Progress in Medical Devices
ISSN: 2957-5478

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Review Article https://doi.org/10.61189/072185gbtgzi

Application of deep learning in the diagnosis of gastrointestinal diseases

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Declaration of conflict of interest: None.

Received November 27, 2024; Accepted January 15, 2025; Published June 30, 2025

Highlights

- This review presents the current status and challenges of gastrointestinal diseases.
- This review discusses the application of deep learning in diagnosing gastrointestinal diseases.
- This review explores the future development of deep learning in disease diagnosis.

Abstract

With the rapid development of artificial intelligence, deep learning technology has been widely applied across various fields. In the medical field, deep learning models, by analyzing medical images and clinical data, can automatically detect features of different types of lesions, such as polyps, ulcers, and cancers, thereby assisting physicians in early diagnosis of disease. This review provides an overview of recent progress in applying deep learning for disease diagnosis in various parts of the gastrointestinal tract, including the esophagus, stomach, small intestine, and colon. It also discusses the challenges and potential future directions for deep learning in this field.

Keywords: Deep learning, gastrointestinal endoscopy, convolutional neural network, computer-aided detection

Introduction

Gastrointestinal (GI) diseases are prevalent worldwide and have been steadily increasing due to lifestyle changes and dietary shifts in modern society, significantly compromising the quality of life of patients. In 2018, GI cancer patients in China accounted for 40% of the global total, with this trend continuing to rise [1]. In 2019, the global incidence of GI diseases reached 7.32 billion, resulting in 8 million deaths, and GI diseases accounted for over one-third of all epidemiological diseases [2].

Common GI diseases include gastroenteritis, ulcerative colitis, Crohn's disease (CD), gastric cancer, and esophageal cancer. Early diagnosis, precise treatment, and prognostic evaluation of these diseases remain key areas of medical research. However, the diagnostic process is complex due to the diverse symptoms, often requiring a combination of clinical manifestations, laboratory tests, endoscopic examinations, and imaging studies. Traditional diagnostic methods rely on the expertise of physicians, and the accuracy and efficiency of diagnosis are limited by manpower and time, highlighting the urgent need for automated and intelligent diagnostic tools.

In recent years, artificial intelligence (AI), especially deep learning (DL) technology, has shown great potential in medical image analysis and disease prediction. DL, a type of multi-layer artificial neural network model introduced in 2006, simulates the neural network of the human brain. Unlike traditional machine learning, DL can automatically extract features from data by building multi-layer nonlinear network structures, without relying on manually designed features (**Figure 1**) [3]. This method is well-suited for large-scale data processing and complex

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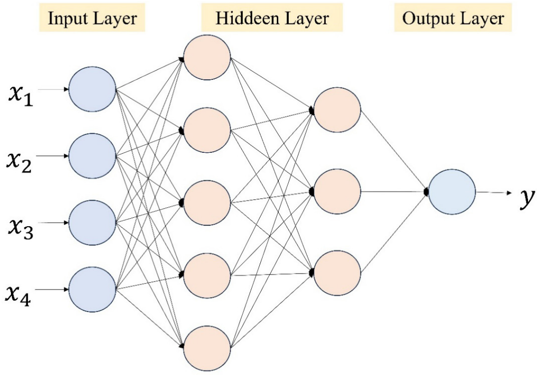

Figure 1. Schematic of deep learning neural network.

pattern recognition. Currently, DL is widely applied in speech recognition, natural language processing, semantic segmentation, and object detection [4]. In medical imaging, DL, such as convolutional neural networks (CNN) and recurrent neural networks, can efficiently process multi-dimensional data, like images, audio, and video, to extract subtle features for diagnostic interpretation. This aids doctors in making diagnostic decisions, improves diagnostic efficiency, reduces workload, and decreases the likelihood of missed or incorrect diagnoses [5]. Compared to traditional machine learning, DL methods are generally more accurate and robust, making them increasingly suitable for clinical practice [6].

This article reviews recent progress in DL technology for the diagnosis of GI diseases and discusses the challenges and future directions for intelligent-assisted diagnosis using deep learning technology.

Application of DL in the diagnosis of GI diseases

Esophageal carcinoma (ESCA)

ESCA is the eighth most common malignant tumor globally and the sixth leading cause of cancer-related death, with approximately 400,000 deaths annually [1]. Early symptoms of ESCA are often subtle, and by the time patients experience significant symptoms, such as dysphagia, weight loss, or other GI issues, the tumor is typically at an advanced stage, leading to a poor prognosis. According to statistics, the 5-year relative survival rate for ESCA from 2019 to 2021 is approximately 27.9% [7]. Early diagnosis of ESCA is crucial for improving patient survival rates. The main types of esophageal malignancies include esophageal adenocarcinoma (EAC) and esophageal squamous cell carcinoma (ESCC), which differ significantly in terms of epidemiology, pathogenesis, and prognosis.

EAC

EAC is one of the main subtypes of ESCA and predominantly occurs in North America and Europe [8]. Barrett's esophagus (BE) is a precursor lesion for the development of EAC, and early detection can effectively prevent BE from progressing to EAC. In recent years, researchers have increasingly utilized deep learning models to automate the detection and diagnosis of early-stage EAC and BE to improve the accuracy and efficiency of early screening.

The study by Ghatwary et al. in 2019 marked an important attempt at using deep learning for EAC recognition [9]. They trained various object detection models based on the VGG16 backbone network, including Regional-based CNN (R-CNN), Fast R-CNN, Faster R-CNN, and Single-Shot Multibox Detector (SSD), using 100 high-definition white light endoscopy images of the esophagus from 22 patients diagnosed with EAC and 17 patients with non-cancerous BE. The results demonstrated that the SSD and Faster R-CNN models performed well in detection, with the SSD model showing a sensitivity of 0.96, specificity of 0.92, and an F-measure of 0.94. The Faster R-CNN model, on the other hand, excelled in localizing the EAC region, achieving a recall rate of 0.83. Ebigbo et al. were the first to apply a DL system for real-time evaluation of early-stage EAC, further advancing the application of DL in EAC detection [10]. They used a total of 129 endoscopic images from the University Hospital Augsburg image database to train a real-time AI system based on deep CNNs and a residual network (ResNet) architecture with DeepLab V.3+, a state-of-the-art encoder–decoder network. The system achieved a sensitivity of 83.7%, specificity of 100%, and an accuracy of 89.9%.

de Groof et al. focused on distinguishing between images containing neoplasms or nondysplastic BE, developing a computer-aided diagnosis (CAD) system with a hybrid ResNet-UNet model [11]. Trained and tested on 1,704 early tumor images, the system showed excellent classification accuracy, sensitivity, and specificity (89%, 90% and 88%, respectively), accurately classifying images as containing neoplasms or nondysplastic BE. In addition, this system outperformed non-expert endoscopists, with comparable delineation performance. Hashimoto et al. combined the Xception-based CNN with the YOLO v2 algorithm for binary classification and detection of neoplasia images (**Figure 2**),

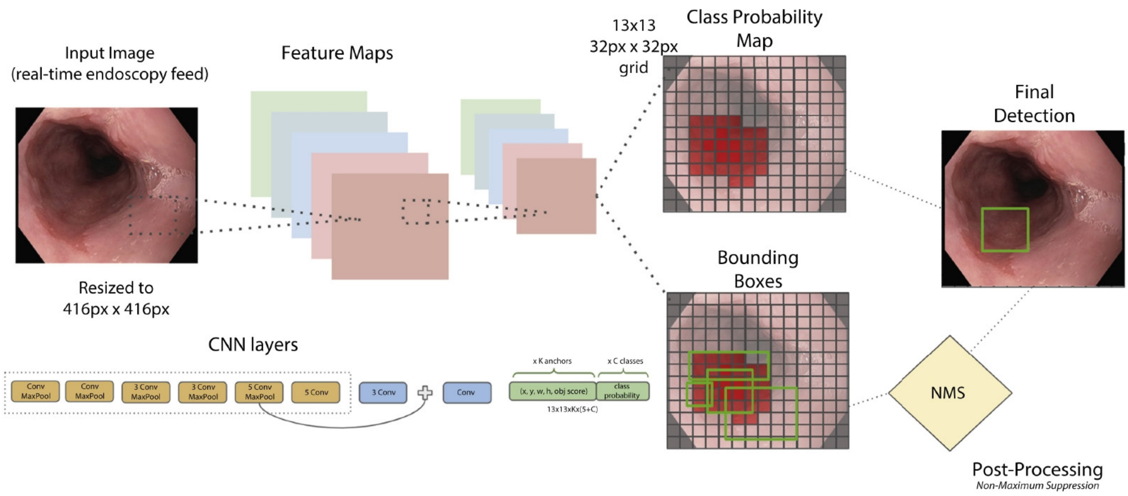

Figure 2. Architecture of the method proposed by Hashimoto et al. CNN, convolutional neural network; NMS, non-maximum suppression. This figure is cited from [12].

achieving a binary classification sensitivity of 96.4%, specificity of 94.2%, and accuracy of 95.4%, along with a mean average precision of 0.7533 [12]. Hussein et al. used the ResNet101 network to classify dysplastic and non-dysplastic BE images, achieving a mean area under the receiver operating characteristic curve (AUC) of 0.93, with sensitivity at 91% and specificity at 79% [13]. Additionally, they trained a model with the FCNResNet50 architecture for detecting dysplastic regions and predicting targeted biopsies, achieving a sensitivity of 97%. These studies demonstrate the exceptional performance of deep learning-based AI systems in diagnosing early EAC and BE, providing valuable auxiliary tools for clinical practice.

ESCC

ESCC is a common malignancy in regions such as Asia, Africa, and South America, with particularly high prevalence in China, where it accounts for over 90% of all esophageal cancer cases [8, 14]. As ESCC often presents with few symptoms in its early stages, many patients have progressed to the advanced stage at the time of diagnosis, leading to poor treatment outcomes. Therefore, early detection is crucial to improving treatment success and reducing ESCC mortality.

Cai et al. collected 2,428 esophagoscopic images from 746 patients during standard white light endoscopy, including 1,332 abnormal samples and 1,096 normal samples [15]. They developed a CAD system using deep neural networks (DNN) to localize and identify early-stage ESCC in routine white light imaging (WLI). Validation on 187 images resulted in a sensitivity of 97.8%, specificity of 85.4%, accuracy of 91.4%, positive predictive value (PPV) of 86.4%, and negative predictive value of 97.6%. With significant advances in optical technologies, tools such as narrow-band imaging (NBI) have further enhanced ESCC detection rate. However, the effectiveness of NBI in early ESCC screening largely depends on the operator's expertise. To address this, Everson et al. constructed an AI system based on CNN, using NBI images from magnified endoscopy to classify early squamous cell neoplasia (ESCN) and normal images under the abnormal intrapapillary capillary loop pattern [16]. This system achieved an accuracy of 93.7%, with sensitivity and specificity for abnormal intrapapillary capillary loop patterns reaching 89.3% and 98%, respectively. Additionally, Guo et al. used 6,473 NBI images, including those of precancerous lesions, early ESCC, and noncancerous lesions, to develop a highly efficient CAD system for intelligent diagnosis of precancerous lesions and ESCC [17]. This system achieved an impressive sensitivity of 98.04%, specificity of 95.03%, and an AUC value of 0.989, greatly enhancing the diagnostic capabilities for esophageal cancer. Li et al. also built a CAD-NBI system based on NBI images and CNN for non-magnified endoscopy to identify early ESCC [18]. The system performed excellently, with sensitivity, specificity, accuracy, positive predictive value, and negative predictive value of 91.0%, 96.7%, 94.3%, 95.3%, and 93.6%, respectively. Compared to the previously reported CAD-WLI system, this CAD-NBI system demonstrated superior specificity and accuracy [15].

In addition to the studies mentioned above, several research teams have applied deep learning models for intelligent recognition of esophageal and non-esophageal cancer images [19-22]. Horie et al. initially applied deep learning to the diagnosis of esophageal

Table 1. Research progress of deep learning in esophageal cancer

Ref.	Model	Lesions	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC
Ghatwary et al. [9]	Multiple CNNs	EAC	96.00	92.00	-	-
Ebigbo et al. [10]	ResNet	EAC	83.70	100.00	89.90	-
de Groof et al. [11]	ResNet-UNet	Neoplasia	90.00	88.00	89.00	-
Hashimoto et al. [12]	CNN-YOLOv2	Neoplasia	96.40	94.20	95.40	-
Hussein et al. [13]	ResNet101	Dysplasia	91.00	79.00	-	0.93
Cai et al. [15]	DNN	ESCC	97.80	85.40	91.40	-
Everson et al. [16]	CNN	ESCN	89.30	98.00	93.70	-
Guo et al. [17]	SegNet	ESCC	98.04	95.03	-	0.99
Li et al. [18]	FCN	ESCC	91.00	96.70	94.30	-
Horie et al. [19]	SSD	ESCA	98.00	-	-	-
Sui et al. [20]	VB-Net	ESCA	88.80	90.90	-	-
Takeuchi et al. [21]	VGG16	ESCA	71.70	90.00	84.20	-
Yasaka et al. [22]	CNN	ESCA	87.00	92.00	92.00	0.95

Note: FCN, fully convolutional network; EAC, esophageal adenocarcinoma; ESCC, esophageal squamous cell carcinoma; ESCA, esophageal carcinoma; DNN, deep neural networks; CNN, convolutional neural networks; SSD, Single-Shot Multibox Detector; ESCN, early squamous cell neoplasia.

cancer, training on 8,428 static images using the SSD network architecture within the Caffe deep learning framework [19]. They validated the model on independent test images from 97 patients, achieving a sensitivity of 98%, further demonstrating the powerful potential of deep learning for early diagnosis of ESCC. An overview of these studies is provided in **Table 1**.

Gastric diseases

Gastric diseases, particularly gastric cancer and gastric ulcers, are common GI tract diseases with high mortality. Gastric cancer ranks the fifth most common cancer worldwide and the fourth leading cause of cancer-related deaths. Due to its tendency to be diagnosed at advanced stages, gastric cancer has a very high mortality rate, with a 5-year survival rate of less than 40% [23, 24]. In 2018, approximately 780,000 people worldwide died from gastric cancer [1]. Traditional diagnostic methods, such as gastroscopy, CT scans, and magnetic resonance imaging, rely on the visual judgment and experience of doctors. While effective, these methods still have limitations, such as image noise interference, misdiagnosis, and errors due to fatigue. Recently, the introduction of DL has provided new solutions for the early diagnosis of gastric diseases. Researchers have developed various deep learning models, applying them to medical imaging data, such as endoscopic images, to enhance diagnostic accuracy.

Since 2018, a research team in Japan has conducted several studies on using AI for gastric cancer detection [25-28]. Hirasawa et al. [25] were the first to evaluate the ability of CNNs in detecting gastric cancer in endoscopic images. They used 13,584 endoscopic images of gastric cancer to train an SSD model and collected 2,296 independent images. In this study, the CNN system detected 92.2% of gastric cancer cases in the test set. Subsequently, the research team conducted a pilot study applying the CNN system to video images, which showed an accuracy of 94.1% [26]. Ikenoyama et al. compared the performance of this CNN system in diagnosing early gastric cancer with that of experienced endoscopists [27]. The results showed that the CNN had significantly higher sensitivity than the experienced endoscopists, with faster diagnostic speed. However, this CNN had lower PPV and specificity compared to endoscopists. This indicates that while CNNs may reduce the risk of missed cancer diagnoses, they may also increase the number of biopsies for non-cancerous lesions. In 2020, the team added 4,453 gastric ulcer images to their dataset and developed an "advanced CNN" (A-CNN) [28]. The A-CNN achieved a sensitivity of 99.0%, specificity of 93.3%, and PPV of 92.5% for gastric cancer classification, while the sensitivity, specificity, and PPV for gastric ulcer classification were 93.3%, 99.0%, and 99.1%, respectively. These results demonstrated that the new system could effectively classify gastric cancer and gastric ulcers.

Additionally, other research teams have also explored intelligent detection for gastric cancer. Noda et al. trained and validated the ResNet50 network using 906 cancer images and 717 non-cancer images from endocytoscopy (ECS), and the CNN showed a specificity of 90.9%, outperforming endoscopists in diagnosing early gastric cancer (EGC) [29]. Jin et al. used a mask-based convolutional neural network (Mask R-CNN, **Figure 3**) to automatically detect EGC in endoscopic images, with excellent performance [30]. Zhang et al. proposed an

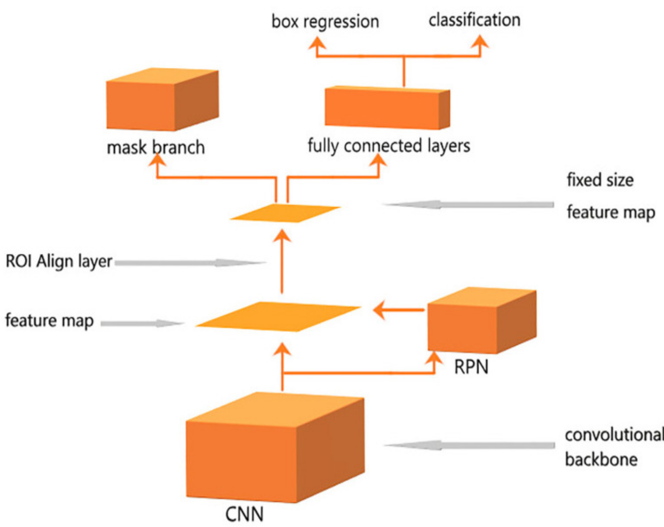

Figure 3. Mask region-based CNN architecture developed by Jin et al. CNN, convolutional neural networks; RPN, region proposal network; ROI, region of interest. This figure is cited from [30].

improved version of Mask R-CNN (IMR-CNN) to enhance the detection of EGC and segmental lesions in gastric endoscopic images [31]. Their model outperformed the original Mask R-CNN, significantly assisting doctors in diagnosing EGC from endoscopic images.

In addition to gastric cancer, DL techniques have also been widely applied in the recognition of other gastric lesions such as gastric ulcers. Zhang et al. implemented intelligent diagnostic system for peptic ulcers (PU), early gastric cancer (EGC), high-grade intraepithelial neoplasia (HGIN), advanced gastric cancer (AGC), and submucosal tumors (SMTs) in gastric endoscopic images using the ResNet34 model and the DeepLabv3 structure [32]. Xia et al. proposed a novel automatic gastric lesion detection system, employing the ResNet34 and Faster-Region-based CNN networks to differentiate between erosions, polyps, ulcers, submucosal tumors, xanthomas, and normal images in magnetic-controlled capsule endoscopy (MCE) images [33]. The system achieved an accuracy of 77.1% and an AUC value of 0.84, demonstrating good performance in diagnosing focal gastric lesions.

Fu et al. developed a new multi-scale model, StoHisNet, based on Transformer and CNN, for multi-class classification tasks of gastric pathological images [34]. The model achieved an accuracy of 94.69%, an F1 score of 94.96%, a recall rate of 94.95%, and a precision rate of 94.97% on the SEED public competition dataset of gastric pathological images, showing strong generalization ability across different datasets. Bhardwaj et al. evaluated the accuracy of various CNN models in identifying gastric diseases using images from the Kvasir dataset and deep transfer learning models [35]. Their research demonstrated the effectiveness of deep transfer learning techniques for the early prediction and classification of gastric cancer. **Table 2** presents the research progress of deep learning in gastric diseases.

Intestinal diseases

Small Intestine

The small intestine, a complex and highly convoluted structure connecting the stomach and colon, is challenging to fully examine with conventional imaging techniques due to its unique anatomical location. However, with the advent of advanced technologies such as small bowel endoscopy and capsule endoscopy, the diagnostic rate of small intestinal diseases has significantly improved. Despite these advancements, the interpretation of images still largely depends on the experience of clinicians, and diagnostic delays or misdiagnoses may occur due to image similarities. Deep learning-based medical image analysis offers promising potential for intelligent, auxiliary diagnosis of small intestine diseases.

Fan et al. utilized a Caffe framework to train the AlexNet architecture (**Figure 4**) on GPU and fine-tuned it to successfully distinguish small intestinal ulcers, erosions, and normal tissues in wireless capsule endoscopy (CE) images [36]. Their experimental results demonstrated high accuracy, sensitivity, and specificity in identifying ulcers and erosions, with AUC values exceeding 0.98. In subsequent studies, Aoki et al. applied the SSD architecture to detect small intestinal erosions and ulcers in CE images, achieving an accuracy of 90.8% and a specificity of 90.9%, further validating the effectiveness of DL in detecting small bowel disorders [37]. Ding et al. developed a CNN-based algorithm that efficiently differentiated abnormal from normal images in small bowel capsule endoscopy examinations [38]. Their model demonstrated a higher sensitivity (99.88% vs. 74.57%) and shorter reading time compared to gastroenterologists.

In the detection of specific lesions in the small intestine, Tsuboi et al. trained and validated an SSD-based deep CNN system with 2,237 CE images of vascular dilation [39]. The system achieved automatic detection of vasodilatation

Table 2. Research progress of deep learning in gastric diseases

Ref.	Model	Lesions	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC
Hirasawa et al. [25]	SSD	Gastric cancer	92.20	-	-	-
Namikawa et al. [28]	A-CNN	Gastric cancer	99.00	93.30	-	-
		Gastric ulcers	93.30	99.00	-	
Noda et al. [29]	ResNet50	EGC	82.10	90.90	86.10	0.93
Jin et al. [30]	Mask R-CNN	EGC-WLI	91.06	89.01	90.25	0.94
		EGC-NBI	97.59	89.01	95.12	0.81
Zhang et al. [31]	IMR-CNN	EGC	95.30	92.50	93.90	-
	ResNet34	EGC, HGIN	-	91.20	-	-
Xia et al. [33]	Faster RCNN	Gastric focal lesions	96.20	76.20	77.10	0.84
Fu et al. [34]	StoHisNet	Gastric pathological image	94.95	95.03	94.69	-

Note: Gastric focal lesions include erosion, polyp, ulcer, submucosal tumor, xanthoma, normal mucosa, and invalid images; gastric pathological image includes normal tissue, tubular adenocarcinoma, mucinous adenocarcinoma, and papillary adenocarcinoma. EGC-WLI, early gastric cancer under the white light image; EGC-NBI, early gastric cancer under the narrow-band imaging; HGIN, high-grade intraepithelial neoplasia; CNN, convolutional neural networks; SSD, Single-Shot Multibox Detector.

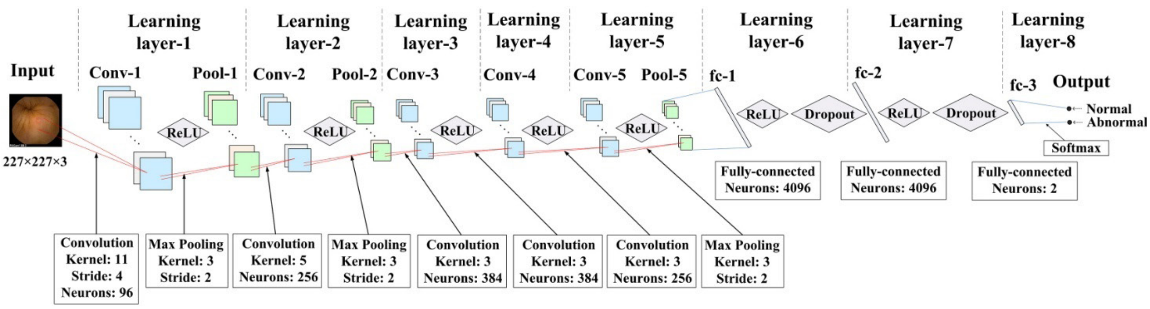

Figure 4. Illustration of CNN architecture diagram proposed by Fan et al. CNN, convolutional neural networks. This figure is cited from [36].

in CE images with sensitivities, specificities, PPV, and negative predictive value of 98.8%, 98.4%, 75.4%, and 99.9%, respectively. Klang et al. employed the Xception CNN to train on 17,640 CE images from 49 patients, achieving an accuracy ranging from 95.4% to 96.7% [40]. The model accurately distinguished between normal mucosa and mucosal ulcers, further demonstrating the practical applicability of CNN for automatic detection of mucosal ulcers in CD patients. Additionally, they tested the effectiveness of the EfficientNet-B5 network on 1,942 images of strictures, 14,266 images of normal mucosa, and 11,684 images of ulcers. The model achieved an average accuracy of 93.5% ± 6.7% in classifying strictures versus non-strictures, showcasing the powerful capabilities of DL in complex lesion classification [41]. Leenhardt et al. combined segmentation methods with CNN-based deep feature extraction to classify images of gastrointestinal angioectasia and normal images from the capsule endoscopy computer-assisted diagnosis for capsule endoscopy (CAD-CAP) database [42]. Their algorithm achieved a specificity of 96%, effectively detecting gastrointestinal angioectasia in static frames of small bowel capsule endoscopy and improving the diagnostic performance for small bowel diseases. Hosoe et al. used ERFNet to classify various lesions in small intestine capsule endoscopy images, including bleeding, vascular malformations, ulcers, and tumors [43]. Sensitivity and specificity were calculated from 271 detection results across 35 cases, with sensitivity at 93.4% and specificity at 97.8%.

Xie et al. applied the EfficientNet-B5 deep learning model for the automatic detection of CD lesions, including ulcers, non-inflammatory stenosis, and inflammatory stenosis, achieving high accuracy rates of 96.3%, 95.7%, and 96.7%, respectively [44]. Additionally, they performed grading of the ulcer surface, size, and depth, which also showed high accuracy, demonstrating the great potential of deep learning in both automatic detection and objective grading of small bowel CD lesions. Furthermore, Zhu et al. developed a real-time CAD system combining YOLO and ResNet50 for lesion detection and classification during double-balloon enteroscopy [45]. This system detected lesions such as

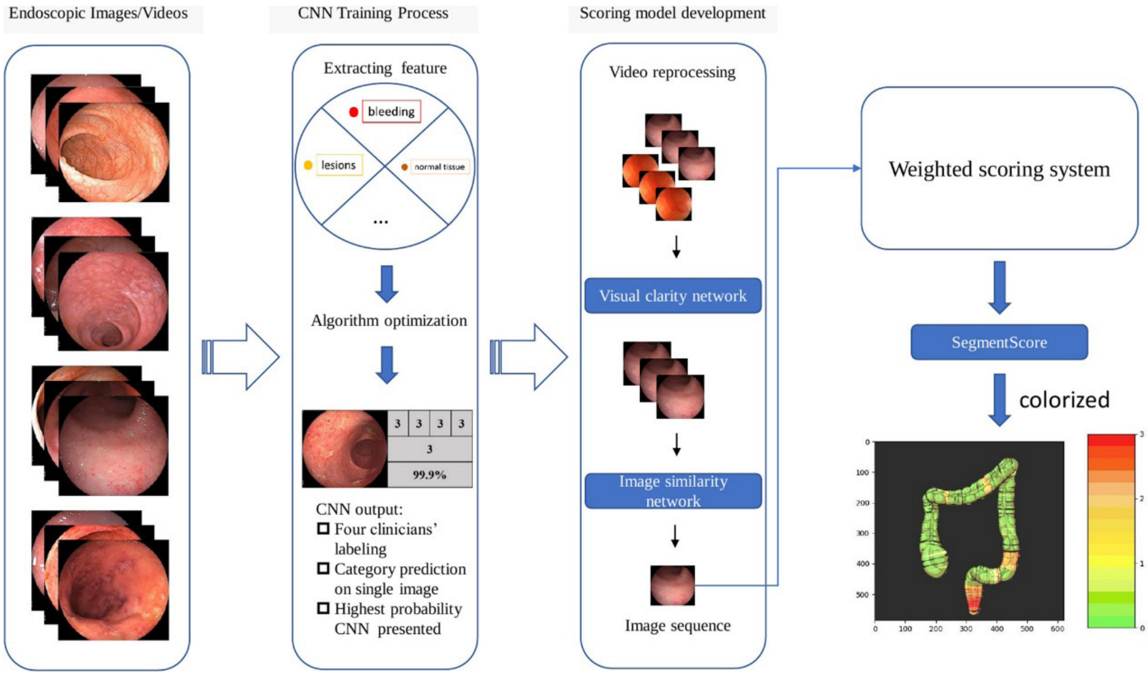

Figure 5. Workflow of CAD system designed by Fan et al. CAD, computer-aided diagnosis. This figure is cited from [51].

protrusions, diverticula, erosions, ulcers, and vascular dilation, achieving a sensitivity of 92% and an AUC of 0.947, while a classification accuracy of 86%, demonstrating excellent experimental performance.

Colon

The colon is a high-prevalence site for intestinal diseases, including colon cancer, colon polyps, and ulcerative colitis. Among these, colon cancer ranks as the third most common cancer worldwide and the second leading cause of cancer-related deaths [14]. The diagnostic accuracy of colonoscopy, a key tool in diagnosing colorectal diseases, is often limited by the experience of the physician and the quality of the images, resulting in variability in diagnostic results. Adenoma detection rate, a crucial metric for assessing colonoscopy quality, is closely associated with the risk of interval colon cancer. To enhance adenoma detection rate, the application of real-time automatic polyp detection systems has garnered significant attention.

Urban et al. trained a CNN model using 8,641 manually annotated colonoscopy images, achieving a polyp recognition accuracy of up to 96.4% and an AUC of 0.991, which effectively improves polyp detection and localization [46]. Wang et al. developed and validated a deep learning algorithm for high-precision detection and recognition of adenomatous polyps in colonoscopy images [47]. This algorithm not only demonstrated high sensitivity and specificity but also enabled real-time analysis of colonoscopy videos, helping to improve polyp detection performance by endoscopists and reduce variability in detection. In addition, Chen et al. analyzed narrow-band images of small colorectal polyps based on a DNN-CAD system, achieving a PPV of 89.6% and a negative predictive value of 91.5% on the test set, along with shorter detection times [48].

In terms of multi-class classification of colonoscopy images, Wang et al. proposed a deep learning-based method for classifying medical colonoscopy images into four categories: polyps, inflammation, tumors, and normal conditions [49]. By transferring learning from AlexNet, VGGNet, and ResNet networks, this method not only ensured classification accuracy but also improved polyp recognition rates. Additionally, Sarwinda et al. utilized ResNet-18 and ResNet-50 deep learning architectures for classifying colonic gland images, finding that ResNet-50 outperformed ResNet-18 in terms of accuracy, sensitivity, and specificity, further demonstrating the reliability and reproducibility of deep learning in biomedical image analysis [50].

Beyond that, Fan et al. developed a CAD system for scoring ulcerative colitis in various regions of intestinal endoscopy videos using deep learning techniques [51]. As shown in **Figure 5**, the system comprises a classification module, a pre-processing CNN model, and a weighted scoring system, capable of reliably completing

Table 3. Research progress of deep learning in intestinal diseases

Ref.	Model	Lesions	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC
Fan et al. [36]	AlexNet	Ulcer	96.80	94.79	95.16	0.989
		Erosion	93.67	95.98	95.34	0.986
Aoki et al. [37]	SSD	Ulcer and erosion	88.20	90.90	90.80	0.958
Ding et al. [38]	CNN	Multi-lesions	99.88	-	-	-
Tsuboi et al. [39]	SSD	Angioectasia	98.80	98.40	-	0.998
Klang et al. [40]	Xception CNN	CD	-	-	-	0.990
Klang et al. [41]	EfficientNet-B5	Stricture	-	97.20	93.50	0.962
Leenhardt et al. [42]	CNN	GIA	100.00	96.00	-	-
Hosoe et al. [43]	EFRNet	Bleeding, angiodysplasia, ulceration, and neoplastic lesions	93.40	97.80	-	
Xie et al. [44]	EfficientNet-B5	CD	94.80	96.80	96.30	0.989
		Noninflammatory stenosis	95.10	95.90	95.70	0.989
		Inflammatory stenosis	96.00	96.90	96.70	0.992
Zhu et al. [45]	ResNet50+ YOLO	Protruding lesion, diverticulum, erosion & ulcer and angioectasia	92.00	93.00	86.00	0.947
Urban et al. [46]	CNN	Colon polyp	-	-	96.40	0.991
Wang et al. [47]	CNN	Colon polyp	94.38	95.92	-	0.984
Chen et al. [48]	DNN	Colorectal polyps	96.30	78.10	-	-
Wang et al. [49]	Multiple CNNs	Polyps, inflammation, tumor, and normal	-	-	94.48	-
Sarwinda et al. [50]	ResNet	Colorectal cancer	87.00	83.00	80.00	-
Fan et al. [51]	ResNet50	UC	87.50	96.68	86.54	

Note: The multi lesions in literature include inflammation, ulcer, polyps, lymphangiectasia, bleeding, vascular disease, protruding lesion, lymphatic follicular hyperplasia, diverticulum, parasite, and other. CD, Crohn's disease; GIA, gastrointestinal angioectasia; UC, ulcerative colitis; CNN, convolutional neural networks; DNN, deep neural networks; SSD, Single-Shot Multibox Detector.

Mayo and Ulcerative Colitis Endoscopic Index of Severity visual classification tasks and automatically scoring inflammatory activity across full-length endoscopy videos. Experimental results indicate that the system provides accurate, efficient, and reproducible scores. These studies not only showcase the immense potential of DL in diagnosing colonic diseases but also provide robust support for future clinical applications. An overview of deep learning in intestinal diseases is provided in **Table 3**.

Conclusion

In recent years, deep learning, as an important branch in the field of artificial intelligence, has made significant strides in the medical field, particularly in the diagnosis and treatment of GI diseases. This review highlights the high prevalence of GI diseases and the importance of early diagnosis, followed by a brief introduction to the concept and applications of deep learning. It then explores the background of deep learning in the context of GI diseases, noting that its application provides new approaches for early screening and precise diagnosis. Deep learning-assisted diagnosis has shown remarkable results in improving diagnostic accuracy, reducing clinician workload, and increasing early detection rates for diseases such as esophageal cancer, gastric cancer, small bowel ulcers, and colon cancer.

Despite the significant progress made in applying deep learning for GI disease diagnosis, several challenges remain. Most current studies are retrospective and single-center, limiting their generalizability. Future research should focus on conducting prospective, multi-center studies to enhance the robustness and reliability of the models. Furthermore, deep learning models requires large, high-quality labeled datasets, which are often difficult to obtain in the medical field due to issues such as limited incidence and data sensitivity. Lastly, as deep learning-based intelligent diagnostic technologies continue to evolve, addressing issues related to their legal and compliant use in clinical practice, as well as safeguarding patient privacy and data security, will be crucial.

The future of deep learning in intelligent diagnostic assistance remain promising. As technology advances, deep learning models are expected to demonstrate improved generalization capabilities and higher accuracy. Additionally, research on multimodal learning will allow deep learning models to integrate data from various sources, providing more personalized healthcare services and comprehensive diagnostic support. As deep learning applications become more standardized and secure in clinical practice, technology is poised to play an increasingly important role in healthcare. It is believed that with the continuous advancements of technology, deep learning is expected to significantly impact the medical field and transform the landscape of disease diagnosis and treatment.

Author contributions: Liying Pang performed the data analyses and wrote the manuscript; Xudong Guo, Qin Zhang supervised the study, making significant contributions to the writing and revision of the paper.

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