Current status and prospect on artificial intelligence for digestive endoscopy

Artificial intelligence in digestive endoscopy

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ABSTRACT

In recent years, AI has rapidly developed and set off a research boom in several fields of medicine, showing great potential and promising to bring revolutionary changes to the medical field. Currently, researches on AI in digestive endoscopy are in full swing, and many great results have been achieved. This paper provides a systematic description of the research related to AI in digestive endoscopy and discusses the challenges and prospects of AI in digestive endoscopy.

Keywords: Artificial Intelligence, Digestive Endoscopy, Deep Learning

INTRODUCTION

Artificial intelligence (AI) is a new science and technology that makes machines mimic certain thinking processes and behaviors of human beings. In recent years, AI has set off a research boom in many fields of medicine, showing great potential. Digestive endoscopy is a hot field of medical AI research, and relevant research is in full swing at home and abroad, with significant breakthroughs in several fields. The intelligent development of digestive endoscopy is expected to solve the problems of large demand for endoscopy, shortage of endoscopists, uneven quality of examination and high training cost. We searched PubMed, China National Knowledge Infrastructure (CNKI) and other databases for studies on AI in digestive endoscopy up to November 2021. Now we summarize the progress of AI in digestive endoscopy and discuss the shortcomings and challenges, with hope to provide ideas for the exploration of AI in digestive endoscopy.

AI IN GASTROSCOPY

Diagnosis of Esophageal Lesions

Esophageal cancer is the sixth most common cause of cancer-related death globally, and esophageal squamous cell carcinoma (ESCC) accounts for more than 90% of esophageal cancers in China. Studies have found that the five-year survival rate of patients with advanced esophageal cancer is less than 20%, and the five-year survival rate of patients with early esophageal cancer is more than 80%.[1-2] Hence, early diagnosis and treatment is the key to improve the prognosis of patients with esophageal cancer. Yunshi Zhong *et al.* developed a novel system of computer-aided detection (CAD) to localize and identify early ESCC under conventional endoscopic white-light imaging, and its sensitivity, specificity, accuracy, positive predictive value and negative predictive value reached 97.8%, 85.4%, 91.4%, 86.4% and 97.6%, respectively. with the assistance of AI, the accuracy of diagnosis increased from 81.7% to 91.1%, and the diagnostic ability of endoscopists was greatly improved.[3] The AI model developed by Jiangming Xu *et al.* can assist in distinguishing the type of intrapapillary capillary loops in ESCC, and its classification accuracy reached 89.2% with a high level of diagnosis.[4] Guoxin Zhang *et al.* trained to obtain a system that can differentiate esophageal protruded lesions. It also can be used to distinguish esophageal leiomyoma, esophageal cyst and esophageal papilloma.[5]

Barrett's esophagus (BE) is a precancerous lesion of esophageal adenocarcinoma (EAC), and considering the high mortality rate of patients with EAC, early identification of neoplastic BE is beneficial to reduce their mortality.[6] The AI model constructed by Alanna Ebigbo *et al.* can accurately distinguish normal BE from early EAC with an accuracy of 89.9%.[7]

Diagnosis of Gastric Lesions

According to statistics,[1] there were about 1,033,000 new cases and 783,000 deaths of gastric cancer worldwide in 2018; Gastric cancer is the fifth most common malignancy worldwide and the third leading cause of cancer-related deaths worldwide. The five-year survival rate of patients with advanced gastric cancer ranges from 5% to 25%, and the five-year survival rate of patients with early gastric cancer (EGC) is as high as 90%.[8]

Gastric atrophy and intestinal metaplasia are precancerous conditions of gastric cancer, which is of great importance in the development of gastric cancer. Honggang Yu *et al.* constructed a system called ENDOANGEL that can detect gastric precancerous conditions by image-enhanced endoscopy and conducted a multicenter diagnostic study. The results showed that the diagnostic accuracy of this system was high, which was similar to that of experts and superior to that of non-experts, and provided the possibility of a wide range of applications in assisting the diagnosis of gastric precancerous conditions.[9] The team also developed a system for assisting in the identification of EGC with an accuracy rate of 92.5%,[10] and its effectiveness was further validated in a multicenter clinical trial.[11] Xiaoping Zou *et al.* also developed a real-time artificial intelligence-assisted system for detecting EGC and validated it in endoscopic images from multiple centers, with accuracy of 85.1% to 91.2% in different centers, which is expected to be an important aid for EGC screening.[12]

The development of magnifying staining endoscopy has improved the diagnosis rate of EGC, but the difference in diagnostic level between physicians has been a major challenge. Chaohui Yu *et al.* developed an AI model to accurately identify EGC by magnifying endoscopy with narrow band imaging (ME-NBI) and improve the diagnostic level of endoscopists.[13] Jie Tian *et al.* also developed a model for identifying EGC under ME-NBI. The area under the receiver operating characteristic curve (AUC) of the model was 0.808, and the diagnostic level was similar to that of senior doctors.[14] AI has great potential in clinical applications and is expected to provide an important auxiliary power for the diagnosis of EGC in magnifying staining endoscopy.

It is crucial for endoscopic curative resection to accurately delineate cancer margins, differentiation degree and depth. Therefore, Honggang Yu *et al.* developed an AI model for predicting the resection margin of EGC under indigo carmine chromoendoscopy (CE) or white light endoscopy (WLE), achieving 85.7% and 88.9% accuracy, respectively.[15] Meanwhile, the team also constructed another model that can accurately identify the differentiation status and delineate margins of EGC in ME-NBI endoscopy with accuracy of 83.3% and 82.7%, respectively, which can provide an aid for endoscopic treatment of early cancer. [16]

In December 2020, Honggang Yu *et al.* held a large-scale human-machine competition to evaluate the performance of the AI system developed by the team in diagnosing EGC and predicting invasion depth and differentiation status. 46 endoscopists from 44 hospitals in 19 provinces in China participated in this study. The AI system and endoscopists identified 100 lesions from Peking University Cancer Hospital in the same setting. The results showed that the AI system acquired 89.00%, 78.57% and 71.43% accuracy in diagnosing EGC, predicting invasion depth and differentiation status, respectively, which was above the average diagnostic level of endoscopists (85.67%, 63.75% and 64.41%, respectively). At the same time, this AI system achieved real-time lesion diagnosis synchronized with video, using less time than endoscopy specialists.[17] This AI system has great potential for EGC screening and can be useful in clinical practice.

Helicobacter pylori (Hp) infection is closely associated with functional dyspepsia, peptic ulcer and gastric cancer. However, the gold standard for diagnosis of HP infection under gastroscopy is biopsy, and it is difficult to make an accurate judgment of HP infection solely by endoscopic imaging. The AI-assisted system developed by Jianmin Si *et al.* has a high diagnostic value with accuracy of 84.5% in diagnosing HP infection.[18]

Gastric ulcers are one of the more common lesions in the stomach, and endoscopists capable of identifying benign and malignant ulcer vary. Hence, Honggang Yu *et al.* developed a system to identify gastric ulcer and distinguish benign and malignant ulcer. It had accuracy of 98.0%, 98.0%, and 85.0% in distinguishing normal mucosa from benign ulcers, normal mucosa from malignant ulcers, and benign from malignant ulcers, respectively, which has good application prospects.[19]

Monitoring blind spots

Digestive endoscopy is one of the most common methods to diagnose lesions in the upper gastrointestinal tract. However, endoscopists operate at varying levels, reducing the detection rate of gastric cancer and precancerous conditions. A complete view of the entire GI tract is a prerequisite to avoid missing lesions. According to the gastroscopy operation Guidelines written by the European Society of Gastrointestinal Endoscopy[20] and gastroscopy screening protocols in Japan,[21] Honggang Yu *et al.* divided the observation area of gastroscopy into 26 parts and innovatively developed an AI system based on deep learning to monitor the blind spots during gastroscopy, which achieved average accuracy of 90.02% in predicting 26 sites.[22] In a subsequent single-center randomized controlled trial, they validate the effectiveness and safety of this system in painless gastroscopy. The results showed that the blind spots rate of 5.86% in the experimental group with AI assistance was much lower than that of the control group without AI assistance (22.46%). In addition, the team conducted a multicenter randomized clinical trial to further validate the generalizability and effectiveness of the model.[11] To evaluate the performance of the model in different gastroscopy types, the team also conducted a 3-parallel-group and randomized trial to compare the blind spot rate of endoscopists in the painless, ultra-fine, and plain gastroscopy groups with and without AI assistance, showing that the system significantly reduced the blind spot rate gastroscopy in all subgroup.[23] This system can be a good tool for monitoring and improving the quality of gastroscopy.

Evaluation of Esophagogastric Varices

Rupture of gastroesophageal varices is the most common fatal adverse event of cirrhosis. Endoscopy is regarded the standard for diagnosis and risk stratification of gastroesophageal variceal bleeding. However, accurate assessment for varices relies on the extensive experience and theoretical basis of the endoscopist, resulting in a more subjective judgment of the findings. Therefore, Honggang Yu *et al.* developed an AI model trained with 8566 images of gastroesophageal varices from 3021 patients and 6152 images of normal esophagus and stomach from 3168 patients, which achieved 97.00% and 92.00% accuracy in detecting esophageal varices and gastric varices, respectively. The accuracy of predicting the size, form, color, bleeding signs is comparable to or even better than that of endoscopists.[24] The same high diagnostic level was achieved in multicenter validation. Thus, the model is expected to be an important tool to assist endoscopists in a more objective and precise evaluation of risk stratification of gastroesophageal varices.

AI IN COLORECTAL ENDOSCOPY

Assessing The Quality of Bowel Preparation

Bowel cleanliness is one of the most important factors affecting the detection rate of adenomas and polyps. Good bowel preparation can ensure adequate visualization of the intestinal mucosa, thus improving the quality of colonoscopy. However, the current clinical assessment of bowel cleanliness is more subjective or incomplete, which affects the evaluation of patients for early colonoscopy review. According to the Boston score standard, Honggang Yu *et al.* developed a bowel preparation quality-control system, which achieves a high accuracy of 91.89% for the recognition of the four-category images of the Boston score. And it can not only prompt bowel preparation every 30 seconds, but also display the cumulative proportion of bowel preparation scores in real time, thus assessing the quality of bowel preparation more objectively and stably.[25]

Ancillary Detection of Intestinal Lesions

Colorectal cancer is the third most lethal malignancy worldwide.[1] Improving the detection rate of adenomas is critical to reduce the incidence of colorectal cancer. Each 1.0% increase in adenoma detection was associated with a 3.0% reduction in interval colorectal cancer risk.[26] A meta-analysis found that the rate of missed adenomas during colonoscopy was as high as 26%.[27] At present, the two main reasons for missed adenoma detection include the following: inadequate observation of the mucosa and concealed polyps that are difficult to identify. The development of AI presents an opportunity to solve the above problems.

To address the problem of inadequate observation of the mucosa, Honggang Yu *et al.* developed an AI system for monitoring the real-time withdraw speed, and obtained the "Hamming distance" by calculating the similarity between images through computer vision technology, which innovatively realized the withdraw speed monitoring of the lower gastrointestinal tract and could prompt the withdraw speed in real time.[28] When the withdraw speed is too fast, it prompts the endoscopist to slow down and observe the intestinal mucosa carefully. In a single-center randomized clinical trial, the rate of adenoma detection doubled in the AI-assisted group compared with the non-AI-assisted group (16% vs. 8%).

To solve the problem of concealed intestinal polyps that are difficult to identify, Misawa M *et al.* developed an AI-assisted polyp detection system and validated it with a new public database. The per-polyp sensitivities for all, diminutive, protruded, and flat polyps were 98.0%, 98.3%, 98.5%, and 97.0%, respectively.[29] The automated polyp detection system developed by Xiaogang Liu and Pu Wang *et al.* also has high sensitivity and specificity, which can significantly improve the detection rate of adenomas and polyps in clinical trials and is expected to play an important role in clinical practice.[30-34]

Ancillary Diagnosis of Intestinal Lesions

It is very important to identify the type of polyp for the treatment and prognosis of patients. Benign polyps have minimal risk of cancer and no need no need for preventive resection; adenomatous polyps and serrated polyps require to be resected to prevent colorectal cancer; and colorectal cancer requires immediate endoscopic or surgical intervention to prevent further progression.[35] The intelligent detection model of colorectal cancer obtained by training with 464,105 images by D.J. Zhou *et al.* has a high diagnostic level in distinguishing benign and malignant lesions, which is helpful to improve the detection rate of colorectal cancer in clinical practice.[36]

Endoscopic submucosal dissection (ESD) and endoscopic mucosal resection (EMR) are applied in treating superficial colorectal neoplasms, but are contraindicated by deeply invasive colorectal cancer. Thus, it is important to determine the invasion depth of tumor. S. Liu *et al.* developed an AI system and validated their model using 1634 white-light colonoscopy (WLC) images. The results showed that the system can distinguish noninvasive or superficially submucosal invasive neoplasms from deeply invasive CRC with high accuracy, sensitivity and specificity, helping to determine the application of ESD and EMR.[37]

AI IN CAPSULE ENDOSCOPY

Capsule endoscopy, as a non-invasive examination, is increasingly used for the diagnosis of gastrointestinal diseases, especially for small-bowel diseases. However, capsule endoscopy generates numerous images, and analysis is time-consuming and boring, which easily leads to visual fatigue of endoscopists and makes it difficult to ensure diagnostic accuracy. Therefore, AI-assisted systems have become a hot topic in the industry. Its main research directions include the following:

Reduce Reviewing Time and Improve Efficiency

Zhen Ding *et al.* developed a model based on deep learning with more than 100 million images to distinguish abnormal and normal small bowel images, achieving a sensitivity of 99.88%. The AI capsule endoscopy review time was only 5.9 min, which greatly improved the work efficiency.[38]

Improve The Accuracy of Lesion Diagnosis

AtsuoYamda *et al.* trained an AI system with sensitivity, specificity and accuracy of

88.2%, 90.9% and 90.8%, respectively, for identifying erosions and ulcerations under capsule endoscopy, which not only improved the accuracy of lesion diagnosis, but also greatly reduced the workload of endoscopists.[39] An AI-assisted model for identifying gastric lesions trained by Zhaoshen Li *et al.* using magnetic capsule endoscopy images had a sensitivity of 96.5%, which could greatly reduce the difference in diagnostic level between endoscopists.[40] Zhen Ding *et al.* also developed an AI system to assist in identifying and diagnosing small intestinal bleeding with a sensitivity of 99.0%, which made it more focused on the diagnosis of small intestinal bleeding. [41]

AI IN ERCP

It was found that 7% to 12% of patients with cholelithiasis have common bile duct stones as a result of gallstones migrating from the gallbladder into the bile duct.[42] To date, endoscopic retrograde cholangiopancreatography（ERCP）remains the first choice of treatment for bile duct stones.[43] ERCP is one of the difficult operations in digestive endoscopy, and there are the main factors affecting the difficulty of stone extraction With Endoscope: the number and size of common bile duct stones, angulation and diameter of the distal common bile duct. Analysis and stratification of these factors can ensure that the endoscopist can more accurately predict the difficulty of stone extraction, while adopting a more appropriate treatment. Based on this, Honggang Yu *et al.* developed an intelligent difficulty scoring and assistance system that can automatically measure stone size and distal common bile duct and duodenoscope diameters with a precise level of measurement.[44] It can play an important role in assisting endoscopists to select appropriate surgical accessories and treatment and to make more accurate surgical plans.

AI IN ENDOSCOPIC ULTRASOUND

Endoscopic ultrasound (EUS) is an important tool for the diagnosis of biliary and pancreatic diseases. however, a great deal of professional knowledge and rich experience are the prerequisites for excellence in endoscopic ultrasound. In addition, the long training period and high training cost of have greatly hindered the promotion and application of EUS in clinical practice.[45] The rapid development of AI in the field of medical imaging has brought an opportunity for the promotion of EUS.

Monitoring Quality and Supporting Training

Honggang Yu *et al.* developed a deep-learning–based pancreas segmentation and station recognition system, which could be used to assist endoscopists to recognize the six basic sites of pancreatic sweep with accuracy of 94.2%. It can not only monitor the quality of pancreas examination, but also serve as a good training system for guiding novice physicians.[46] Meanwhile, the team also developed an augmentation system for standardized bile duct (BD) scanning and assisted endoscopists in identifying the four basic stations of BD scanning, with accuracy of 93.3% and a Dice of 0.77 for BD segmentation, which not only assisted in identifying the standard workstations and suggested endoscopists to perform the corresponding operations, but also segmented BD with high precision, automatically measured the diameter of bile duct, and simplified the operation.[47] These two systems significantly improved the accuracy of site identification of endoscopists in the experiments.

Improving Accuracy in Identifying Lesions

The diagnosis and differentiation of pancreatic lesions is also a challenge in ultrasound endoscopy. Maria NB *et al.* developed an AI model using 1,174,461 unique EUS images, which could accurately distinguish autoimmune pancreatitis from other study conditions (pancreatic ductal adenocarcinoma, chronic pancreatitis and normal pancreas) with sensitivity and specificity of 90% and 85%, respectively, and has the potential to become an important auxiliary tool in the clinical diagnosis of autoimmune pancreatitis.[48]

CHALLENGES AND PROSPECTS OF AI IN DIGESTIVE ENDOSCOPY

AI has been developed significantly in endoscopy, especially the deep learning algorithms that have emerged in recent years, which is comparable with endoscopic experts in disease diagnosis, lesion detection, and operation quality control. In the future, it is expected to solve the problems existing in the clinical practice of digestive endoscopy, such as difficulty in identifying lesions and poor operation. However, it is only the first step to develop model in the application of AI to digestive endoscopy, and there are still serious challenges in integrating the model into the complex clinical practice.

Data Sharing

Deep learning discovers distributed feature of data by automatically characterizing features of objects such as images and sounds.[49] Large and representative dataset is a prerequisite to ensure that the automatic tuning process achieves an optimal solution and is also a useful tool for robustness test of the model.[50-51] However, the incidence of important diseases in digestive endoscopy such as early gastrointestinal cancer, inflammatory bowel disease, serrated polyps is relatively low. With the increasingly widespread application of deep learning, the lack of data is becoming a common problem faced by AI researchers in digestive endoscopy.[52-53]

It is no doubt that promoting data sharing can greatly alleviate the pressure of data quantity facing the development of AI in digestive endoscopy, but a series of tasks including data collection, cleaning, and local calibration need to be completed by a huge amount of manpower. Besides, anonymity as well as a broad informed consent process should be ensured, and the confidentiality of patient privacy may become a critical barrier during data sharing at a larger scale of dissemination.[54]

Transparency of the Model

Transparency of data and AI algorithms is another major issue. The relationship between transparency of deep learning and AI models is multi-layered. On the one hand, the accuracy of model predictions largely depends on the accuracy of the training data annotations input to the algorithm. Therefore, it is crucial for model accuracy to ensure transparency of the labels so that the training process of the algorithm can be monitored by the third party.[55]

On the other hand, transparency of the model is also reflected in the interpretability of its results. interpretability is the ability of a model to enable humans to understand or explain the basis of a decision or prediction.[56] If predictions can be explained, then humans can validate whether their predictions are valid or not.[57] Thus, the interpretability of a model may improve physicians' acceptance of predictions.[58] Although the application of deep learning in digestive endoscopy has been in full swing, the exploration of interpretability is still limited. Honggang Yu *et al.* used heat map to demonstrate the regions of focus when deep learning predicts EGC, making an initial attempt at interpretability.[10] The interpretability of the model can be further improved by visualizing high-dimensional data and masking mapping,[59] but its effectiveness still needs to be further explored. In the future, attempts regarding interpretability may be the key to promote the clinical application of AI in digestive endoscopy.

Quality Standards of the Model

AI in digestive endoscopy has gone through the initial stage – validation. However, the lack of data standards, testing platforms, and third-party databases makes it difficult to obje

ctively measure the performance of current AI algorithms. At present, the training of AI models still faces a series of problems: (1) the data used in the studies are mostly from a single center and small samples, and there is bias of data selection; (2) the methods and standards of data labeling are not uniform, lacking representativeness; (3) the quality of data is easily affected by factors such as operators' habits, operation level and storage methods, and quality is difficult to guarantee. Compared to building a large-scale data sharing system, it is more feasible and urgent to establish real-time measurement standards based on a fully closed independent sandbox monitoring environment, where data collection, labeling, testing, and scoring are all performed by a fair and impartial third party.[60]

Ethical Challenges of AI In Digestive Endoscopy Diagnosis and Treatment

Large-scale multicenter clinical studies of AI in digestive endoscopy have not been conducted, and the potential drawbacks have not been fully disclosed. Based on the current results of single-center clinical studies, the application of AI may lead to unnecessary polypectomies, causing additional economic burden and potential complications.[30] In addition, another more serious issue is how to establish a sound accountability for medical errors with AI. AI technology will undoubtedly change the traditional physician-patient relationship, and intrinsic to this change is a potential shift in physicians' sense of personal responsibility. For example, in the prediction of the nature of gastrointestinal tumors, misjudgments caused by AI can result in patients undergoing unnecessary surgery or delaying the diagnosis and treatment.[61] The source of accountability is then multiple--the physician, the vendor providing the software platform, the developer who constructed the algorithm, or the source of the training data. It is an important part of the clinical application of AI in digestive endoscopy to establish a sound system of accountability, but it remains to be seen where the ultimate responsibility will lie.

In conclusion, AI is expected to play a crucial role in improving the quality of endoscopy, reducing the rate of missed lesions, and alleviating the lack of training resources. However, most studies are still in exploration and have not yet been applied to clinical practice. Moreover, researchers face serious challenges such as limited data, insufficient transparency of algorithms, inconsistent quality standards, and ethical issues. With the development of technology and industry standardization, it is believed that in the coming future, AI for endoscopy will be widely used in clinical practice, greatly improving the quality of digestive endoscopy and improving the prognosis of patients.

Competing Interests

The author declares no competing interests.

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