

**The Future of AI in Gastroenterology: Advancements, Challenges and Prospects**Shivani Modi<sup>1</sup>, Supriya Peshin<sup>2\*</sup>, Parisha Masud<sup>2</sup>, Inshya Desai<sup>1</sup> and Malay Rathod<sup>3</sup><sup>1</sup>Jefferson Einstein Healthcare Network, PA<sup>2</sup>Norton Community Hospital, Virginia<sup>3</sup>Monmouth Medical Center, NJ**\*Corresponding Author**

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A new world is evolving with the current use of AI in various fields. AI is becoming well known and is an active area of research in many fields. An area of widespread use is the field of medicine, especially gastroenterology. AI in Gastroenterology can enhance diagnostic accuracy by assisting in identifying abnormalities in medical images. Gastroenterology is a field that can particularly benefit from the support of AI tools to analyses pictures from a wireless capsule endoscopy, detect colonic polyps using deep-learning approaches, and use capsule endoscopies to find bleeds in the small intestine that are missed in a regular endoscopy. These areas have been AI successes in the field of gastroenterology, but critical assessment is also necessary to identify upcoming obstacles using AI. The aim of this review paper is to assess the overall use of AI technology, examine current AI applications in gastroenterology, demonstrate the inherent value that AI brings to this field, and discuss the potential directions and scope for future research in this field with AI.

**Keywords:** Artificial Intelligence, Gastroenterology, Deep Learning, Machine Learning, Diagnosing, Capsule Endoscopy**1. Introduction**

Artificial Intelligence (AI) is a branch of computer science dedicated to creating machines capable of performing tasks that typically require human intelligence, such as problem-solving, learning, perception, and understanding natural language. The foundation of AI dates back to the mid-20th century, with Alan Turing's pioneering work, including his 1950 paper "Computing Machinery and Intelligence," which introduced the Turing Test as a benchmark for machine intelligence. A significant milestone was reached in 1956 with the development of the Logic Theorist by Allen Newell and Herbert A. Simon, capable of proving mathematical theorems and showcasing machines' potential for logical reasoning. John McCarthy, who coined the term "Artificial Intelligence" in 1956, organized the Dartmouth Conference, marking the formal establishment of AI as a field of study. McCarthy's development of the Lisp programming language further propelled AI research. Over subsequent decades, AI has evolved from rule-based systems to machine learning and, more recently, deep learning. Advances in machine learning, particularly through neural networks, have led to significant breakthroughs in applications such as speech recognition, image classification, and autonomous vehicles, building on early AI research and benefiting from increased computational power and data availability [40]. AI has changed a lot of fields, which is especially evident in the field of

gastroenterology with the fusion of cutting-edge AI technologies. AI has ignited a surge of advancement that is helping redefine diagnostic procedures. One such procedure is endoscopy, which has witnessed a revolution due to AI-driven image analysis. Before AI, washed data sets of images and patterns needed to be analyzed to reach a diagnosis, which led to errors or missed diagnoses. AI algorithms have enhanced the detection of subtle lesions, polyps, and early signs of malignancies, which improved patient outcomes and saving time for physicians. One of the adverse outcomes of AI is that sometimes physicians are so used to highlighted images using the AI algorithm that they miss some diagnoses, which could have detrimental effects on patients.

AI represents a wide-ranging field, encompassing various disciplines, including machine learning (ML) and its subsets such as deep learning (DL). The core objective of ML is to utilize extensive datasets to uncover patterns of interactions among variables, often enabling the learned function's application to novel data. Within ML, two fundamental categories exist: "supervised" and "unsupervised" learning methods [1]. For example, training a system to identify gastric intestinal metaplasia (GIM) involves supervised learning, using a database of previously operator identified GIM lesions.

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By contrast, unsupervised learning lacks output to predict and seeks to identify inherent patterns within input data, often grouping them subsequently, such as clustering tissue samples based on similar gene expression values [2]. DL, a subset of ML, relies on artificial neural networks inspired by the interplay of neurons in the human brain. DL autonomously processes data input to learn, recognize, and harness predictive factors leading to specific outcomes. It employs structures, like convolutional neural networks (CNN), to handle intricate information [3]. The realization of DL has become feasible due to rapid strides in dedicated hardware, such as enhanced graphics processing units and concurrent software and algorithmic advancements. The global summit on AI in gastroenterology and endoscopy that convened in Washington, D.C., in late 2019 brought together different experts. It is anticipated that AI will revolutionize patient care delivered over the next decade and will be used in operational processes as well. The summit emphasized the need for a dynamic partnership between gastroenterologists, industry pioneers, and regulatory institutions [4].

## 2. Detection of Premalignant and Malignant Lesions

In the upper digestive tract, there are important places to look for early signs of cancer such as Barrett's esophagus (BE), esophageal squamous cell carcinoma, and gastric cancer (GC). For example, AI can assist in diagnosing Barrett's esophagus by analyzing endoscopic images and videos. It can identify subtle changes or abnormalities of the esophageal lining that may indicate Barrett's esophagus which will assist healthcare professionals in early detection. To diagnose BE or any abnormalities and identify problems like dysplasia, physicians usually study tissue samples. It is important for them to take samples from the exact spots where the issues are. AI can help physicians identify these locations and figure out these spots in BE whether there are dysplasia problems or not. AI allows doctors to do more precise biopsies instead of random ones. Sometimes, using regular methods like white light imaging or narrow band imaging misses early esophageal issues. AI might be a solution to this problem [5].

We reviewed eight research papers on BE to detect issues like dysplasia or early esophageal adenocarcinoma (EAC) using images from endoscopies or laser endomicroscopy. Computer methods such as CNNs were used to analyse these images and were highly accurate (at least 89.9%) in identifying normal or problematic conditions, outperforming no specialist physicians [6]. For instance, De Groof et al. used ResNet-UNet to detect early BE neoplasia and pinpoint biopsy sites accurately. Ebigbo et al. used ResNet to distinguish normal BE from early EAC with 89.9% accuracy, 83.7% sensitivity, and 100% specificity. Detecting esophageal squamous cell carcinoma (SCC) is also challenging because of inaccurate methods such as chromoendoscopy or narrow band imaging (NBI) [7,8,41]. Newer methods, such as endocytoscopy or volumetric laser endomicroscopy show detailed images but can be confusing due to their volume [9].

In a series of studies on esophageal cancer, 13 research efforts concentrated on esophageal cancer, of which 11 focused on Squamous Cell carcinoma (SCC). Among these, nine studies

aimed to develop DL models for cancer detection, and two worked on models to predict cancer invasion depth using DL. Most studies employed CNN models, with some using JDFPCA, VGG16 Net, or GoogLeNet for classification. Although accuracy, sensitivity, and specificity values for detecting esophageal SCC varied, all models matched or exceeded endoscopists' abilities to detect and characterize lesions, often showing improved performance. For example, Nakagawa et al. and Shimamoto et al. pursued DL models based on CNNs, to predict esophageal malignancy depth, achieving 89.2% and 91% accuracy, 70.8% and 90.1% sensitivity, and of 94.4% and 95.8% specificity, respectively [10-12].

GC is a prominent global cause of cancer-linked mortality. Detecting early disease signs is pivotal, but existing techniques such as standard endoscopic imaging (e.g., NBI) and advanced methods (e.g., magnifying endoscopy, blue laser imaging) face limitations in spotting early gastric lesions [13]. During a colonoscopy, finding polyps is important in preventing colorectal cancer (CRC). Approximately 2%-6% of cases can develop CRC after a colonoscopy but before the next check, which might be from a missed or new post colonoscopy CRC<sup>13</sup>. Numerous studies have examined what helps find early cancer signs during colonoscopy and what might cause cancer to be missed. Having experienced nurses, fellows, or trained observers present during the procedure can make a difference in finding polyps<sup>14</sup>. Thus, to make polyp detection during colonoscopy better, AI is being used like a second observer, which is called computer-aided detection (CAD).

Understanding how much early CRC has spread is important for deciding how to treat it. If it is not too deep, physicians can remove it with special tools during a procedure called polypectomy. But if it has gone deeper, surgery and more treatments may be necessary because it could spread to other parts of the body. During endoscopy, physicians assess how the cancer looks and its patterns to see how deep it is. But sometimes different physicians see things differently<sup>15</sup>. Using CAD can help ensure everyone sees the same thing.

In other studies, researchers looked at different things related to the lower part of the digestive system. For example, they used special computer models to predict what might happen to patients with CRC or to see how effectively colonoscopies are being performed. In one study, a computer model looked at lots of pictures and predicted how long people might live with cancer<sup>16</sup>. This could help physicians choose the best treatments for those at higher risk. AI helps make computer model to give tips to physicians during a colonoscopy to make sure they do a good job.

## 3. Non-Malignant Conditions

Diagnosing Helicobacter pylori (H. pylori) infection, linked to peptic ulcers and GC, involves invasive methods like breath tests and histopathology. AI can assist with Pylori detection by analyzing other images from endoscopy or histopathological slides or even breath test to identify signs of H pylori infection<sup>18</sup>. Machine learning algorithms can recognize specific pattern or features associated presence of H. Pylori in the histopathological slides

which will provide faster and potentially more accurate diagnosis to the healthcare professionals. In four studies, CNN models detected *H. pylori*<sup>17</sup>. Martin et al.<sup>20</sup> used gastric biopsy images (n = 210 training, 90-106 testing) with 98.9%-99.1% infection accuracy, surpassing larger esophagogastroduodenoscopy datasets (77.5%-87.7%). Endoscopists scored about 79.0%-79.4% accuracy. Nakashima et al.<sup>19</sup> used linked color imaging and DL, achieving 82.5% accuracy, commensurate with experienced endoscopists' *H. pylori* diagnosis.

In gastrointestinal bleeding (GIB), it is crucial to assess risks to identify high-risk patients and make decisions. This also helps manage resources better. Risk tools look at factors linked to a condition to predict outcomes such as survival, hospital stay, rebleeding rates, and further need for endoscopic treatment. For upper GIB, studies aimed to predict rebleeding or the need for endoscopic/surgical treatment by using models [20].

Using a small camera in a pill, called video capsule endoscopy (VCE), is a good way to check for issues like hidden bleeding or Crohn's disease in the small intestine. It is easy and does not require surgery, but it relies on the intestine's movement to travel. This means it takes many pictures (up to 60,000 for one test), and understanding them can take a while [21]. AI has been used with VCE for a decade now. At first, methods like Support Vector Machine (SVM) and multilayer perceptron network were used to understand the pictures [22]. As technology got better, smarter algorithms like CNNs became the best choice to analyse the VCE pictures. Just like in the lower intestine, using computers to help find and diagnose issues can be accompanied by tools that help the camera move inside the small intestine.

We looked at four studies on finding celiac disease (CeD). In three of the studies, they used a smart type of computer called CNN, and in one study, they used a special tool for helping doctors decide. Another study by Wimmer et al. used classifiers called AlexNet, VGGf net, and VGG-16 net and got the best results (92.5% accurate) with VGG-16. In a newer study, Wang et al. developed a clever computer program using a CNN called InceptionV3 and another tool using SVM [LU5] called ResNet50. It was 95.94% accurate, and it could find CeD especially well (97.20% sensitive) and be quite specific (95.63%) in pictures from VCE [23,24].

Many factors affect inflammatory bowel disease (IBD), and each person's body works in its own way. This means that how the disease behaves and how well treatments work can be different for each person-kind of like personalized medicine. Using smart computer programs (AI) in IBD can help not only in diagnosing the disease, measuring the severity how bad it is, or increasing consistency among physicians but also in looking at big sets of information to find hidden patterns in the disease [25].

To predict how well patients with IBD will respond to treatments like thiopurines or biologics, researchers used smart computer models in seven studies. These models, called ML algorithms, were based on analytic models. All of them were relatively accurate,

with scores ranging from 80.0% to 89.8% or Area Under the Curve values from 0.73 to 0.846. For example, Waljee et al. developed a model with information about patients' details and lab results to predict how well they would respond to a treatment called ustekinumab. This could help avoid extra costs for monitoring the treatment. They also created another model to predict whether a patient might need to go to the hospital or use steroids, getting an AUC of 0.87. These AI models could help choose the right treatment for each patient and stop flare-ups before they happen [26].

In addition, two more models using genomic information were developed. Isakov et al. used multiple methods to find genes linked to IBD, reaching 80.8% accuracy. Another model by Kroner et al. used reports about how the tissue looked under a microscope to determine whether colonoscopy was needed, and it was 80.0% accurate [27]. Last, Firouzi et al. created a model that used electronic health records with AI to determine the potential of addressing pancreatic diseases by enhancing disease severity assessment, predicting outcomes in acute or chronic pancreatitis, and distinguishing different types of pancreatic growths, including potential malignancy [28]. AI can aid in early detection of specific pancreatic cancers and differentiate them from less serious conditions. Moreover, AI could improve the accuracy of diagnosing pancreatic diseases through the analysis of tissue samples. Overall, 59 studies have explored AI's role in pancreatic disease management. Among these, six studies focused on early pancreatic cancer detection using imaging or electronic health records to identify high-risk patients, achieving high accuracy and efficiency. Roch et al. developed computer programs for searching electronic records and identifying pancreatic cyst patients with remarkable accuracy. Ozkan et al. designed a smart image-processing system for pancreatic cancer diagnosis with 87.5% accuracy, effectively distinguishing cancer cases using patient age [29,30].

AI can be quite helpful in the field of hepatology as liver diseases can range from mild issues to serious problems like acute liver failure or requiring liver transplant. It can predict how bad a disease is, find diseases early, and tell us how serious a disease is. It can even estimate different parts of diseases. AI can also see patterns in pictures like scans and tissue samples and help choose who should get a liver transplant [31]. Some tried to predict what will happen to patients, some looked at finding and predicting conditions like fatty liver or cirrhosis, and others tried to differentiate among different types of liver tumors. Some studies also used AI to predict complications in the liver related to high blood pressure. The uses seem endless. Some studies used AI to find or classify liver tumors. One of the studies showed with the standardization of imaging in diagnosis and its important role in the clinical diagnosis of liver cancer, AI research based on imaging has emerged by extracting high-throughput features that cannot be detected and defined by human eyes. They used a special kind of AI called DL that can understand pictures, like Schmauch et al., who used ultrasound pictures to find and describe liver problems, and their AI was right about 89% of the time [32,36]. Other studies tried to predict problems in the liver related to high blood pressure

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using pictures from CT scans. Dong et al. developed a model that guessed whether people had certain liver problems with an accuracy of 82%. This could help doctors decide whether someone needs a special test to check for liver problems. Liu et al. developed a model that could find liver problems using special scans with an accuracy of 88.9% to 91.1% [34-36].

There were also studies that tried to identify liver conditions like cirrhosis or fatty liver by using different methods like looking at clinical data or pictures. Yasaka et al. used a special kind of AI to predict liver problems using pictures from MRI scans. They were right about 84% to 85% of the time for different liver problems [35]. Some studies even tried to differentiate among different liver conditions, like Fialoke et al., who used AI to tell the difference between two types of liver problems with an accuracy of 79.7%. These studies show that AI could be really helpful in understanding and treating liver diseases [37].

#### 4. Future of Physician-Patient Communication

Physician-patient communication is essential in healthcare, significantly influencing diagnosis, treatment, and follow-up, thereby impacting patient outcomes and overall healthcare experience. Effective communication allows physicians to understand patients' needs, fears, and expectations, enabling personalized and empathetic care. It also plays a crucial role in shared decision-making, where clear explanations about the disease, treatment options, potential side effects, and prognosis empower patients to actively participate in their healthcare decisions, leading to increased satisfaction, better adherence to treatment plans, and improved health outcomes. Additionally, good communication fosters trust and rapport, which are integral to the healing process, encouraging patients to follow medical advice and disclose critical information [42].

#### 5. AI-Assisted Medical History Taking and Patient Education

GPT-4 can significantly enhance gastroenterology practices by aiding in medical history taking and patient education. Its advanced natural language processing capabilities enable it to ask relevant questions, understand patient responses, and present this information to physicians in a structured format, allowing for quicker and more effective diagnosis and treatment. Furthermore, GPT-4 can explain complex medical concepts in simple terms, helping patients understand their conditions and make informed decisions about their treatment. By providing personalized advice on lifestyle changes, diet, and medication usage, GPT-4 can improve patient compliance, freeing up gastroenterologists to focus on more complex clinical responsibilities and procedural tasks [42].

#### 6. Ethical Considerations and Enhancing Healthcare Delivery

While GPT-4 offers transformative potential in enhancing physician-patient communication, it also introduces ethical considerations, particularly around confidentiality, data security, and bias. Systems using GPT-4 must implement stringent security protocols to protect sensitive patient information and ensure compliance with data privacy regulations. Additionally, human

oversight is crucial to mitigate risks associated with AI errors and biases. Despite its capabilities, GPT-4 should complement, not replace, the human elements of empathy, emotional understanding, and professional judgment in healthcare. As AI technologies like GPT-4 are integrated, maintaining ethical standards, data privacy, and accountability is paramount to ensure the effective, compassionate, and personalized care that lies at the heart of healthcare [42].

#### 7. Current Limitations and Future Scope

Despite AI's impressive progress, current studies face limitations that suggest future research.

AI models often rely on human-labeled data, and their accuracy hinges on labelers' skills. Algorithms may excel only with specific data types, limiting adaptability. Many health care AI models are validated only within their training dataset, risking overfitting. Solutions include creating a shared, well-organized dataset for diverse AI projects and designing flexible algorithms for various data. Validating models across patient groups enhances trust. Applying rules for AI model refinement improves accuracy. Guidelines for reporting AI studies need ongoing enhancement. Current studies using still images may not mirror real-world scenarios; addressing this ensures practical AI performance.

To address these problems, experts suggest creating a dataset that is detailed, widely shared, and of high quality, along with developing algorithms that can handle different situations. However, creating a single dataset for everyone is difficult because of privacy concerns. Another idea is to use "federated datasets," where information from different places is combined to address these issues. In addition, when selecting the best method to analyze data, specific steps should be followed, like using different ways to determine whether results are accurate [38]. It is important to focus on algorithms that give the most accurate results, and adjusting them to improve predictions is crucial.

Most of the current studies use groups of people with similar traits, but to be really sure about results, it is better to use random groups in experiments. Sometimes, custom methods are used in research, but these need to be clearly explained so everyone understands how they work. When researchers create new methods, they should test them on different datasets to make sure they are useful. Comparing different ways of doing things in studies can be tricky, and it is important to report all the information clearly.

People are trying to make sure studies about AI are done the same way by creating guidelines. These rules help researchers report their work better and make it easier to compare different studies. It is important to follow these rules and change them as technology improves. Last, most studies use pictures that do not show things happening in real life.

#### 8. Fixing this will help AI Work Well in Real Situations

To use AI in a vast spectrum, researchers need to create well-organized research. A huge dataset also needs to be developed so that AI can help in diagnosis. AI can help doctors by taking care



of routine tasks so that doctors can focus on important decisions. Instead of using old methods to analyze data, AI can bring new, more accurate methods [39]. For all this to happen, experts from different fields such as data science, medicine, and industry need to work together.

## 9. Conclusion

The recent AI advancements in gastroenterology and hepatology show promise across clinical care areas, including neoplastic lesion detection, survival model enhancement, and treatment response prediction [39]. AI's use with complex datasets might uncover new associations, potentially altering clinical practices. AI assisted technologies can significantly elevate care quality. Assisted precision medicine is emerging, in which AI tailor's treatment plans or predicts patient responses based on extensive clinical data. Although AI doesn't replace human clinical judgment, it has a bright future in enhancing patient care.

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