involves recognizing and addressing harms caused by AI, necessitating a culture of harm disclosure and governance that considers group vulnerabilities.[62] Justice emphasizes fairness and equality, urging efforts to reduce bias in AI and mitigate disparities in healthcare outcomes by ensuring representative and unbiased data. Ultimately, prioritizing justice in AI development can foster public trust and promote more equitable health outcomes.[62]

## 4. Conclusions

Artificial intelligence is transforming practices in interventional gastroenterology by enhancing detection and diagnosis in various areas. Deep learning algorithms, combined with neural networks, have notably reduced blind spots in endoscopic imaging. It demonstrates high accuracy in diagnosing conditions like *H. pylori* infection, gastric cancer, and esophageal dysplasia, often surpassing human performance. In colonoscopy, it improves lesion identification, although issues such as the "black box problem" and biases in training data need addressing. Similarly, AI assists in diagnosing pancreatic lesions, gastrointestinal subepithelial lesions, and gallbladder lesions in endoscopic ultrasound, with promising results. However, challenges related to heterogeneity and validation persist. Overall, while AI offers significant benefits in improving diagnostic accuracy and patient outcomes, ensuring transparency, privacy, integrity, and justice in its development and implementation is crucial to mitigate biases and ensure equitable healthcare access. Maintaining patient autonomy and addressing conflicts of interest are also essential in the responsible integration of AI into clinical practice.

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The authors have no disclaimers to declare.

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