



## Emerging role of artificial intelligence in gastroenterology and hepatology

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**Specialty type:** Gastroenterology and hepatology

**Provenance and peer review:** Invited article; Externally peer reviewed.

**Peer-review model:** Single blind

**Peer-review report's classification**

**Scientific Quality:** Grade A, Grade B, Grade C

**Novelty:** Grade B, Grade C, Grade C

**Creativity or Innovation:** Grade B, Grade C, Grade C

**Scientific Significance:** Grade B, Grade B, Grade C

**P-Reviewer:** Al-Shimmary SMH, PhD, Assistant Professor, Iraq; Cardona F, PhD, Assistant Professor, Spain; Chen XY, PhD, Professor, China

**Received:** July 1, 2025

**Revised:** July 28, 2025

**Accepted:** September 9, 2025

**Published online:** October 21, 2025

**Processing time:** 112 Days and 16.5 Hours



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### Abstract

Artificial intelligence (AI) has emerged as a transformative tool in the diagnosis and management of gastrointestinal (GI) and liver diseases. In clinical practice AI consists of overlapping technologies such as machine learning (ML), deep learning, natural language processing, computer vision, and generative AI. ML is a computer learning system that can provide insight into disease risk factors and phenotypes. Deep learning is an advanced and complex form of ML, structured with different levels of specific algorithms known as convolutional neural networks that can rapidly and accurately process unstructured, high-dimensional data, such as texts, images, and waveforms. Natural language processing is dedicated to facilitating interactions between computers and humans using natural language and helps to analyze, understand, and derive actionable information from unstructured healthcare data, including electronic health records, clinical notes, medical literature, and patient-generated content. Computer vision focuses on enabling computers to see and interpret images and videos and serves as an augmentation tool for endoscopists, improving accuracy and decreasing procedural time. Generative AI is capable of creating new forms of content by learning from a large body of data in the form of text, audio, images, or video and includes large language models. AI has been used in several GI diseases such as esophageal neoplasia, gastric cancer, *Helicobacter pylori* infection, gastritis, GI stromal tumors, colorectal polyps, inflammatory bowel disease, irritable bowel syndrome, GI bleeding, and pancreatobiliary diseases. The potential applications of AI in liver diseases encompass a variety of conditions such as liver masses, metabolic dysfunction-associated steatotic liver disease, viral hepatitis, cirrhosis, and liver transplantation. This review discussed the common terminologies and the current status of AI in gastroenterology and hepatology, exploring its applications and ethical issues.

**Key Words:** Artificial intelligence; Machine learning; Deep learning; Applications; Gastroenterology; Hepatology

**Core Tip:** Artificial intelligence (AI) has emerged as an invaluable transformative tool in diagnosis and management of gastrointestinal and liver diseases. In clinical practice AI technologies such as machine learning, deep learning, natural language processing, computer vision, and generative AI have been used in their applications. There is a need for continued development, validation, and real-world modeling of AI systems before its widespread adoption. Although it does not replace human clinical judgement, it can still be expected that AI application in gastroenterology and hepatology will further be enhanced in the future and become the standard of care in clinical practice.

**Citation:** Shrestha UK. Emerging role of artificial intelligence in gastroenterology and hepatology. *World J Gastroenterol* 2025; 31(39): 111495

**URL:** <https://www.wjgnet.com/1007-9327/full/v31/i39/111495.htm>

**DOI:** <https://dx.doi.org/10.3748/wjg.v31.i39.111495>

## INTRODUCTION

Artificial intelligence (AI) has drastically revolutionized the healthcare system, including the clinical diagnosis and treatment, resulting in the subsequent increase in the quality of life[1]. This has emerged as a transformative tool in the diagnosis and management of gastrointestinal (GI) and liver diseases. In one systematic review it was shown that among several published randomized controlled trials of AI-assisted tools in clinical practice, more studies were done in the field of gastroenterology (30 out of 39), and it was demonstrated that the performance of AI-assisted tools surpassed that of usual clinical care[2]. AI has been used in several GI diseases such as esophageal neoplasia, gastric cancer, *Helicobacter pylori* (*H. pylori*) infection, gastritis, GI stromal tumors (GISTs), colorectal polyps, inflammatory bowel disease (IBD), irritable bowel syndrome (IBS), GI bleeding, and pancreatobiliary diseases. The potential applications of AI in liver diseases encompass a variety of conditions such as liver masses, metabolic dysfunction-associated steatotic liver disease (MASLD), viral hepatitis, cirrhosis, and liver transplantation (LT). The applications of AI in gastroenterology and hepatology are shown in the Figure 1. This review discussed the common terminologies and the current status of AI in gastroenterology and hepatology, exploring its applications and ethical issues.

## COMMON TERMINOLOGIES OF AI USED IN GASTROENTEROLOGY AND HEPATOLOGY

AI involves a computer program that uses a multitude of techniques to resolve different problems and mimics human intelligence[3]. In clinical practice several overlapping tools of AI are used, such as machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and generative AI. The landscape of AI is depicted in Figure 2.

Going through the history timeline of AI, Turin A published his work “computing machinery and intelligence” in 1950 and introduced the Turing test, a measure of computer intelligence. After 6 years, McCarthy officially coined the term “AI” in 1956 at the Dartmouth Workshop[4]. The history timeline of AI is shown in Figure 3.

ML is a computer learning system that can provide insight on disease risk factors and phenotypes. The types of ML can be categorized into supervised, unsupervised, and reinforcement ML[5]. The supervised learning involves model training with labelled data and comprises classification and regression. Unsupervised learning includes unlabeled data and consists of clustering. In the reinforcement learning the model agent takes actions in the environment, and then the received state gives the update and feedback.

DL is an advanced and complex form of ML, consisting of an input layer, multiple hidden layers, and an output layer. A convolutional neural network (CNN) is a specific type of DL architecture powered with AI algorithms that can automatically process images and perform other tasks involving visual data[6]. The layers of DL are shown in Figure 4.

NLP is a subfield of computational linguistics focused on AI models that interpret and generate human language[7]. It equips machines with the capability to comprehend, decode, and produce human language in a relevant and constructive manner and helps to analyze, understand, and derive actionable information from unstructured healthcare data, including electronic health records, clinical notes, medical literature, and patient-generated content.

Computer vision is a branch of AI that helps computers to understand and interpret images and videos. Some examples of the application of this new system in endoscopy include: (1) Automated stratification and risk classification in esophageal varices; (2) Differentiation of ulcerative colitis and Crohn’s disease; (3) Differentiation between benign and malignant biliary strictures during endoscopic retrograde cholangiopancreatography (ERCP); (4) Assisting in selective biliary cannulation during ERCP; (5) Adequate assessment of mucosal examination during upper GI endoscopy or colonoscopy; and (6) Standardized training in endoscopy skills[8].

Generative AI is a category of AI that employs ML, DL, NLP, and computer vision to create a new form of content by learning from innumerable data in the form of text, audio, images, or video following human input. It is often powered by large, pretrained models known as foundation models, which include large language models (LLMs), such as OpenAI’s ChatGPT and Google’s Gemini[9]. The chat interface is the simplest method of interacting with LLM in which

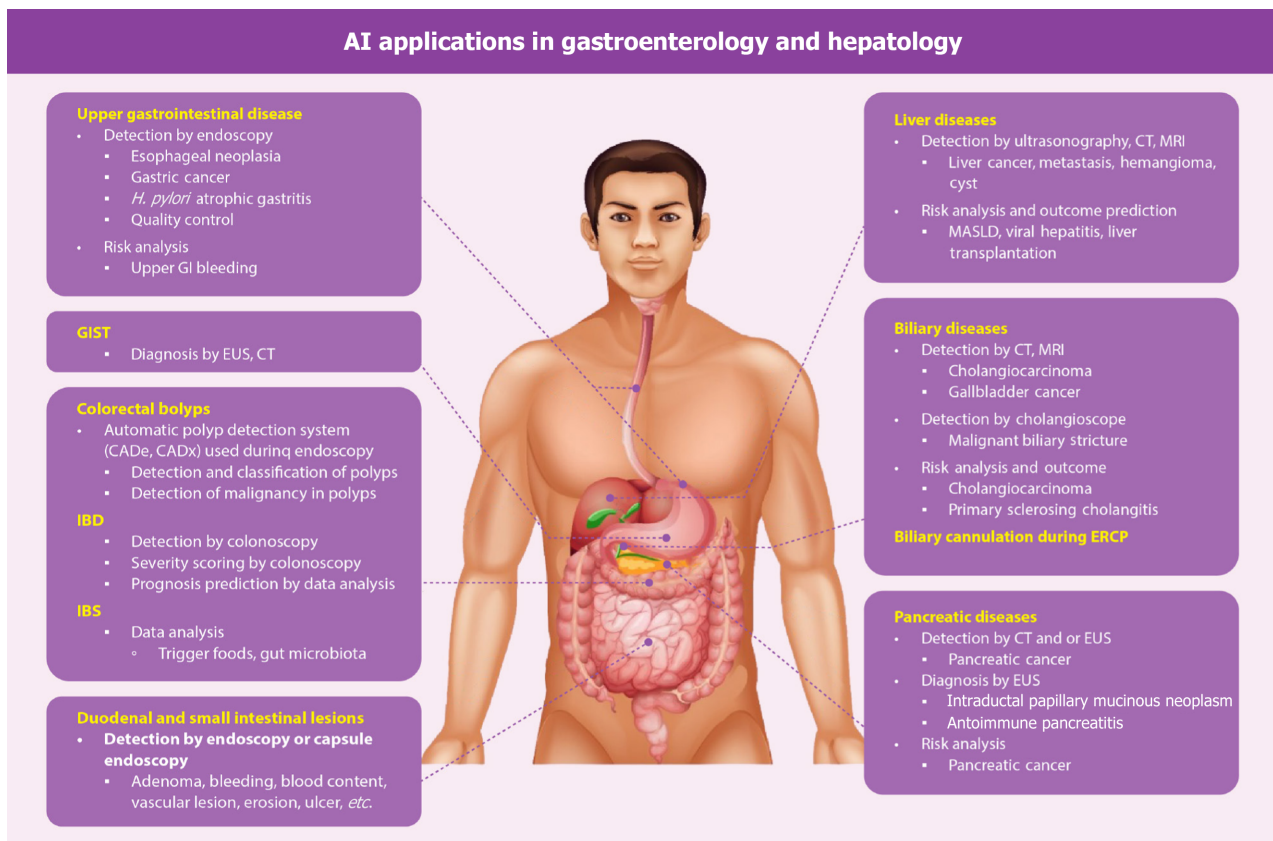


**Figure 1 Artificial intelligence applications in gastroenterology and hepatology.** AI: Artificial intelligence; GIST: Gastrointestinal stromal tumor; EUS: Endoscopic ultrasound; CADE: Computer-aided detection; CADx: Computer-aided diagnosis; IBD: Inflammatory bowel disease; IBS: Irritable bowel syndrome; MRI: Magnetic resonance imaging; MASLD: Metabolic dysfunction-associated steatotic liver disease; ERCP: Endoscopic retrograde cholangiopancreatography; GI: Gastrointestinal; *H. pylori*: *Helicobacter pylori*.

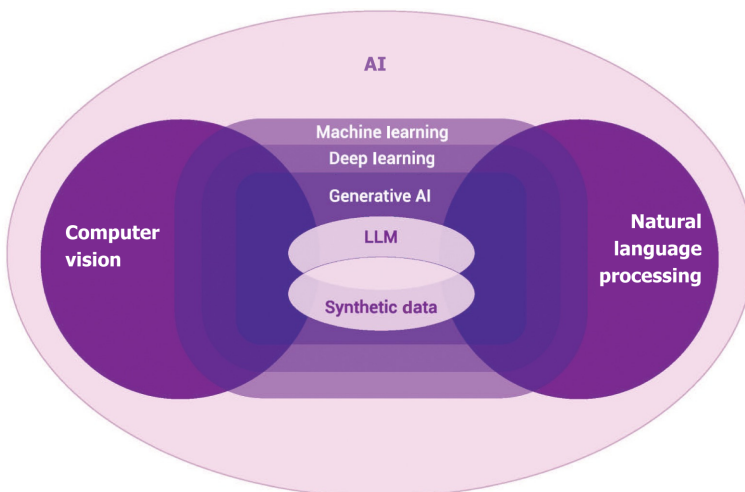


**Figure 2 Artificial intelligence landscape.** Machine learning, deep learning, natural language processing, computer vision, generative artificial intelligence, large language model and synthetic data are types of artificial intelligence. AI: Artificial intelligence; LLM: Large language model.

prior programming experience is not required. In order to perform an intended task, the users input a prompt containing the necessary instructions and contextual information. The file uploads or adjustment of model characteristics like creativity are also allowed in some chat interfaces. Application programming interfaces are used in advanced LLM-based software for more complex or high-throughput use cases and provide simplified programming instruction sets for model interaction and customization[10].

The LLM brings a new era in gastroenterology and hepatology and is utilized in improving diagnostic accuracy during endoscopy, streamlines documentation, and enhances educational and patient engagement strategies, clinical decision support, research, and drug discovery[11]. Generative AI, particularly LLMs, plays a significant role in creating synthetic

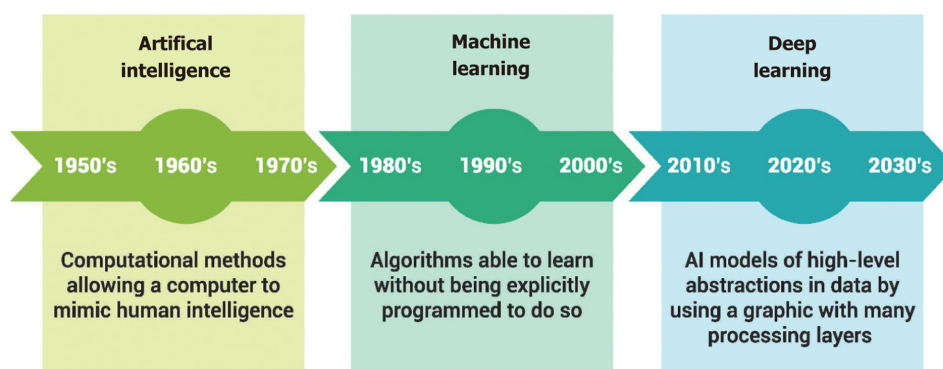


Figure 3 History of artificial intelligence. AI: Artificial intelligence.

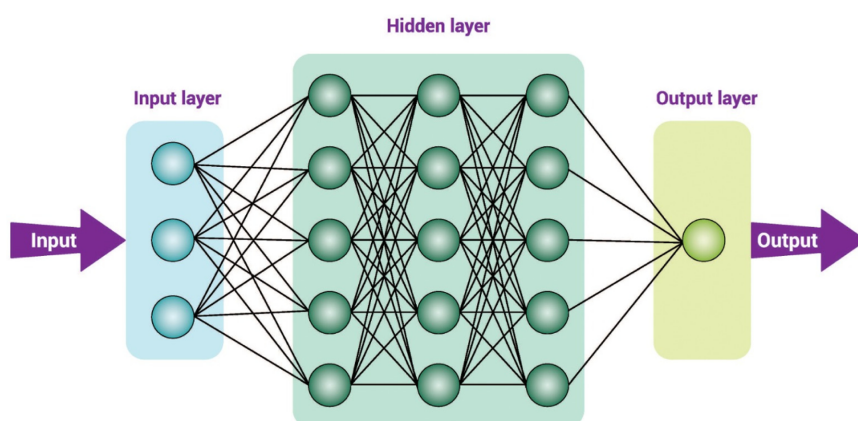


Figure 4 Layers of deep learning.

data. The concerns about the privacy of the patient, restriction of data sharing, and rarity of conditions can be the challenging problems in generating high-quality data required for the implementation of AI[12]; this can be solved by the use of synthetic data[13]. The flowchart of AI after data collection is shown in Figure 5.

## APPLICATIONS OF AI IN GI DISEASES

### Upper GI neoplasia

Upper GI endoscopy fails to identify a number of neoplastic lesions because of the several factors obscuring the vision or improper navigation. This significant miss rate of neoplastic lesions can be properly rectified by the real-time application of AI that helps not only for the detection, characterization, treatment, and reporting of upper GI neoplasia but also improves the proper navigation of the scope. The computer-aided detection system helps to reduce the miss rate, whereas the computer-aided diagnosis system assists in histology prediction of precancerous lesions and depth of invasion. The AI also helps in lesion demarcation, which ensures the complete resection; moreover, AI-assisted anatomical landmarks help in adequate reporting[14].

**Esophageal cancer:** The two histological forms of esophageal cancer are squamous cell carcinoma and adenocarcinoma. Barrett's esophagus, which correlates with the rise of gastroesophageal reflux disease, is a potential premalignant condition and can lead to esophageal adenocarcinoma[15,16].

The early detection of dysplasia in Barrett's esophagus and its timely treatment is believed to decrease the incidence of esophageal cancer. The histopathological examination has been the gold standard for the diagnosis of Barrett's esophagus and dysplastic lesion, but it has the limitation of interobserver agreement[17]. In order to improve the histological diagnosis of Barrett's esophagus and dysplasia, one study designed a DL model that included slides from 542 patients and identified the low-grade dysplasia with a sensitivity and specificity of 81.3% and 100%, respectively; the study identified the non-dysplasia and high-grade dysplasia with a sensitivity and specificity > 90%[18].

A study conducted in Japan utilized a CNN to detect early esophageal cancer and had a 98% sensitivity[19]. Another study utilized a computer-aided detection (CAD) system to identify Barrett's esophagus as having nondysplastic or neoplastic lesions with an overall sensitivity, specificity, and accuracy of 90%, 88%, and 89%, respectively[20]. The analysis of morphological nuclear features performed by computerized morphometry as shown in one study helped to

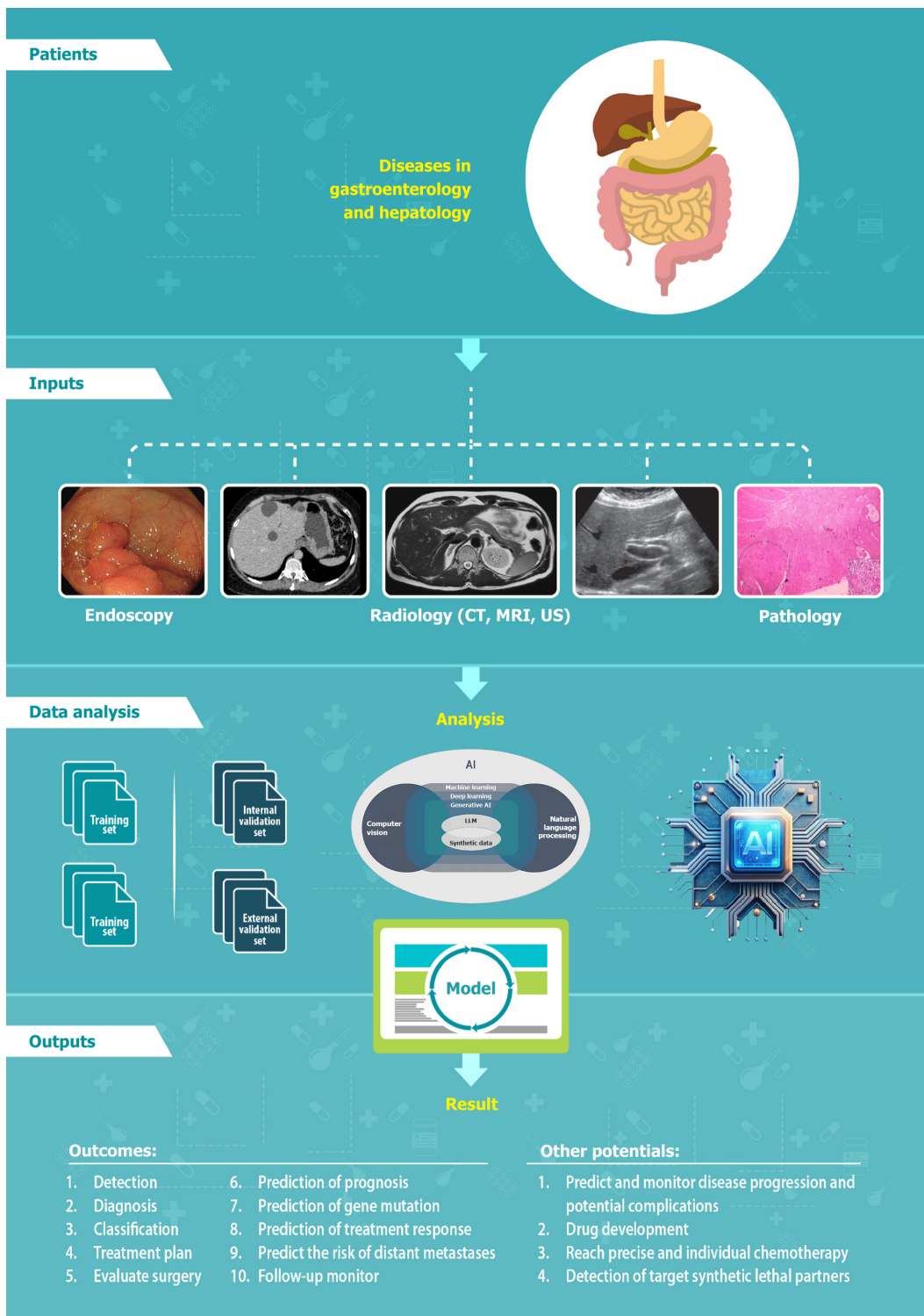


**Figure 5 Flowchart of artificial intelligence after data collection.** Artificial intelligence-assisted endoscopy, radiology, and pathology applications for medical image analysis in the fields of gastroenterology and hepatology, including detecting and evaluating lesions, facilitating treatment, and predicting treatment response and prognosis using several AI models. MRI: Magnetic resonance imaging; US: Ultrasonography; AI: Artificial intelligence; LLM: Large language model.

determine the degree of Barrett's esophagus-associated dysplasia and predicted the time to progression to adenocarcinoma[21].

A study performed with volumetric laser endomicroscopy with an added feature of an algorithm to develop a prediction score had a sensitivity and specificity of 90% and 93%, respectively, for detecting early esophageal neoplasia [22]. In one study CAD was able to identify Barrett's neoplasia in image-based validation with a sensitivity, specificity, and accuracy of 95.3%, 94.5%, and 94.7%, respectively, and in video-based external validation with sensitivity, specificity, and accuracy of 93.8%, 90.7%, and 92.0%, respectively[23]. These studies of AI in the identification of patients with esophageal neoplastic or preneoplastic lesions are shown in Table 1.

**Table 1 Use of artificial intelligence in the identification of patients with esophageal neoplastic or preneoplastic lesions**

| Lesions        | Diagnostic or predictive modality | AI classifier            | AI validation methods                                                                                                       | Number of images, slides or videos in training dataset                                                              | Number of images, slides or videos in test dataset                                                                                                                                             | Best average results (%)                  |                                      | Ref.                         |
|----------------|-----------------------------------|--------------------------|-----------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------|--------------------------------------|------------------------------|
|                |                                   |                          |                                                                                                                             |                                                                                                                     |                                                                                                                                                                                                | Accuracy                                  | Sensitivity/specificity              |                              |
| NDBE, LGD, HGD | Histology                         | Deep learning            | Training, validation, and test sets created (by a random 70/20/10 split) from 542 patients (164 NDBE, 226 LGD, and 152 HGD) | 8596 bounding boxes                                                                                                 | 840 boxes                                                                                                                                                                                      | F1 score; NDBE: 0.91; LGD: 0.90; HGD: 1.0 | NDBE: > 90; LGD: 81.3/100; HGD: > 90 | Faghani <i>et al</i> [18]    |
| ESCC and EAC   | Upper GI endoscopy (WL or NBI)    | CNN                      |                                                                                                                             | 8428 from 384 patients (397 ESCC, 32 EAC)                                                                           | 1118 (956/162) from 50 control, 41 ESCC, 8 EAC                                                                                                                                                 | 55.7                                      | 98.0/16.0                            | Horie <i>et al</i> [19]      |
| EN-BE          | Upper GI endoscopy                | Deep learning CAD system |                                                                                                                             | 494364 Labeled endoscopic images collected from all intestinal segments                                             | 1704 unique esophageal high-resolution images of rigorously confirmed EN-BE and NDBE, derived from 669 patients                                                                                | 89.0                                      | 88.0/90.0                            | de Groof <i>et al</i> [20]   |
| EN-BE          | Upper GI endoscopy                | CNN-CAD                  | Phase 2 image-based validation; phase 3 video-based external validation                                                     | 75198 images and videos (96 patients) of neoplastic and 1014973 images and videos (65 patients) of nonneoplastic BE | Phase 2 107 images (20 patients) of neoplastic and 364 images (14 patients) of nonneoplastic BE; phase 3 32 videos (32 patients) of neoplastic and 43 videos (43 patients) of nonneoplastic BE | Phase 2: 94.7<br>Phase 3: 92.0            | 95.3/94.5<br>93.8/90.7               | Abdelrahim <i>et al</i> [23] |

AI: Artificial intelligence; NDBE: Non-dysplastic Barrett's esophagus; LGD: Low grade dysplasia; HGD: High grade dysplasia; ESCC: Esophageal squamous cell carcinoma; EAC: Esophageal adenocarcinoma; EN-BE: Early-stage neoplasia in patients with Barrett's esophagus; GI: Gastrointestinal; NBI: Narrow-band imaging; WL: White light; CNN: Convolutional neural network; CAD: Computer-aided detection; BE: Barrett's esophagus.

**Gastric cancer:** Gastric cancers are more common in the distal stomach (antrum and body), but proximal gastric cancers are increasing in frequency[24]. The two histological forms of gastric cancer are intestinal and diffuse-type cancers[25]. The potential premalignant gastric lesions, such as chronic atrophic gastritis, benign gastric ulcers, hypertrophic gastropathy, and gastric polyps, might increase the risk of gastric cancer[26]. Several algorithms have been devised to improve the detection of such premalignant gastric conditions. In one study CNN needed only 47s to analyze 2296 stomach images in identifying gastric cancer lesions with a sensitivity of 92.2%[27]. Another study showed that a CNN-CAD system was able to identify the invasion depth of gastric cancer with sensitivity, specificity, and accuracy of 76.47%, 95.56% and 89.16%, respectively[28]. A study conducted in China used a CNN system for the histopathological diagnosis of gastric cancer with a sensitivity and specificity of 100% and 80.6%, respectively[29]. These studies of AI in the identification of patients with early gastric cancer is shown in Table 2.

### **Helicobacter pylori diagnosis**

Chronic and recurrent *H. pylori* infection is a well-established risk factor for gastric adenocarcinoma. The diagnosis of *H. pylori* by assessing the endoscopic gastric mucosal biopsy has been an important part of gastric cancer screening, but the process of specific staining of a gastric biopsy is time consuming. Studies have shown that AI was able to predict *H. pylori* infection with a sensitivity and specificity of 87% and 86%, respectively[30]. Another study used AI in endoscopic gastric biopsy samples to develop an algorithm to detect *H. pylori* and had a sensitivity of 100%[31].

### **Gastritis**

Since the prevalence of chronic gastritis is high, it is mandatory to look not only for the *H. pylori* infection but also for atrophy, intestinal metaplasia, and the proper types of gastritis. One study showed that the use of CNN was able to identify gastritis subtypes, namely autoimmune (A), bacterial (B), and chemical (C) gastritis, with an overall accuracy of 84%. The sensitivity and specificity for gastritis B was 100% and 93%, respectively[32].

**Table 2 Use of artificial intelligence in the identification of patients with early gastric cancer**

| Lesions | Diagnostic or predictive modality | AI classifier  | Number of images in training dataset | Number of images in test dataset | Best average results (%) |                         | Ref.                       |
|---------|-----------------------------------|----------------|--------------------------------------|----------------------------------|--------------------------|-------------------------|----------------------------|
|         |                                   |                |                                      |                                  | Accuracy                 | Sensitivity/specificity |                            |
| EGC     | Upper GI endoscopy (WL, CE, NBI)  | CNN            | 13584 from 2639 lesions              | 2296 from 77 lesions             | NA                       | 92.2/NA                 | Hirasawa <i>et al</i> [27] |
| EGC     | Upper GI endoscopy                | CNN-CAD system | 790 images                           | 203 images                       | 89.16                    | 76.47/95.56             | Zhu <i>et al</i> [28]      |
| EGC     | Histology                         | CNN            | 2123 whole slide images              | 3212 whole slide images          |                          | 100/80.6                | Song <i>et al</i> [29]     |

AI: Artificial intelligence; EGC: Early-stage gastric cancer; GI: Gastrointestinal; NBI: Narrow-band imaging, WL: White light; CE: Chromoendoscopy; CNN: Convolutional neural network; CAD: Computer-aided detection; NA: Not available.

## GISTs

GISTs are the most common mesenchymal neoplasms of the GI tract, arising from the interstitial cells of Cajal within the myenteric plexus of the muscularis propria; they occur most commonly in the stomach followed by the small intestine[33-35]. Most of the GISTs are due to mutations in the proto-oncogene *KIT*[34]. Their three histological types are spindle, epithelioid, and mixed[33,36]. These are the tumors with malignant potential, and hence all GISTs > 2 cm and most GISTs < 2 cm with high risk factors should be resected[37]. A meta-analysis of seven studies showed that the endoscopic diagnosis of GISTs can be conducted with AI-assisted endoscopic ultrasound (EUS) with a pooled sensitivity and specificity of 92% and 82%, respectively[38]. These studies showed that AI could help in the early detection of GISTs, allowing for timely intervention.

## Colorectal polyps

Colorectal polyps are slow-growing overgrowths arising from the mucosal surface of the colon and rectum and may be neoplastic or non-neoplastic. Colorectal adenomas and serrated lesions are two main classes of pre-cancerous colorectal polyps. Adenomatous polyps will gradually show dysplastic changes, and those that develop high-grade dysplasia will become malignant with time[39-41]. Hence, early detection of adenomatous polyps is crucial for the timely treatment and better outcome.

**Polyp detection:** The colonoscopy for the detection of polyps has its own limitation resulting in a decreased adenoma detection rate (ADR) because of poor bowel preparation, inability to visualize the blind spots, difficulty navigating challenging situations, and fatigue. In one study it was found that ADR was inversely related to the risk of interval colorectal cancer (colorectal cancer diagnosed between 6 months and 10 years after the index colonoscopy)[42]. AI techniques for automatic polyp detection systems used during colonoscopy, namely CAD detection and CAD diagnosis, have been extensively studied[43,44]. One study enrolled 1058 patients to evaluate the effect of an automatic polyp detection system and concluded that the AI system notably increased the ADR[44]. Another study used an automatic computer-vision method for colonic polyp detection and found that the use of energy maps was effective for the detection of polyps with a sensitivity and specificity of 70.4% and 72.4%, respectively[45].

**Polyp classification:** The characterization of polyps is important to classify the polyps as malignant or non-malignant. AI helps in the detection and characterization of colorectal polyps[46]. Several studies have used computer-aided methods for the classification of colorectal polyps[47-50]. One study analyzed the use of narrow-band imaging (NBI) magnifying colonoscopy to predict the histology of colorectal tumors and found the accuracy of this system as 97.8%[51]. During endocytoscopy microscopic visualization is done using mini probes[52]. One study has shown that the management of diminutive and small colorectal polyps can be done effectively by the use of CAD in endocytoscopy[53].

Laser-induced autofluorescence has the capacity to detect colonic dysplasia *in vivo*[54]. Diagnostic algorithms based on fluorescence spectroscopy has been developed to diagnose the presence or absence of colonic adenoma by using the fluorescence excitation-emission matrices method[55]. One study has shown that chromoendoscopy, used to enhance lesion detection in colitis surveillance, identified more lesions than NBI, but most were not dysplastic[56]. The software designed for the automated classification of colonic polyps by probe-based confocal laser endomicroscopy had high performance, comparable to that of off-line diagnosis of probe-based confocal laser endomicroscopy videos established by expert endoscopists[57].

**Detection of malignancy in polyps:** It is very important to diagnose malignancy in polyps and determine the depth of submucosal invasion. Surgery is recommended for deep submucosal invasion because of the risk of local recurrence that can occur when treated with only endoscopic resection[58]. Endoscopic resectable malignant polyps are treated by different endoscopic treatments, such as endoscopic mucosal resection, submucosal dissection, and full-thickness resection[58-60]. Considering the different therapeutic modalities for malignant polyps, proper endoscopic diagnostic techniques should be available to use for the right therapeutic options. The depth of invasion can be determined by several endoscopic techniques, such as NBI, high-definition white light endoscopy, and EUS[61]. The CAD system used

by one study utilized ultra-high magnification endocytoscopy to assess the depth of invasion and found a sensitivity and specificity of 98.1% and 100%, respectively[62].

## IBD

During the treatment of IBD, it is important to achieve mucosal healing, which means endoscopic healing and histological healing. The persistence of histological mucosal inflammation increases the risk of disease exacerbation and dysplasia. However, it is difficult to assess the histological healing only by conventional colonoscopy. In this scenario the use of AI in the form of a CAD system might help to get the information about the mucosal healing, similar to that received by the histological examination. One study of a CAD system evaluated the images from the colonoscopies in patients with ulcerative colitis and showed the identification of persistent histological inflammation with a sensitivity and specificity of 74% and 97%, respectively[63]. In one study deep neural network evaluation of an ulcerative colitis algorithm was used to recognize patients with ulcerative colitis in endoscopic remission with a 90.1% accuracy and histological remission with a 92.9% accuracy[64]. A CNN study in patients with Crohn's disease using the images of the small bowel mucosa during capsule endoscopy (CE) showed the mucosal condition, whether normal or mucosal ulcer, with an accuracy ranging from 95.4% to 96.7%[65].

## IBS

IBS is characterized by its subtypes, namely IBS with diarrhea, IBS with constipation, mixed IBS, and IBS without a significant pattern of abnormal stool[66]. The pathophysiology of IBS is complex and involves the interplay of genetics, diet, gut microbiome, and the brain-gut axis, leading to altered motility, visceral hypersensitivity, and immune response [67]. The symptom flare-ups in most of the patients with IBS have been found to be triggered by certain foods, and unique AI-aided mobile applications have been developed to identify those potential trigger foods. One mobile application used photos of food to develop a personal informatics system, which allows patient-provider collaboration and supports precise individual management[68]. A novel food and symptom journal application was found to be a feasible and usable tool for patients with IBS and helped to determine the food triggers[69]. By using these AI-aided smartphone applications, frequent and continuous data can be received from the patients and can be utilized by the clinicians to provide precision feedback. Recently, the gut microbiota has been linked to the symptoms and pathogenesis of IBS[70]. One study of a unique AI prediction model analyzed gut microbiota to identify patients with IBS with a sensitivity and specificity of > 80% and > 90%, respectively[71].

## Upper and lower GI bleeding

The endoscopic examination identifies the cause of GI bleeding in most of the patients with upper or lower GI bleeding. In some patients with recurrent bleeding, the repeated endoscopic examination may be needed to identify the bleeding point and cause of the bleeding. ML models may be generally useful for the risk stratification of patients with GI bleeding and can predict the recurrent bleeding and outcome for these patients[72-76]. In a retrospective analysis of 22854 patients with peptic ulcers, an ML model was used and validated in 1265 patients. The ML model used the patient's data such as age, level of hemoglobin, gastric ulcer, GI diseases, malignancies and infections to identify the patients with recurrent ulcer bleeding. In the study the ML model was able to identify the recurrent ulcer bleeding within 1 year with an accuracy of 84.3%[76].

## Small bowel evaluation by CE

CE is used to evaluate the small bowel and can capture nearly 60000 images, making analysis cumbersome. The use of AI might help in analyzing those images more efficiently and accurately in a shorter period of time. The CAD system developed in one study used a CNN that identified six intestinal motility events with an accuracy of almost 96%[77]. The automatic bleeding system, which analyzed 10000 CE images based on a CNN, was used in another study to detect GI bleeding and found a 99.9% precision value[78]. A novel learning method has been devised for the detection of polyps and has an overall accuracy of 98% for polyps, bubbles, turbid, and clear images[79]. Moreover, a CAD system using a CNN was also able to detect angiectasia, the most common lesion of the small bowel, with a sensitivity and specificity of 100% and 96%, respectively[80]. Studies have shown that an AI system with DL is useful for detection of erosion, ulcer, and hookworm in CE images[81-83].

# APPLICATIONS OF AI IN PANCREATOBILIARY DISEASE

## Pancreatic diseases

**Pancreatic cancer:** Pancreatic cancer is responsible for almost 5% of all cancer deaths worldwide[84]. The most significant prognostic factor in pancreatic cancer is the tumor size, which if less than 10 mm has a 5-year survival more than 80% and if more than 10 mm is less than 50%[85,86]. The early detection of pancreatic cancer by imaging faces a great challenge, and the sensitivity of detecting pancreatic cancer by CT scan is not high for small lesions[87,88]. One study showed that the AI algorithm used in CT images achieved a sensitivity and specificity of 80.2% and 90.2%, respectively, for the early detection of pancreatic cancer. They may be improved by a larger number of training images[89].

Another more powerful modality to detect small lesions in the pancreas is EUS[88,90]. The AI-based EUS used in one pilot study was able to diagnose pancreatic cancer successfully with an area under the curve (AUC) of 0.94[91]. Few studies have shown that the application of ML and DL to EUS imaging of the pancreas achieved equal or better results

than endoscopists[92]. The detection of early pancreatic cancer is feasible only if the high-risk group can be identified properly. The study done in Taiwan showed that a logistic regression model could appropriately predict pancreatic cancer risk in patients with type 2 diabetes mellitus[93].

**Intraductal papillary mucinous neoplasm:** AI-based EUS models are under development to diagnose different types of pancreatic cystic lesions, including intraductal papillary mucinous neoplasm[94]. DL-based study for automatic identification of patients with pancreatic neoplasms at abdominal CT has shown good results with an AUC of 0.91 and a sensitivity for solid lesions of any size of 98%-100% and for cystic lesions measuring 1.0 cm or larger of 92%-93%[95]. A DL model was used in one AI-based EUS study to diagnose malignancies of intraductal papillary mucinous neoplasm and achieved a sensitivity, specificity and accuracy of 95.7%, 92.6% and 94.0%, respectively[96].

**Autoimmune pancreatitis:** The accurate diagnosis of autoimmune pancreatitis (AIP) poses a challenge as the mass forming AIP might be misdiagnosed as pancreatic cancer. Thus, surgical resection could occur unnecessarily. AI-aided EUS used in one study was able to differentiate AIP accurately from pancreatic ductal adenocarcinoma and benign pancreatic conditions[97].

### **Biliary disease**

**Biliary tract cancers:** AI technology such as DL has been used in medical imaging to improve diagnostic performance of biliary tract cancers, which include cholangiocarcinomas and gallbladder cancer[98]. The analysis of clinical data, serum biomarkers, imaging, and cell-free tumor DNA in whole genome sequencing can be analyzed by AI to diagnose early cholangiocarcinoma and predict patient outcomes[99].

**Biliary stricture:** AI-based digital single-operator cholangioscopy has been used during assessment of an indeterminate biliary stricture and helped experts and less-experienced endoscopists in obtaining better histopathological samples and cutting the interobserver disagreement among experts[100].

**Primary sclerosing cholangitis:** Primary sclerosing cholangitis (PSC) is a chronic cholestatic syndrome of unknown etiology and is characterized by fibrosing inflammatory destruction of intrahepatic or extrahepatic biliary ducts[101]. PSC is often progressive and leads to biliary cirrhosis and other complications. Because of the absence of proven medical therapy, orthotopic LT is an option with good outcomes in patients with end-stage PSC[102]. PSC is also associated with cholangiocarcinoma at an incidence of 10%-30%[102]. One study used ML in a PSC risk estimate tool to accurately predict outcomes of PSC. It outperformed the noninvasive prognostic scoring systems in accuracy to predict liver failure[103].

### **Biliary cannulation during ERCP**

ERCP is an endoscopic procedure used with a therapeutic intent in biliary diseases. The procedure can be challenging in cannulating the papilla in cases of anatomical variation, and sometimes the post-ERCP pancreatitis may be the unwanted event that patients might encounter. An AI system based on CNN used during ERCP in one study assisted in identifying the ampulla in patients with anatomical variation with 76% precision and aided in biliary cannulation[104].

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## **APPLICATIONS OF AI IN LIVER DISEASES**

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### **Liver masses**

Hepatocellular carcinoma (HCC) is the fifth most common cancer globally[105] with a 5-year survival of 18%[106]. The study done with multivariate models has shown that hepatitis C virus infection, HBV surface antigen, HBV core antibody, increased body mass index, diabetes, and low platelet count can predict the risk of HCC in patients with cirrhosis[107]. The diagnostic modalities such as ultrasonography, CT, magnetic resonance imaging (MRI) and EUS are used for the detection and diagnosis of liver masses, and AI-based techniques have been developed for the hepatic mass identification. One study has shown that DL with CNN can differentiate liver masses at dynamic contrast enhanced CT with high accuracy (AUC = 0.920)[108].

Another study showed that DL was able to classify common hepatic lesions on typical MRI features with 92% accuracy, 92% sensitivity, and 98% specificity[109]. The study has shown that focal liver lesions could be identified and characterized (malignant *vs* benign) by DL using supervised-attention mechanism from liver ultrasound images[110]. In another study application of AI using EUS-based CNN model was able to identify and distinguish benign and malignant focal liver lesions accurately[111]. AI has also been used in histopathology to classify liver cancer histopathological images[112]. An AI algorithm was used in one study to evaluate the patients who were high risk for the development of HCC[113].

Another study showed that the AI-aided contrast-enhanced MRI was capable of preoperative prediction of microvascular invasion in patients with HCC[114]. The utility of AI combined with MRI and patient data was also shown in yet another study[115]. AI-aided histopathological images in one study showed that they were superior to the existing prognostic factors; the poor prognostic factors in this study were determined by the macrotrabecular architectural pattern and a lack of immune infiltration[116]. Another study showed the utility of AI-based ultrasonography to predict the response of the transcatheter arterial chemoembolization and post-radiofrequency ablation[117,118].

## MASLD

MASLD, previously known as nonalcoholic fatty liver disease, is the term for steatotic liver disease and is associated with cardiometabolic risk factors such as obesity, diabetes, hypertension, and dyslipidemia. The pathophysiology of MASLD begins with the buildup of fat in the liver, driven by metabolic dysfunction, followed by metabolic dysfunction-associated steatohepatitis, which progresses to inflammation and liver fibrosis, eventually resulting in cirrhosis, end-stage liver disease, and HCC[119]. Hence, the early detection of MASLD is vital to prevent the development of this category of HCC.

Liver steatosis can be defined histologically or radiologically. The liver biopsy is considered the gold standard for diagnosing metabolic dysfunction-associated steatohepatitis and monitoring fibrosis progression but is more invasive and costly. AI-enabled digital pathology has emerged as an important tool for achieving the more reliable and standardized result of liver biopsy[120-122]. The studies have shown that an automated tool could assess and quantify liver fibrosis and determine its architectural patterns in steatotic liver biopsies[123-126]. Several studies have shown that the automated tools such as the qFibrosis® system allowed the precise identification of collagen fibers and liver tissue architecture[127-131].

The radiological method of detecting liver steatosis is more accessible to the patient due to its less invasive nature. Recently, the detection of liver steatosis by ultrasonography has been improved by the use of DL algorithms, such as CNNs[132,133]. The systematic review has shown that AI models integrated into noninvasive diagnostic tools such as ultrasonography, elastography, CT, MRI, and clinical parameters have promising diagnostic potential for liver fibrosis and nonalcoholic fatty liver disease[134]. Currently, elastography is regarded as the most commonly used modality for staging liver fibrosis[135]. One study used AI-assisted shear wave elastography based on a DL method to compare with liver biopsy and found the similar accuracy for diagnosing cirrhosis (AUC = 0.98) and fibrosis (AUC = 0.98)[136]. Another study used ultrasound shear wave elastography imaging with stiffness value-clustering and ML algorithm to classify chronic liver disease from healthy cases and found a sensitivity and specificity of 93.5% and 81.2%, respectively[137].

AI-assisted predictive models using the vast amounts of categorized patient data have been developed to identify individuals at high risk. One study used the application of ML methods to predict nonalcoholic steatohepatitis (NASH) in patients with nonalcoholic fatty livers[138]; the study used electronic health records from the Optum analytics to create supervised ML models trained on NASH and healthy patients and found AUCs of various models ranging from 83%-88% [138]. The NASH map model utilized a non-invasive tool using 14 variables to classify patients as probable NASH or non-NASH; the study showed good sensitivity in predicting NASH status[139].

## Viral hepatitis

Most HCC cases are linked to cirrhosis caused by chronic HBV or hepatitis C virus infections[140]. The predictive models for determining the risk of hepatitis-related cirrhosis have been developed by several AI-based tools[141-145]. An AI-based prediction model in one study showed that a universal gut-microbiome-derived metagenomic and metabolomic signature predicted cirrhosis with a diagnostic accuracy of 91%[146].

## LT

LT is a lifesaving procedure in acute and chronic end-stage liver disease in which other medical treatments are no longer effective. It restores normal health and lifestyle and extends lifespan by 15 years[147]. However, there are several challenges of LT including insufficient donors, high mortality on the waiting list, and graft failures. There is a lot of mismatch between the number of organs donated *vs* the number of organs needed and the availability of recipients. The model for end-stage liver disease (MELD), donor risk index, and D-MELD (the product of donor age and preoperative MELD) have been used as criteria for organ allocation during LT; however, these scoring systems may not ensure fair and equitable distribution of donated organs[148,149]. AI-generated synthetic liver transplant waitlist data from the United Network for Organ Sharing database showed that they replicate a complex hepatic dataset, mimic clinical correlations and survival patterns, and rigorously protect patient privacy[150]. AI has been used in LT with considerable outcomes for organ allocation, donor-recipient matching, post-LT survival, or graft failure[151]. One study created a neural network to predict 90-day LT waitlist mortality using the United Network for Organ Sharing database from 2002 to 2021 from which patients who were transplanted within 90 days of listing were excluded. The study showed that the neural network algorithm outperformed MELD and MELD-sodium scores with an AUC of 0.936 *vs* 0.860[152,153]. With the use of pre-transplant donor and recipient data, AI was able to predict short and long-term survival with higher accuracy[154].

During living donor LT (LDLT), the proper functioning of the liver graft in the recipient should be evaluated meticulously. At the same time it is essential to check whether the donor is left with enough liver parenchyma for future function and regeneration[155]. One study showed that ML can improve the accuracy of graft weight prediction in LDLT [156]. Another study showed that a DL algorithm-assisted CT volumetry method can accurately estimate the graft weight in LDLT[157]. Complications leading to graft failure or death after LT include graft dysfunction/rejection, infections (bacterial, fungal, viral), biliary complications (leaks, strictures), vascular complications (thrombosis, stenosis of arteries/veins), post-transplant malignancies, and organ system failures (renal, cardiovascular, neurological)[158]. AI applications can be used to facilitate the early identification and intervention of complications and possibly complication prediction.

ML algorithms can predict graft failure after LT by utilizing known donor, transplant, and recipient characteristics at the time of the transplant decision, thereby achieving high accuracy in matching donors and recipients[159]. AI has also been used to identify novel factors associated with death after transplantation[160,161]. AI plays a role in enhancing LT by analyzing complex data for preimplantation biopsy evaluation, developing robust recipient prognosis algorithms, improving imaging analysis, and providing decision-making support[162].

## ETHICAL ISSUES IN AI

With the increasing development of AI in gastroenterology and hepatology, we face ethical dilemmas raising concerns about data privacy, algorithmic bias, and the potential for patient harm[163]. Large datasets are required for training and validation in DL-based AI models and might be an issue for the patient data privacy and security with the potential of data breaches[164,165]. The general data protection regulation is a comprehensive European Union regulation that harmonizes data privacy laws across Europe[165]. The trust and accountability of such AI-driven data are achieved only by implementation of regulatory frameworks[166].

Getting patient consent in the traditional methods may not be enough for the use of all patient data in AI applications. The right of the patient to understand the role of AI in diagnosis and treatment options should be addressed properly. The complexity of AI integration should be included in the informed consent to make patients aware of it[167]. Another important ethical concern is data ownership and sharing. AI algorithm bias can occur when they are trained on biased datasets and can perpetuate or amplify existing health inequities. Race, age, ethnicity, gender, and geographic region biases in algorithms can lead to discriminatory outcomes[168,169]. Because of the overdependence on AI-generated models, the role of clinician expertise in decision-making could be inadvertently affected[170]. Careful individualized approaches might be needed as poorly trained or validated algorithms can lead to misdiagnosis, biased care, and potential harm[171]. A balanced and comprehensive approach to patient care is necessary and can be achieved by the implementation of international ethical guidelines for health-related research involving humans[172].

Apart from the ethical concerns, the financial constraint is the prime factor in implementation of AI in clinical practice as it requires substantial investment in technology infrastructure, ongoing maintenance, and specialized training. Moreover, the role of various stakeholders, including healthcare providers, patients, and regulatory organizations, is vital. In order to understand the potential and limitations of AI in clinical practice, the proper addressing of both the financial implications and stakeholder perspectives is essential[173].

In summary these ethical concerns need to be addressed properly before implementation of AI in gastroenterology and hepatology. We need to prioritize data privacy and security, use diverse and representative datasets to mitigate bias, and validate the studies thoroughly to assess the performance of AI tools across different populations. In order to achieve the trust and accountability, AI algorithms need to be transparent and explainable. It should be understood that AI is used to augment, not replace, human expertise. Hence, a balanced approach is needed by establishing clear guidelines and regulations for the development and deployment of AI in gastroenterology and hepatology.

## CONCLUSION

AI has emerged as an invaluable transformative tool in diagnosis and management of GI and liver diseases. However, there is a need for continued development, validation, and real-world modeling of AI systems before its widespread adoption. Although it does not replace human clinical judgement, it can still be expected that AI applications in gastroenterology and hepatology will further be enhanced in the future and become the standard of care in clinical practice.

## FOOTNOTES

**Author contributions:** Shrestha UK contributed to the conceptualization and design, writing the original draft, and reviewing and editing.

**Conflict-of-interest statement:** The authors declare that they have no conflicts of interest.

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**S-Editor:** Fan M

**L-Editor:** Filipodia

**P-Editor:** Zhang YL

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