Research trends on artificial intelligence and endoscopy in digestive diseases: A bibliometric analysis from 1990 to 2022

Du RC *et al*. Artificial intelligence and endoscopy

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INTRODUCTION

Gastrointestinal cancers (esophageal cancer, gastric cancer, colorectal cancer, *etc.*) account for 26% of global cancer incidence and 35% of all cancer-related deaths, which seriously threaten the health of global populations[1]. Gastrointestinal tumors diagnosed at an early stage had a better prognosis than those diagnosed at a late stage. For example, the five-year survival rates of early gastric cancer and advanced gastric cancer were > 90% and < 30%, respectively. Performing endoscopy is the most effective approach to detect gastrointestinal tumors. More than 100 million subjects receive gastrointestinal endoscopy examinations each year. However, the current challenge is that the early diagnosis rate of tumors is low, and many lesions cannot be found in routine digestive endoscopy because of the large area of gastrointestinal mucosa, unobvious characteristics of early lesions, the existence of blind zones and uniform quality of examinations conducted by different endoscopists[2]. It is of great importance to improve the quality of endoscopy examinations to discover the lesions.

Artificial intelligence (AI) is intelligence processed by machines, as opposed to intelligence of humans and other animals, which emerged as a powerful and novel technology influencing many aspects of health care. In recent years, image recognition technology of AI has been dramatically improved and widely used in the medical field of diagnostic imaging[3-6]. AI represents a fundamental breakthrough in the field of diagnostic endoscopy by assisting endoscopists with the detection of gastrointestinal tumors[7]. Deep learning networks represented by convolutional neural network (CNN) systems are a hot research topic at present and have been widely applied in the fields of pathology, radiology and endoscopy[8]. The first study focusing on gastrointestinal endoscopy and computer simulation was reported in 1990, which showed that computer simulation was used as a tool to train endoscopists by constructing a model describing the three-dimensional structure of the appropriate parts of the gastrointestinal tract[9]. With the development of AI, it has been extensively used in gastrointestinal endoscopy examinations, such as upper gastrointestinal endoscopy, colonoscopy, wireless capsule and ultrasonic endoscopy.

Bibliometric analysis refers to a statistical approach that helps to comprehensively analyze the hotspots, trends and each unit and scholar's cooperation of published articles in this field[10,11]. In this study, we aimed to analyze the research hot spots and trends in the field of AI and endoscopy from 1990 to 2022 using a quantitative method. We also explored the application of AI-assisted endoscopy in detecting different digestive diseases to provide assistance for the research and clinical application of AI and endoscopy.

MATERIALS AND METHODS

Search strategy

All relevant and qualified data were collected from the Web of Science database. The search strategy was a combination of the following keywords and terms: ("artificial intelligence" OR "AI" OR "deep learning" OR "machine learning" OR "machine intelligence" OR "computer" OR "computational intelligence" OR "neural network" OR "knowledge acquisition" OR "automatic" OR "automated" OR "feature extraction" OR "image segmentation" OR "neural learning" OR "artificial neural network" OR "data mining" OR "data clustering" OR "big data") AND ("endoscopy" OR "endoscope"). Moreover, only publications written in English between 01 January 1990 and 01 November 2022 were considered.

Study selection

Two authors (Ren-Chun Du and Yao-Bin Ouyang) independently evaluated all relevant articles in two stages, and a full discussion was held to resolve any differences and conflicts (the inclusion of literature, classification of disease and endoscopy, and weight of different studies, *etc.*) with the third author (Yi Hu). At the first stage of evaluation, basic research, reviews, case reports and meta-analysis were excluded. In the second stage, the contents of the remaining articles were carefully assessed according to the patient, intervention, comparison, outcomes (PICOs) criteria. "P" (patient): Patients with digestive diseases or health care; "I" (intervention): AI-assisted endoscopic examination; "C" (comparison): Routine endoscopic examination; "O" (outcome): The accuracy of AI and routine endoscopic examination in detecting digestive diseases; and "S" (study design): Retrospective studies, prospective randomized controlled trials (RCTs) and non-RCTs.

Data extraction

The included articles were assessed and downloaded into various file formats for analysis by the two investigators. The following data were extracted: Author, institution, country, endoscopy type, disease type, performance of AI (including sensitivity, specificity, and accuracy), citations, year of publications, and H-index. Each study was weighted according to the number of test samples and the weighted average of the performance data of AI in diagnosing diseases was calculated. Any discrepancy was evaluated by the kappa value to assess the agreement between two investigators.

Data analysis

The data were imported into VOSviewer software (version 1.6.18), GraphPad Prism (version 8) and CiteSpace (version 6.1.R3) to generate the visual graphs. CiteSpace and VOSviewer were used to perform the quantitative and qualitative analyses. The cluster network was generated by VOSviewer to assess the most productive and cooperative authors, countries and institutions. Each dot of the visual graphs represents an author, institution and country, and these dots were clustered into various groups based on their cooperations. The size of the dots corresponded to the number of articles, while the strength of the connection was based on the frequency of cooperations. The options used in CiteSpace included a time slice set to “1990-2022,” with one year per slice and the selection criteria set to “g-index.” The scale factor k was set to “25”, and “pathfinder” was selected to preserve the optimal structure while reducing the total links[12]. Keywords were used to label clusters and show cluster labels by a latent semantic indexing algorithm.

RESULTS

Study selection and characteristics

As shown in Figure 1, 3885 papers were enrolled from the Web of Science through our search strategy. At the first stage of selection, 1437 publications were excluded because of publication type, and 88 publications were excluded because of language. The contents of the remaining 2360 articles were carefully assessed. Ultimately, 446 articles meeting the inclusion criteria of this study were included.

Next, we summarized the characteristics of the included articles. The chronological distribution of annual publication numbers from 1990 to 2022 is shown in Figure 2A. The first study we obtained was published in 1990[9]. Less than 10 annual publications were reported in this field before 2015. As depicted in the diagram, the number of publications rapidly increased after 2015, and peaked in 2021, accounting for 23.5% of all publications. Figure 2B displays the cumulative number of publications. The number of annual publications gradually increased after 2013 except for a decrease in 2017. The number of annual citations is shown in Figure 2C, which was relatively low from 1990 to 2010 (below 100 citations for each year). It increased slowly after 2006 and quickly after 2018, remaining at a high number after 2020 (over 2000 citations). The annual H-index is shown in Figure 2D, which was relatively low (< 10) before 2016, but then increased rapidly and peaked at 28 in 2019, followed by a slight decrease from 2020 to 2022.

Analysis of country, institution and authors

The cooperation network of publication countries is displayed in Figure 3A, including a total of 50 countries and 524 co-operations. Next, the H-index, total citations and publications of the top 10 most productive countries were analyzed and presented in Supplementary Table 1. China emerged as the most productive country with 128 publications, 4089 citations and an H-index of 36 Figure 3B shows the cooperation cluster network of institutions, with a total of 106 institutions and 708 cooperations displayed. These institutions were clustered into different groups according to their cooperations. The top 10 most productive institutions were further analyzed for their publications, citations and H-index, and the results are presented in Supplementary Table 2. The Tada Tomohiro Institute of Gastroenterology and Proctology had the highest number of publications (22), citations (1454), and H-index (17). Next, the publications, citations, H-index and cooperations of the 10 most productive authors were also analyzed. A total of 63 authors and 996 co-operations are shown in Figure 3C. As shown in Supplementary Table 3, Tada Tomohiro was the most productive author with 23 publications, an H-index of 17 and 1456 citations, followed by Yu HG, Wu LL, and Ishihara S.

Analysis of keywords and burst detection of publications

To obtain a comprehensive understanding of the popular topics in the realm of AI and endoscopy, a study is conducted utilizing keyword co-occurrence analysis. The analysis involves examining the relevant keywords associated with each paper, based on their titles and abstracts. A total of 131 keywords, appearing at least 5 times, are identified and represented using a bubble graph to visualize citation data. VOSviewer is employed to generate a comprehensive keyword co-occurrence visualization map, where the keywords are grouped into distinct clusters market with a unique color code. Three categories were identified: AI, deep learning and endoscopy (Figure 4A). The co-occurrence visualization map based on the average year of publication is shown in Figure 4B. "Magnification" and "adenomas" mainly appeared before 2017. The keywords “classification”, “endoscopy”, and “cancer” became more common after 2017. Keywords colored in yellow are the latest, such as “AI”, “deep learning”, and “CNN”.

Burst detection is a method employed for detecting a sudden surge in the occurrence of novel concepts during a specific period. As shown in Figure 4C, wireless capsule endoscopy ranked first in terms of outbreak intensity (4.83) over the past three decades, followed by color (3.82) and texture (3.82). Computer-assisted diagnosis became the focus of research after 1993. It is worth noting that AI, neoplasia, upper gastrointestinal endoscopy, society, and endoscopic imagine were the strongest bursts since 2022.

Analysis of cocited reference cluster

A network of references that are cocited by publications is referred to as a cocited network. When a group of references are repeatedly cited, it could generate a cluster network diagram (Figure 5A) and a literature cocitation diagram (Figure 5B). The “Pathfinder” and “Pruning Networks” options were utilized to conduct the optimal network. Each node on the network signifies a cited article and the size of it is based on the total cited frequency of pertinent articles. The literature that was cocited was then categorized into 10 major labels: Wireless capsule endoscopy, deep learning, AI, machine learning, CNN, response evaluation, capsule endoscopy, endoscopy imagine, gastrointestinal tract, and small bowel (Figure 5A). Figure 5B shows a timeline view of distinct cocitations. Deep learning, CNN and response evaluation have always been popular research topics. Wireless capsule endoscopy, AI, and machine learning have been popular research topics since 2000.

Analysis of the most cited studies

Table 1 shows the specifics of the 10 most cited studies from 1990 to 2022. Each study was cited between 145 and 323 times. Three of these studies were published in *Gastroenterology*, and the remaining 7 studies were published in *Gastric Cancer*, *GUT*, *Gastrointestinal Endoscopy*, *IEEE Journal of Biomedical*, *Health Informatics*, *Lancet Gastroenterology*, and *Hepatology*. The most cited article was the application of AI using a

CNN for detecting gastric cancer in endoscopic images. Five articles focused on AI applied in the detection of polyps. Another 5 articles focused on AI applied in cancer detection.

Research trends in AI applied in disease diagnosis

The proportion of the number of diseases in the field of AI and endoscopy was counted. As shown in Figure 5C, gastrointestinal polyps accounted for the largest proportion of disease in this area (14.6%), followed by gastric cancer (13.5%). The proportion of the endoscopy type was also counted. As shown in Figure 5D, conventional endoscopy accounted for the largest proportion in this area (42.3%), followed by capsule endoscopy (35.5%).

We further analyzed the temporal variation in the diagnostic performance of AI-assisted endoscopy for digestive diseases. The sensitivity, specificity and accuracy of AI-assisted endoscopy in Barrett's esophagus, gastric cancer and polyps are shown in Figure 6A-C. For Barrett's esophagus, the studies published in 2018 showed the highest sensitivity (97.0%), specificity (88.0%) and accuracy (92.0%). The weighted average sensitivity, specificity and accuracy of AI in detecting Barrett's esophagus from 2018 to 2021 were 90.4%, 84.0%, and 87.6%, respectively. In terms of gastric cancer, the studies in 2019 showed the highest accuracy (90.8%) and specificity (93.3%), and the studies in 2020 showed the highest sensitivity (92.3%). The weighted average sensitivity, specificity and accuracy of AI in detecting gastric cancer from 2019 to 2022 are 82.8%, 89.8% and 88.3%, respectively. For detecting colorectal polyps, the studies in 2019 showed the highest sensitivity (97.1%), the studies in 2022 showed the highest specificity (97.7%), and 2021 showed the highest accuracy (96.9%). The weighted average sensitivity, specificity and accuracy of AI in detecting polyps from 2019 to 2022 are 89.6%, 82.1% and 93.7%, respectively. As shown in Figure 6D-E, the detection rate of gastrointestinal bleeding remained stable above 95% from 2018 to 2021 (weighted average: 96.2%). The adenoma detection rate remained stable at approximately 29%

from 2018 to 2020. A higher detection rate (46.2%) was achieved in 2022 (weighted average: 31.3%).

DISCUSSION

To the best of our knowledge, this is the first bibliometric analysis to comprehensively illustrate the application of AI-assisted digestive endoscopy in digestive diseases. A basic literature analysis was performed, as well as a subgroup analysis of AI-assisted digestive endoscopy in diagnosing various diseases.

The term "AI" was first proposed in 1956[13]. Cortes *et al*[14] suggested the first algorithm for pattern recognition 60 years ago. In 2006, a fast learning algorithm for deep belief networks was proposed[15]. Since then, the number of publications and citations in this field has risen steadily. Machine learning is one of the fastest growing areas of technology[16]. Deep learning is an important branch of machine learning and is further divided into deep neural networks, recurrent neural networks and CNNs[17]. The best results were achieved by CNN in the field of image analysis[18]. In this study, we analyzed the most influential authors, institutions and countries regarding AI and endoscopy. Among these countries, China had the largest number of publications, citations and H-index. Moreover, China, United States, and Japan are the centers of the co-occurrence map. Wireless capsule endoscopy is one of the most effective endoscopic techniques used in the examination of gastrointestinal diseases such as polyps and ulcers[19] and has been a research hot spot and topic since 2014.

AI-assisted endoscopy for disease detection covers almost all endoscopy in the field of digestive endoscopy. Colorectal cancer is the world's fourth most deadly cancer, with almost 900000 deaths annually[20]. AI-assisted colonoscopy has broad prospects in the screening and diagnosis of colorectal cancer. In our study, colorectal cancer accounted for 9.19% of the total disease. Urban *et al*[21] showed excellent performance in AI-assisted colonoscopy studies using CNN based on the deep learning method. The CNN identified polyps with an accuracy of 96.4%. Similarly, Shin *et al*[22] compared two different approaches named the hand-crafted feature method and CNN based on the deep learning method, and the results demonstrated that the CNN-based deep learning framework had better performance for detecting polyps, achieving over 90% accuracy, sensitivity, and specificity. The detection rate of adenoma reflects the quality of colonoscopy. A prospective cohort study was conducted to develop an automatic polyp detection system based on deep learning, and the detection rate of polyps and adenomas could be improved from 29% to 45% and 20% to 29%, respectively[23]. Wang *et al*[24] also studied the development and validation of a deep-learning algorithm for the detection of polyps during colonoscopy, which proved that AI could assist endoscopists efficiently in discovering colorectal adenomas and polyps with high accuracy (per-image sensitivity: 94.4%, per-image specificity: 95.5%). Moreover, Pfeifer *et al*[25] evaluated a newly developed deep CNN with a large sample size (15534 test images), and the deep CNN's sensitivity and specificity for detecting polyps were 90% and 80%, respectively.

Gastric cancer, Barrett's esophagus and *Helicobacter pylori* (*H. pylori*) infection are common upper gastrointestinal diseases. Hirasawa *et al*[26] first reported that AI using a CNN applied in conventional endoscopic images could achieve a diagnostic sensitivity of 92% for gastric cancer in 2018. It is worth noting that the CNN system only required 47 s to analyze 2296 images, which is faster than analyses completed by endoscopists. Ikenoyama *et al*[27] constructed a CNN to detect early gastric cancer with 2940 test samples, and the sensitivity was 58.4%. The prognosis of esophageal cancer is relatively poor. The first report of AI-assisted endoscopy applied in the diagnosis of esophageal cancer was conducted by Horie *et al*[28]. A CNN was trained to diagnose esophageal cancer using 8284 conventional endoscopic images, and eventually, high sensitivity and accuracy were achieved. The weighted average specificity of AI in detecting Barrett's esophagus from 2018 to 2021 was 84.0%. In 2020, a study with 20 samples achieved a specificity of 85.5%[29]. Another study in the same year with a sample size of 100 achieved a specificity of 78%[30]. *H. pylori* is the main pathogenic factor of gastric diseases. Shichijo *et al*[31] reported 89% sensitivity and 87% specificity for the diagnosis of *H. pylori* infection using CNN, and the diagnostic accuracy was significantly higher than that achieved by endoscopists. A consistent result was also achieved by another study[32].

Many studies have shown that cooperation between AI and endoscopists could improve the diagnostic ability to diagnose gastrointestinal diseases. Ikenoyama *et al*[27] compared the performance of endoscopists with an AI classifier based on CNN in detecting early gastric cancer through 2940 test images. Eventually, the results showed that AI had a significantly higher sensitivity than endoscopists. Niikura *et al*[33] obtained similar results in another study, and the diagnostic rate of gastric cancer per image in the AI group was higher than that in the group of experts. Yen *et al*[34] showed a higher accuracy of AI than experts in detecting peptic ulcer bleeding. Zhang *et al*[35] compared a CNN-based image recognition system with visual inspection by endoscopists in identifying polyps. The results showed a significant improvement in accuracy with the application of AI.

Certain limitations existed regarding the use of AI. First, algorithm performance could be different when using endoscopy equipment manufactured by different companies[23,24]. Second, as AI algorithms are highly dependent on the integrity of the database, the number of training images might result in a different diagnostic ability of AI[26]. Third, data privacy and security considerations are also critical, which could be of great concern to endoscopists[36,37]. The potential ethical and legal issues of this technology in clinical application should not be underestimated.

A bibliometric analysis was previously conducted to examine AI applied in digestive endoscopy[38]. A basic analysis of bibliometric indicators was performed. Our study recorded the data of each article in detail. We also analyze the effectiveness of AI-assisted endoscopy in disease detection, specific analysis of digestive endoscopy, and gastrointestinal diseases and evaluate the accuracy of AI.

Our study aimed to provide a comprehensive analysis of AI applied in diagnostic endoscopy: (1) The emergence of deep belief networks contributed to an increase in research in this field; (2) the intelligent detection and recognition of colorectal polyps is the most concerning and researched area at present; (3) capsule endoscopy is one of the most influential keywords; (4) the accuracy of AI in detecting Barrett's esophagus, colorectal polyps and gastric cancer from 2018 to 2022 is 88.08%, 93.71%, and 88.29%, respectively, and the detection rates of adenoma and gastrointestinal bleeding from 2018 to 2022 are 31.38% and 96.20%, respectively; and (5) AI-assisted digestive endoscopy could improve the diagnosis rate of endoscopists in disease detection, and CNN-based diagnosis programs for endoscopic images showed promising results. However, there are some limitations existed in this study. First, the search for publications was limited to the Web of Science core collection database, which may result in incomplete literature searches of other databases. Second, a number of studies that were not in English might be missed. Third, several bias may affect the results, such as publication bias.

CONCLUSION

In conclusion, AI could improve the detection rate of digestive tract diseases and has been applied widely in the field of endoscopy. Multicenter prospective studies with larger samples should be conducted in the future to further explore the accuracy of AI based on different methods.

Figure 1 Flowchart of study enrollment.

Figure 2 The annual number and H-index values. A: The annual number of published articles; B: The number of annual cumulative articles; C: The global annual number of the publications; D: The annual H-index values of the publications.

Figure 3 Cooperation network. A-C: The cooperation network of countries (A), institutions (B), and authors (C) in the field of AI and endoscopy from 1990-2022.

Figure 4 Co-occurrence map. A and B: The co-occurrence map based on keywords; C: The top 25 keywords with the strongest citation bursts.

Figure 5 Diagrams. A: Cluster network diagrams; B: Literature cocitation diagrams; C and D: Proportion of the number of diseases (C) and endoscopy type (D) in the field of AI and endoscopy.

Figure 6 Temporal variation in the diagnostic performance of artificial intelligence-assisted endoscopy for digestive diseases. A-C: Temporal variation in the sensitivity, specificity and accuracy of artificial intelligence (AI)-assisted endoscopy in Barrett's esophagus (A), gastric cancer (B), and polyps (C); D and E: Temporal variation in the detection rate of AI-assisted endoscopy in bleeding (D) and adenoma (E).

Table 1 The top 10 most cited articles in the field of AI and endoscopy from 1990-2022

Rank	Journal	Title	Citations of web of science	Affiliations	Ref.
1	*Gastric Cancer* 2018; **21**: 653-660	Application of artificial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images	323	Tada Tomohiro Inst Gastroenterol and Proctol, Saitama, Japan	Hirasawa *et al*[28], 2018
2	*GUT* 2019; **68**: 1813-1819	Real-time automatic detection system increases colonoscopic polyp and adenoma detection rates: A prospective randomised controlled study	307	Sichuan Provincial People's Hospital, China	Wang *et al*[23], 2019
3	*Annals Of Internal Medicine* 2018; **169**: 357-366	Real-Time Use of Artificial Intelligence in Identification of Diminutive Polyps During Colonoscopy A Prospective Study	227	Showa University, Japan	Mori *et al*
4	*Gastroenterology* 2018; **154**: 568-575	Accurate Classification of Diminutive Colorectal Polyps Using Computer-Aided Analysis	208	Triservice General Hospital, National Defense Medical Center, Taiwan	Chen *et al*
5	*Gastrointestinal Endoscopy* 2019; **89**: 25-32	Diagnostic outcomes of esophageal cancer by artificial intelligence using convolutional neural networks	194	Japanese Foundation for Cancer Research, Japan	Horie *et al*[28], 2019
6	*IEEE Journal of Biomedical And Health Informatics* 2017; **21**: 41-47	Automatic Detection and Classification of Colorectal Polyps by Transferring Low-Level CNN Features From Nonmedical Domain	191	Chinese University of Hong Kong, China	Zhang *et al*[35], 2017
7	*Gastroenterology* 2013; **144**: 81-91	Real-Time Optical Biopsy of Colon Polyps With Narrow Band Imaging in Community Practice Does Not Yet Meet Key Thresholds for Clinical Decisions	169	Stanford University, United States	Ladabaum *et al*
8	*Gastroenterology* 2020; **159**: 512-520	Efficacy of Real-Time Computer-Aided Detection of Colorectal Neoplasia in a Randomized Trial	155	Humanitas University, IRCCS Humanitas Research Hospital, Italy	Repici *et al*

9	*Gastrointestinal Endoscopy* 2019; **89**: 806-815	Application of convolutional neural network in the diagnosis of the invasion depth of gastric cancer based on conventional endoscopy	150	Fudan University, China	Zhu *et al*
10	*Lancet Gastroenterology And Hepatology* 2020; **5**: 343-351	Effect of a deep-learning computer-aided detection system on adenoma detection during colonoscopy (CADe-DB trial): a double-blind randomised study	145	Sichuan Provincial People’s Hospital, China	Wang *et al*

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5	Yohei Ikenoyama, Toshiaki Hirasawa, Mitsuaki Ishioka, Ken Namikawa et al. "Detecting early gastric cancer: Comparison between the diagnostic ability of convolutional neural networks and endoscopists", Digestive Endoscopy, 2020 Crossref	26 words — 1%
6	Younghak Shin, Ilangko Balasingham. "Comparison of hand-craft feature based SVM and CNN based deep learning framework for automatic polyp classification", 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2017 Crossref	23 words — 1%

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24	Wenju Du, Nini Rao, Dingyun Liu, Hongxiu Jiang, Chengsi Luo, Zhengwen Li, Tao Gan, Bing Zeng. "Review on the Applications of Deep Learning in the Analysis of Gastrointestinal Endoscopy Images", IEEE Access, 2019 Crossref	6 words — < 1%
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