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Role of Artificial Intelligence in Gastroenterology and Hepatology

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Abstract

The term artificial intelligence (AI) refers to a collection of techniques designed to mimic human intelligence in some way. Gastroenterology is not an exception, as imaging is used for diagnostic purposes in various medical specialties. A number of applications of AI are available here, including the detection of polyps, the identification of their malignancy, the diagnosis of *Helicobacter pylori* infection, gastritis, inflammatory bowel disease, gastric cancer, esophageal neoplasms, and pancreatic and hepatic cancers. This review will discuss the main applications of artificial intelligence in hepatology and gastroenterology, as well as their limitations.

Keywords: Artificial Intelligence, Radiology, Gastroenterology, Hepatology

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Introduction

In medicine, AI refers to the development of computers that can perform tasks requiring human intelligence. A great deal has been accomplished in the field of AI since it was first developed in the 1950s. AI is often referred to as machine learning (ML) or deep learning (DL), which refers to techniques within AI that enable computers to learn and adapt without explicit instructions. The goal of ML is to predict outcomes based on data using self-learning algorithms. Learning is either supervised or unsupervised within ML. A supervised learning algorithm learns from a dataset in which a hierarchy of features has previously been assigned so that it can distinguish between different data inputs and predict outcomes. Unsupervised learning uses datasets that have not been categorized by humans. After analyzing the data, the algorithm identifies patterns and labels [1].

Artificial neural networks (ANNs) can be taught using both supervised and unsupervised techniques. Node units, which are organized in successive layers, are part of ANNs, a category of ML algorithms. ANNs are based on the neural network concept. Similarly to neurons, artificial neurons (nodes) are capable of transmitting signals through dendrites and axons. ANNs, unlike biological ones, can receive other forms of signals besides activation signals, which is what makes them different from each other [2].

A deep neural network (DNN) is an ANN composed of multiple layers, and DL is the process of utilizing such a system. A DNN's first layer represents input information, and its last layer represents output information. Hidden layers are those between input and output. By layering simple data with complex information, the system is able to make complex decisions [3].

The representation learning capability of deep learning allows it to change the frameworks in each layer, thereby providing better results. Transfer learning is one of the major advantages of this system. For example, a model trained for one task may be used for another task once it has learned the characteristics of the image. It is predicted that AI will be an increasingly important technology in some medical specialties, particularly those that require interpretation of images, like dermatology, gastroenterology, radiology, and pathology. Using AI in gastroenterology is the purpose of this mini review. A number of AI applications in endoscopy are being developed, including the identification, classification, and assessment of colorectal polyps, wireless capsule endoscopy (WCE), the evaluation of esogastric pathology using upper endoscopy, and the analysis of ultrasound images obtained by endoscopic ultrasound. In gastrointestinal endoscopy, AI can improve diagnosis and treatment [4].

Colorectal Polyps

Colorectal polyps are growths on the lining of the colon or rectum. There is a high probability of benign polyps developing in the colon and rectum. The results indicate that they are not cancerous. Depending on how many polyps you have, you may have one or more. The prevalence of these diseases increases with age. The polyps come in a variety of forms. The most common type of polyp is an adenomatous polyp. This is a type of growth that develops on the mucous membrane that lines the large intestine. It is commonly one of these types of tumors that is called an adenoma: (i) Tubular polyp, which protrudes out in the lumen (open space) of the colon and (ii) Villous adenoma, which is sometimes flat and spreading, and is more likely to become a cancer.

People with polyps may also have some inherited disorders, such as: Familial adenomatous polyposis, Gardner syndrome (a type of Familial adenomatous polyposis), Juvenile polyposis, a disease that causes many benign growths in the intestine before 20 years old, In addition to Lynch syndrome, hereditary non-polyposis colorectal cancer increases the risk of many types of cancer, including intestine cancer and Puisz-Jeghers syndrome (a disease that results in intestinal polyps, usually of the small intestine, which are usually benign) [5].

Detection of polyps

CADe (computer-aided polyp detection) and CADx (computer-aided polyp diagnosis) are two implementations of AI for colonoscopy. Intensive research has been conducted on both of these techniques.

The rate of missed polyps during colonoscopy might be as high as 25%, including preparation of the bowel, the rate of adenoma detection rate (ADR), and even fatigue. In this study, Fernández et al. [10] investigated the capability of an automatic method based on the creation of energy maps for detecting colonic polyps. This technique was 72.4% specific and 70.4% sensitive, even though only 24 videos containing polyps were analyzed. Furthermore, authors like Wang et al. [11] recently conducted a prospective randomized controlled study to investigate the effect of an automatic polyp detection system. Study participants were randomized to receive standard colonoscopies or computer-aided diagnoses. A higher incidence of small adenomas that could be detected by the AI system led to a notably increased ADR and mean number of adenomas per patient (Figure 1) [6].

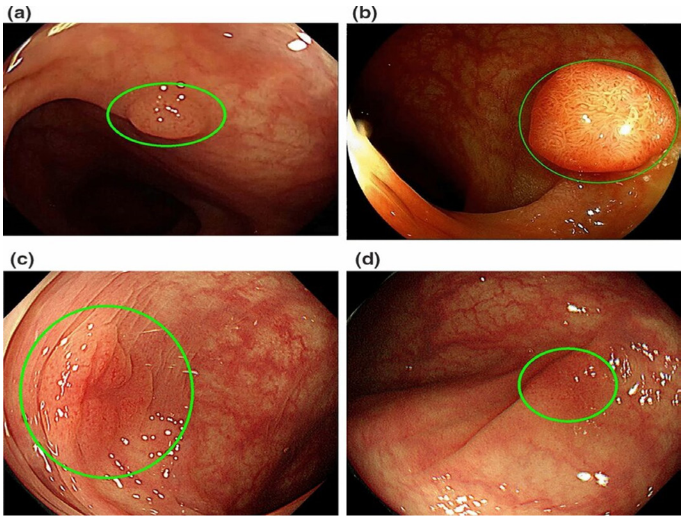

Figure1: Automated polyp detection. In this practical application of AI in gastrointestinal endoscopy [6].

An overview of polyp classification

In spite of the fact that polyps are small, it is important to classify them. Depending on the situation, an endoscopist can either remove them or leave them in place. An enhanced imaging technique is needed for a close-up analysis of the polyps to be able to make these decisions. Polyps are classified into malignant or nonmalignant according to their malignantness [7-11]. The shape, texture, and color of polyps are considered by AI to make this differentiation. The classification of polyps can be accomplished using chromoendoscopy, narrow-band imaging, endocytoscopy, laser-induced autofluorescence, and confocal endomicroscopy.

To predict the histology of colorectal tumors using narrow-band imaging magnifying colonoscopy, Takemura and his co-authors [12] examined narrow-band imaging magnifying colonoscopy. In spite of the learning curve in the NBI classification system, and even though the study was conducted in only one center, the system was nearly 97.8% accurate. In contrast, endocytoscopy uses mini probes to provide microscopic visualization. An automated system could be used to diagnose small and diminutive polyps using endocytoscopic imaging [12-15]. According to their results, the system is 89% accurate when dealing with diminutive and small polyps.

Colonic dysplasia can be detected *in vivo* using laser-induced autofluorescence. In WavSTAT, laser light is absorbed by tissue through laser-induced autofluorescence spectroscopy, which is incorporated into biopsy forceps. Optical fingerprints are created by analyzing the light that is emitted by the tissue. The purpose of chromoendoscopy is to enhance the appearance of tissue by applying topical dyes. A combination of this technique and another technique, such as NBI, is often used.

Endoscopists can visualize epithelial tissue during endoscopy with probe-based confocal laser endomicroscopy. The performance of an automatic software with an off-line method used by expert endoscopists to support probe-based confocal laser endomicroscopy. Based on their findings, both techniques are highly sensitive and specific [16].

H. pylori diagnosis

Gastric cancer is frequently caused by *H. pylori*. Gastric cancer screening in Asia involves diagnosing *H. pylori* in Asia involves assessing the mucosa for *H. pylori*. Since this process is time-consuming and involves a steep learning curve, AI might be useful for improving diagnostic performance [17, 18].

A method for detecting *H. Pylori* was developed by Dr. Sebastian and his colleagues using specific stained gastric biopsies. Based on Giemsa-stained biopsies from 87 cases, the algorithm had 100% sensitivity.

Malignant polyps: detection and treatment

Diagnosing malignancy in polyps is very important because making the right diagnosis guides the optimal treatment for the patients. If deep submucosal invasion is present, surgery is required because there is a high risk of possible metastasis to the lymph nodes. Taking this into consideration, proper endoscopic diagnostic tools should be used in order to be able to use the right therapeutic options [19-22].

Endoscopic treatment consists of endoscopic mucosal resection, endoscopic submucosal dissection, or endoscopic full-thickness resection. Currently, several endoscopic techniques are available to assess the depth of invasion. Those are NBI, high-definition white light endoscopy, and EUS. Recently, another CAD system for assessing the grade of invasion, which uses ultra-high magnification endocytoscopy. They concluded that this system might be a helpful diagnosing tool in the future, having both high sensitivity and specificity of 98.1% and 100% [23].

Gastritis

Among the most common diseases is chronic gastritis. Inflammation levels, intestinal metaplasia and atrophy are all evaluated during diagnosis, as is *H. pylori* contamination. Convolutional neural networks (CNNs) were used in the study. In order to classify gastritis properly (autoimmune, bacterial, and chemical), the capacity of this network was evaluated. 84 percent of the tests were accurate [2, 24. 25].

Gastric cancer

Early detection and proper characterization of gastric lesions are as important as colorectal lesions for establishing optimal treatment options. Chronic gastritis and polyps are gastric lesions that can be premalignant. A number of studies have examined algorithms developed to detect premalignant gastric conditions.

In a recent study, CNN system had an overall sensitivity of 92.2% when diagnosing gastric cancer lesions. Gastric cancer invasion grade using an AI CNN system. Using this system, expert endoscopists were able to differentiate between early gastric cancer and deep submucosal invasion to the extent of 76.47% and 95.56%, higher than those achieved with standard systems by expert endoscopists [5, 26-32].

Inflammatory bowel disease

It is the histologic healing of the mucosa that matters most when it comes to inflammatory bowel disease. Patients who suffer from a type of disease that evolves over several years are more likely to experience disease exacerbation and dysplasia when histologic inflammation is still present. Using images from colonoscopies of patients with ulcerative colitis, the accuracy of a CAD system. Based on the results, they concluded that the system was capable of identifying persistent histologic inflammation with 74% sensitivity and 97% specificity [33].

Another DNN system uses colonoscopy images from ulcerative colitis patients. Eight hundred and seventy-five ulcerative colitis patients underwent colonoscopies to test the system's accuracy. Histologic remission was 92.9% accurate, and endoscopic remission was nearly 90.1% accurate. Using images from capsule endoscopy, Eyal along with his co-authors used a DL algorithm to automatically detect ulcers located in the small intestine in patients with Chron's disease. In order to identify normal mucosa or mucosal ulcers from image data from the mucosa, a convolutional neural network was trained. Between 95.4% and 96.7% of predictions were accurate [34, 35].

Esophageal neoplasia

Cancer of the esophagus is one of the most aggressive types of cancer. Squamous cell carcinoma and adenocarcinoma are the most common histological types. Histopathological response and overall survival rate are positively correlated with localized esophageal cancer treated with chemotherapy.

As a potential premalignant condition, Barrett's esophagus is one of the most common esophageal lesions [36]. As dysplasia progresses, the risk of Barrett's esophagus increases. Therefore, early detection plays a significant role in improving prognosis. Barrett's esophagus is nowadays diagnosed by histopathology, which has limitations when it comes to interobserver agreement, but is still the gold standard. Recent developments have enabled CAD studies based on image analysis to overcome this limitation [37].

A DL model was developed to aid in improving the diagnosis of dysplastic lesions. The study included slides from 542 patients and classified them into three categories: nondysplastic, low-grade dysplasia, and high-grade dysplasia. Based on images, the model was trained and validated to identify low-grade dysplasia with an 81.3% sensitivity and 100% specificity, and nondysplastic Barrett esophagus with >90% sensitivity and specificity. A CNN was also used to detect esophageal cancer early at the Cancer Institute in Japan. With this system, superficial esophageal cancer could be distinguished from advanced esophageal cancer with 98% accuracy [2, 5, 38].

In order to detect neoplasia in Barrett's esophagus, developed a hybrid ResNet-UNet model. By using CAD, the system was able to differentiate between nondysplastic Barrett's esophagus and neoplastic Barrett's esophagus. Specifically, it had a sensitivity of 90%, an accuracy of 89%, and a specificity of 88%. Computerized morphometry is another tool used to determine the degree of dysplasia in Barrett's esophagus. As part of a study, a number of indices of epithelial nuclei were measured, such as size, shape, texture, architectural distribution, and symmetry. Therefore, this study proposes computerized morphometry as a sustainable method for assessing dysplasia and predicting adenocarcinomas. An esophagus layer scan using volumetric laser endomicroscopy can provide a high-resolution image of the esophagus' layers. However, its limitations regarding the amount of data needed for real-time interpretation have made its use difficult despite its high potential to improve dysplasia diagnosis in Barrett's esophagus [39-44]. A clinical volumetric laser endomicroscopy prediction score was used as an input to Swager et al. [29] algorithm to overcome this limitation. Endoscopists could benefit from an algorithm that detects early neoplasia with 90% sensitivity and 93% specificity.

Endoscopic Ultrasound (EUS)

An EUS examination is particularly useful when diagnosing pancreatic lesions and differentiating them from chronic pancreatitis. The number of studies on DL systems is limited at the moment due to limited resources [45].

Among 262 patients with chronic pancreatitis and pancreatic cancer, Zhu and his team conducted a study. The texture characteristics of specific regions of interest were selected using computer-based techniques. Based on the EUS images, 105 characteristics were extracted, and nine categories were identified. In general, the accuracy of the system was 94.2%, sensitivity was 96.25%, and specificity was 93.38% [22, 46].

Das and her colleagues [23] developed a model that can distinguish chronic pancreatitis from pancreatic cancer using digital image analysis on EUS images. Among three groups of patients, the analysis was conducted. There were three groups: one with normal pancreas, one with chronic pancreatitis, and one with pancreatic adenocarcinoma. The study concluded that direct image analysis of EUS images is highly accurate in distinguishing between the three entities, despite having a small number of patients (110 in the normal pancreas group, 99 in the chronic pancreatitis group, and 110 in the adenocarcinoma group) (Figure 2) [5, 47-52].

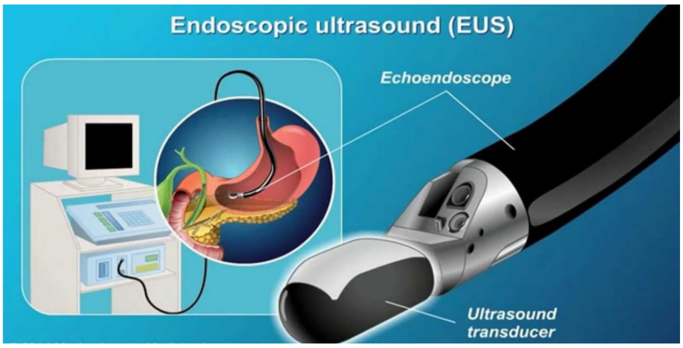

Figure 2: EUS.

Differentiating between chronic pancreatitis and autoimmune pancreatitis is an important consideration. According to Dr. Zhu [22] study, 181 cases of chronic pancreatitis and 81 cases of autoimmune pancreatitis were investigated. Their findings suggest that textural feature CAD might be useful in detecting chronic pancreatitis versus autoimmune pancreatitis when local ternary pattern variance is present.

WCE

With WCE, the small bowel can be visualized by the physician.

While WCE is useful for diagnosing multiple abnormalities, including mucosal pathology, bleeding, or polyps, it does have some limitations. A classic evaluation requires the analysis of nearly 60,000 images and up to 8 hours of video [52, 53].

Based on these limitations, Zheng et al. [54] found that endoscopist experience does not affect the detection rate of abnormalities in a classic WCE evaluation. It is possible to remove image frames that provide no information to the reader with the software that is used with WCE, as well as to improve the reader's efficiency by using color to locate frames containing blood. Each time a new application for WCE appears, a new CAD system must be designed, which is one limitation of CAD systems used with WCE. A system that uses CNN to predict six intestinal motility events with almost 96% accuracy [54]. With WCE, you can create databases to serve the development of future CAD systems utilizing the large number of images it provides. An analysis of small bowel WCE videos was carried out retrospectively by 12 French endoscopy centers. The researchers extracted pathological findings from 4174 videos [55].

An automatic bleeding detection system based on a CNN can detect gastrointestinal bleeding. A 99.9% precision value was found with their method after analyzing 10,000 WCE images. An innovative learning method for polyp detection was proposed. They categorized images based on similar features, according to the theory that similar images should belong to the same category [56]. Overall, the method was 98% accurate for polyps, bubbles, turbid images, and clear images. CAD systems using CNNs were tested for detecting angiectasia, the most common small bowel lesion. For algorithm testing and ML, two datasets of still frames were created. Erosion, ulcer, and hookworm detection systems were also reported to be comparable to direct learning systems (Table 1).

Radiology

Since AI is highly applicable to a wide range of pathologies, it has become an essential part of radiology diagnostic and therapeutic procedures.

In addition to computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US), ML prototypes have been used to process a wide range of images. Recent interest has been generated by radiomimicry, a term first described in 2012, because it can reveal the correlation between biological processes and technology [57, 58].

Table 1: Endoscopic procedures using CAD and AI [2].

Upper digestive tract endoscopy	Diagnosis of *H. pylori*
	Inflammatory gastric disease (autoimmune, bacterial, and chemical chronic gastritis)
	Gastric cancer
	Esophageal cancer and premalignant conditions (Barret's esophagus)
Lower digestive tract endoscopy	Polyp detection
	Polyps' classification
	Detection of malignancy in polyps
	Inflammatory bowel disease (ulcerative colitis and Chron's disease)
WCE	Angiectasia
	Polyps
	Erosions/ulcers
	Hookworms
Endoscopic ultrasound	Chronic pancreatitis
	Pancreatic cancer
	Autoimmune pancreatitis
	EUS Electrography

AI in Radiology - Applications in Gastrointestinal Pathology

Pancreatic disease

AI has been used to investigate a variety of pancreatic diseases, including acute pancreatitis, chronic pancreatitis, pancreatic cystic neoplasms, and pancreatic ductal adenocarcinomas. Prognostic models and scores for acute and chronic pancreatitis were improved with the use of AI [59-63]. Using AI, pancreatic cystic neoplasms were detected, differentiated, and predicted for their malignant potential. In order to differentiate between benign and malignant conditions, AI was used to evaluate pancreatic ductal adenocarcinoma. Furthermore, AI can be used to interpret tissue samples.

Due to the fact that pancreatic cancer is the seventh leading cause of death worldwide, and a five-year survival period is dependent on how large the lesion is, it is necessary to use proper diagnostic tools to identify patients at high risk and to provide early detection. Several algorithms were compared for predicting pancreatic cancer risk. LYVE1, REG1B, and TFF1 urine biomarkers were examined in their study of 379 patients. Pancreatic cancer risk can be stratified using a biomarker-based risk score [64].

Screening for pancreatic cancer with CT is commonly done, however its sensitivity is low, especially for small lesions. A CT scanning model to overcome this issue and detect pancreatic cancer at an early stage. It achieved a specificity of 90.2% and a sensitivity of 80.2% for 314 normal scans and 136 pancreatic ductal adenocarcinoma cases. Pancreatic cancer can be diagnosed more accurately with EUS. A CAD system using EUS images was developed for the diagnosis of pancreatic cancer. A total of 202 EUS images from pancreatic cancer patients were extracted, as well as 130 images from non-cancer patients. A sensitivity of 83.3% and a specificity of 93.3% were achieved by their system [2, 65].

Another system that uses endoscopic ultrasound imaging for real-time CAD of pancreatic masses. In their system, CNNs were combined with long short-term memory neural networks. A total of 65 patients with focal pancreatic masses were included in the study, and 20 images were selected from those patients. 98.26% of the model's predictions were accurate. The severity of acute pancreatitis determines the outcome. A rapid and appropriate risk classification is essential for establishing the proper treatment and monitoring of acute pancreatitis. In a study, ANNs were used to develop a system that can predict acute pancreatitis severity. According to the Atlanta criteria, severe pancreatitis was defined in their study as 208 patients. Alanine aminotransferase, heart rate, hemoglobin levels, creatinine, hemoglobin levels, and white blood cell count were selected as risk variables. A 50% sensitivity level was reached by the system [66].

Cystic neoplasms of the pancreas are also important pancreatic lesions. Detecting them and using proper curative treatment is possible due to their slow progression to invasive carcinoma. There are currently limited technologies available for determining cancer risk [67]. Intrapapillary mucinous neoplasms (IPMNs) were predicted from CT scans of pancreatic cysts and parenchyma regions in 103 patients. After resection, IPMNs were classified as low or high risk. An area under the curve of 0.81 was obtained using tenfold cross-validation combined with clinical variables [68-70].

Liver disease

In addition to liver cancer, hepatitis, and alcohol-induced cirrhosis, metabolic syndrome is causing a continuous growth curve. Liver cancer

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makes up the third highest cause of cancer deaths, according to a 2022 article about global cancer incidence. It is therefore imperative that proper diagnostic tools that provide early detection of cancer as well as proper staging tools be used in order to provide effective treatment for cancer [71]. There are many liver diseases that affect the liver, such as hepatocellular carcinoma, nonalcoholic fatty liver disease, benign tumors, viral hepatitis, chronic liver disease, and primary sclerosing cholangitis. A combination of AI and abdominal US can be used to assess diffuse liver disease as well as focal liver lesions. Fibrosis and NAFLD are currently diagnosed with liver biopsy, the gold standard. In spite of its high sensitivity and specificity, hemorrhage, peritonitis, and pneumothorax are some of the complications associated with this procedure [2, 72-74]. Thus, potential diagnostic techniques are needed in the future.

In a CAD system, an ultrasound shear-wave elastography tool for analyzing and categorizing chronic liver disease. They analyzed 85 images, including 54 healthy subjects and 31 chronic liver disease patients. Based on this model, the accuracy was 87%, while sensitivity and specificity were high at 83.3% and 89.1%, respectively [75]. In order to detect and characterize mass lesions simultaneously using DL developed an algorithm. Three hundred and sixty-seven ultrasound images were used from three hundred and sixty-seven individuals. Tests were conducted on 177 subjects with the algorithm accompanied by annotations from a radiologist. Lesion discernment and characterization achieved high receiver operating characteristic curves of 0.93 and 0.916, respectively. As part of their study, used the DL method in conjunction with a CNN to distinguish between liver masses at CT. These images were acquired at three different phases: non-contrast-agent enhanced, arterial, and delayed. Under supervised training, liver masses were divided into five categories: hepatocellular carcinomas, other malignant liver tumors, indeterminate or mass-like lesions, and rare benign masses, hemangiomas, and cysts [76]. Based on 100 liver masses, a CNN was trained and tested on differential diagnosis, with a median accuracy of 0.84. Multiple studies have evaluated the success of AI when used in conjunction with MRI for the diagnosis of liver and pancreatic lesions. CNN and 3D MRI images were used to differentiate liver tissue types in hepatocellular carcinoma patients. Following the successful testing of their method on 20 patients, encouraging results were obtained. MRI sequences are currently used only for T2-weighted images for grading liver lesions automatically. In addition, an analysis of the MRI sequence for automatic classification. Ninety-five patients were studied, with 125 benign and 88 malignant lesions. An overall accuracy of 0.77 was achieved when analyzing DCE-MR and T2-weighted images [77].

It is crucial to identify the viral genetic markers associated with the progression of fibrosis in patients with hepatitis who may be at risk of developing cirrhosis. Through the use of ML, linear projection, and Bayesian networks, several sites were identified as correlated with fibrosis progression [78]. Among the symptoms of primary sclerosing cholangitis are inflammation and fibrosis of the ducts within the liver. Furthermore, the disease is premalignant, and there are no effective medical treatments available. 509 patients with primary sclerosing cholangitis and assessed their risks and outcomes. We considered nine variables when estimating disease decompensation risk: patient age, bilirubinemia, serum alkaline phosphatase, albumin, AST, platelets count, hemoglobin, sodium, and number of years since diagnosis. Using an ML algorithm, their tool accurately predicted hepatic decompensation [79].

AI has recently been applied to predicting graft failure and, thus, overcoming the problems associated with liver transplantation, such as the high mortality rate on waiting lists, the insufficient availability of donors, and graft failures. Additionally, AI was used to analyze factors associated with death after transplantation, such as diabetes [80].

Discussion

In the field of gastroenterology and hepatology, AI is a promising tool for diagnosis, prognosis, and treatment. To date, only a few devices have been approved for use in AI systems despite promising studies evaluating their specificity and sensitivity. There are some of them that are used in endoscopy for detecting colon tumors, such as EndoBRAIN-EYE, EndoBRAIN, WISE VISION, WavSTAT4, and GI Genius. In addition, EndoBRAIN-Plus can determine tumor depth. Endoscopists can detect colon polyps more easily with the help of CAD EYE and Discovery systems.

A liver lesion can be detected by Liver AI for CT scans. Ultrasonography is performed with Poseidon and Ultrasound systems. Endoscopy techniques can be improved with AI by gradually replacing biopsy techniques in the future, which are currently the gold standard for a variety of lesions. WCE is a very laborious and useful technique for evaluating the small intestine, which is made easier with the implementation of ML systems.

In recent years, pancreatic cancer has become one of the most studied diseases due to its high mortality rate due to late diagnosis. About 20% of patients benefit from surgery in these cases, but it is the only effective treatment. At the present time, there are five diagnostic tools available: US, EUS, CT, MRI, and positron emission tomography-CT. In terms of sensitivity and specificity, EUS seems to be the most effective at detecting pancreatic lesions out of these five tools. EUS is primarily limited by the specialist's experience when it comes to diagnosis. Professionals in this field can detect abnormalities with the help of AI. The sensitivities and specificities of AI were analyzed in a meta-analysis of 10 studies. When comparing their study to the literature, which shows no significant variation in diagnostic accuracy using AI, they found a smaller variation in diagnostic accuracy using AI. Moreover, EUS appears to be the most sensitive at detecting lesions of 3 cm, which represents an important step in early diagnosis. A comparison of EUS sensitivity to MRI and CT shows that it is 94.4%, compared to 53% for MRI and 67% for CT. The AI also addresses the issue of non-variceal upper gastrointestinal bleeding, which contributes to a high mortality rate. An ANN has been used to predict mortality in patients with non-variceal upper gastrointestinal bleeding. AIM65 and the Rockall-Blatchford scores were used in their analysis of 914 patients. Their ANN was more accurate than the three scores analyzed separately, predicting mortality with >95% accuracy.

It was stated in the October 2022 position statement of the European Society of Gastrointestinal Endoscopy (ESGE) regarding AI, particularly in relation to diagnosing and managing gastrointestinal neoplasia, that, for AI to be implemented in a clinical setting, a high-quality standard must be established for both diagnosis and treatment of gastrointestinal neoplasia. In order to increase the rate of detection, AI should provide aid to less experienced endoscopists when diagnosing potential lesions, not to more experienced ones. Future histopathology examinations of polyps may not be replaced by AI in the foreseeable future, according to the ESGE. The use of AI should not replace histopathologic examination, but rather help endoscopists make the right decisions regarding colorectal polyps. Additionally, they recommend comparing the performance of less experienced endoscopists assisted by AI with that of experienced endoscopists in future research. Among the limitations of AI, the most important are that further studies must be done to determine its effectiveness on a larger number of patients, and that CADe systems are expensive, so trial programs must be conducted before purchasing.

Several researchers like Dr. Ahmad [66] concluded in 2022 that CADe significantly improved the rate of polyp detection on colonoscopy. Eight experienced endoscopists performed the study in a cancer screening program that included 614 patients randomized into a CADe or control group. Although polyp detection rates were higher in the CADe group (85.7% vs 79.7%) despite no significant difference in ADR between the two groups (2.4 vs 2.1). Another study published in 2022, evaluated a CADe program which was used for 3 months in one facility, the largest from the study, compared to another 5 units that served as controls. The center using CADe had an ADR of 40.1%, which was lower than that of the control sites, which had an ADR of 41.8%. It may be suggested that other factors, such as motivation and training, are also important in this process based on the fact that this result differed from multiple randomized controlled trials.

In conclusion, AI offers physicians and patients future perspectives regarding diagnosis, prognosis, and treatment decisions, but further research is necessary.

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None.

Conflict of Interest

None.

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