Chapter 45
Artificial Intelligence in Endoscopy

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Introduction

Once the subject of futuristic Sci-Fi movies and books, Artificial Intelligence (AI) has become part of our everyday lives. Algorithms developed by Amazon, Google, and Facebook utilize AI to predict texts, recognize and translate language, suggest purchases, and achieve facial recognition. AI was introduced in 1956 at what is now called the Dartmouth Conference. The conference was organized by John McCarthy, who at the time was an Assistant Professor of Mathematics at Dartmouth. He invited several mathematicians and scientists to gather for summer to perform an intense study of computerized intelligence. He believed that aspects of human intelligence could be precisely described in such a way that a machine could simulate it. He is also credited with coining the term Artificial Intelligence. AI is simply defined as the ability of a computer software system to be able to perform human cognitive functions. Examples of cognitive functions include

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image recognition, identifying patterns, solving problems, and ultimately learning. The first step in image recognition is that a computer must learn a pattern or part of a pattern. For this, large amounts of data are required. The computer must also make computations, which require massive amounts of computational power [1]. Since the 1950s there was relatively little AI activity as both data and computational power were lacking. As computers have become more affordable and more advanced with increasing processing power, as well as the addition of the internet allowing for access to immense amounts of available data, we are now seeing substantial expansion in AI developments today. As AI makes its way into our daily lives, it also has great potential to aid the clinician in the diagnosis and treatment of diseases.

Definitions and Terminology

The idea of Artificial intelligence (AI) was first described in the 1950s by British mathematician Alan Turing. He defined this intelligent behavior of a computer as its ability to achieve human-level performance in cognitive tasks [2]. He believed that a machine could identify patterns within data and learn from these patterns to perform a specific task that would otherwise require human intelligence. Examples of these tasks include problem-solving, independent pattern recognition, and learning. Essentially all AI today is based on machine learning.

Machine Learning (ML)

Machine Learning (ML) is under the umbrella of AI; however, essentially all AI today uses machine learning. The term ML was first introduced in 1959 by Arthur Samuel from IBM. ML refers to a computer system that can develop the ability to learn by using data without specific programming and can develop predictive algorithms by analyzing input data and recognizing patterns [3]. Computers can be taught

simple tasks when they are given data, and the algorithm can complete every portion of a problem and come to the correct conclusion. In more advanced tasks, this algorithm becomes much more difficult to create. Thus it is easier to let the computer help make the algorithm and then solve the problem. Machine learning essentially uses different approaches to teach computers to accomplish tasks where no satisfactory human-made algorithm exists. There are three main types of learning methodologies: *supervised learning* is when the computer is given human-labeled data and desired outputs, and the computer learns general rules to categorize inputs to determine the desired outputs; *unsupervised learning* is when the computer is given unlabeled data and is tasked with uncovering the hidden pattern within the data to group and further categorize the data until it can differentiate the desired output; *reinforcement learning*, is when the algorithm learns from trial and error scenarios [4, 5].

Deep Learning (DL)

As depicted in Fig. 45.1, Deep Learning (DL) is a specialized form of machine learning and is based on multiple layered

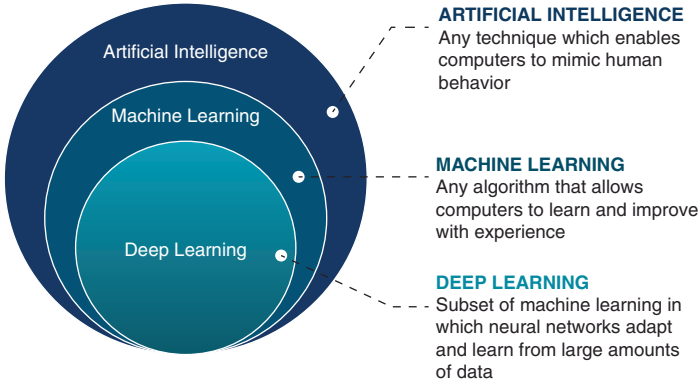

Figure 45.1 Artificial intelligence, machine learning, and deep learning

neural networks. Neural networks are the hidden layers within a machine learning algorithm that identify unseen patterns and are able to group similar data into categories, which can be further categorized by additional hidden layers until the desired output is identified. While ML often consists of 1–2 layers of neural networks, DL contains several, often up to 150 layers. This allows the computer to take unlabeled data and further subcategorize it to be able to make predictions and conclusions about the data. This eliminates the need for manual feature extraction and makes DL models ideal for processing data in the form of images and videos. Once the framework of the neural network has been established with vast quantities of labeled data, or in this instance images, the computer has the ability to extract relevant features straight from the data and make inferences and predictions on raw, unlabeled data. An important feature of DL algorithms is the more data the algorithm has, the better it is able to perform, so as we collect more images and video images over time, the more accurate the predictions should become. This has made DL instrumental in processing images and videos, which has helped in endoscopic detection and diagnoses of diseases [6].

Current Applications of Artificial Intelligence in Endoscopy

As computing power and data storing capacities have improved, so too has the exploration of the application of artificial intelligence (AI) in medicine. The following is a review of the applications of AI in endoscopy that are in use currently.

Evaluation of Barrett's Esophagus

Barrett's Esophagus (BE) poses a difficult diagnostic problem as it is a known risk factor for the development of esophageal adenocarcinoma and may harbor dysplastic

changes that are not readily evident on conventional endoscopy. The current solution to this problem is random biopsies (Seattle protocol); however, this approach is labor-intensive and has a relatively low per-lesion sensitivity of 64% for the detection of dysplasia [7]. The Seattle protocol consists of four-quadrant biopsies every 2 cm of the Barrett's segment. Two centimeters of BE would equate to approximately 14 cm^2 of surface area. A single biopsy samples approximately 0.125 cm^2, so the Seattle protocol would only cover 0.5 cm^2 of the esophageal mucosa, which would only be 3.5% of the Barrett's segment [8]. Recently the American Society of Gastrointestinal Endoscopy (ASGE) has endorsed the use of advanced imaging techniques to aid in targeted biopsies to replace random four-quadrant biopsies. The society determined performance criteria that new technologies should meet in order to be considered effective, including the sensitivity of more than 90%, a specificity of 80%, and a negative predictive value of 98% [9]. Technologies that have been developed include volumetric laser endomicroscopy, wide-area transepithelial sampling, chromoendoscopy, and magnification endoscopy. While these techniques have shown promise in achieving the ASGE criteria, they still are time-consuming and require special expertise, which limits their use. This has led to the investigation of the use of AI to aid the nonexpert endoscopist in diagnosis.

The evaluation of BE with standard white light endoscopy (WLE) and the addition of narrow-band imaging (NBI) is one of the longest-standing techniques. AI algorithms were developed for WLE/NBI images by van der Sommen et al. to detect early neoplastic lesions with BE. The algorithm was based on 100 images from 44 patients with BE to develop specific color and texture filters and machine learning to differential dysplastic from nondysplastic BE [10]. The system achieved a sensitivity and specificity of 86% and 87%, respectively, showing the potential of computer-assisted diagnosis of neoplasia within BE using standard, widely available endoscopic techniques. Hashimoto et al. improved upon this idea, creating an AI algorithm utilizing 916 retrospectively col-

lected images of histology-proven high-grade dysplasia or T1 adenocarcinoma in BE as well as 916 control images [11]. These images were obtained with standard WLE, NBI, as well as Near Focus which is an imaging technique on Olympus™ endoscopes that allows the focus to adjust to objects within 2mm of the endoscope. The system was trained to first identify any neoplastic image within a video and flag it as an image of interest. Once flagged, the image would be analyzed, and the area of neoplasia would be identified with a rectangular box. The algorithm was validated utilizing 458 test images with an overall sensitivity of 96.4%, specificity of 94.2%, and accuracy of 95.4%. Importantly the algorithm is able to make predictions on >40 frames per second, which made real-time evaluation a potential possibility. Ebigbo et al. realized this potential in their computer-aided diagnosis model, which utilized AI and deep learning (DL) to identify early adenocarcinoma in BE [12]. They used a state-of-the-art encoder-decoder to transfer live endoscopic images to their AI system. The AI system can be activated at any time during the endoscopy by the practitioner once the segment of interest has been reached. Once activated, the system randomly analyzes images from the live feed and produces a blue bar that displays the probability of cancer in the given segment, with positivity being considered a probability over 90%. The system underwent validation on real-time images from endoscopic video on 14 patients, which contained 36 images of early AC and 26 of normal BE. The model's predictions were compared to the corresponding pathological examination of resected specimens. The AI system had a sensitivity of 83.7%, specificity of 100%, and an overall accuracy of 89.9% showing its potential for real-time use.

Volumetric laser endomicroscopy (VLE) is a newer endoscopic imaging modality that has been developed to aid in the diagnosis of dysplasia within BE [6]. VLE uses the second-generation optical coherence tomography in a balloon-based system. After endoscopic deployment of the device balloon within the area of BE, an infrared light generates a circumferential scan of 6cm segment of the esophagus. The scan

reaches a penetration depth of 3mm into the tissue with an axial resolution of 7 μm allowing for visualization of esophageal layers and submucosal vascular networks [13]. The scans then must be manually reviewed for concerning features, including surface intensity greater than subsurface intensity, lack of layering, and presence of irregular and dilated glands. Once an area of suspicion is determined, the area is marked between two laser cautery marks for subsequent biopsy with WLE. The technology has shown promise, improving neoplasia diagnostic yield in BE by 55% compared to random biopsies alone in a multicenter US trial. However, it can be burdensome because of the large amount of complex visual data that must be processed [3]. An AI software known as intelligent real-time image segmentation (IRIS) was developed to assist the endoscopist with quickly and accurately identifying areas of suspicion. The system identifies the three established VLE features associated with histologic dysplasia and color codes them, then displays them superimposed over the VLE imaging. Areas on the VLE image that contain all three colors then can be marked for subsequent biopsy. A prospective randomized trial is currently underway comparing the use of VLE with and without IRIS, with primary outcomes being the time of interpretation, biopsy yield, and a number of biopsies (NCT03814824). Results of this study are pending as of January 2022.

Wide-area transepithelial sampling (WATS) is another technique to increase the diagnostic accuracy of random biopsies surveillance for BE. The technique consists of passing a brush through the working endoscopic channel and rotating the brush repeatedly back and forth across BE tissue until pinpoint bleeding is observed. The brush is then removed, and its contents smeared onto two glass slides; the bristles are then cut into a transport medium. The slides and transport medium are transported to a central pathologist that specializes in WATS specimens. The transport medium and slides are then analyzed by a high-speed, computer-assisted neural network that has been optimized for esophageal mucosa—the computer flags all abnormal cells, which

produces a high-resolution image for the pathologist to review. The concept was first validated by a study by Vennalaganti et al., in which 149 BE WATS specimens were reviewed by four pathologists with a very high interobserver agreement (percent agreement calculated at 88.6%) [14]. A multicenter, prospective, randomized trial was then conducted comparing Seattle protocol to Seattle protocol plus WATS. The addition of WATS to biopsy sampling resulted in an additional 23 cases of high-grade dysplasia/esophageal adenocarcinoma, which was a 14% increase. Interestingly, 11 of the 23 additional cases identified by WATS had no evidence of dysplasia on biopsy histology alone. WATS added an average of 4.5 mins to the procedure. [15]

Esophageal Squamous Cell Carcinoma

While AI has shown promise in aiding in the diagnosis of esophageal adenocarcinoma, it has also been applied to the identification of esophageal squamous cell carcinoma (ESCC). Squamous cell carcinoma of the esophagus is more prevalent in Asian populations, which results in less experience in Western communities in the diagnosis and treatment of this relatively rare disease. The current gold standard in screening is Lugol chromoendoscopy, which requires the application of Lugol's solution to the lower esophagus. While this method has a high sensitivity (>90%), it has a relatively low specificity of near 70%, thought to be secondary to overidentification of inflammatory mucosa as neoplastic [7]. In addition to the low specificity, the Lugol's solution can cause GERD-like symptoms, discomfort, as well as allergic reactions. There have been several advancements in endoscopic techniques to try to replace the Lugol chromoendoscopy, including confocal laser endomicroscopy, endocytoscopy, and high-resolution microendoscopy; all are variations of identifying and interpreting microscopic images in order to better target biopsies. Despite these advancements, which have shown good performance on test images, their use remains

quite limited because of the relatively low access. To this end, Horie et al. created a convolutional neural network trained on 8428 retrospectively obtained training images utilizing WLE alone [16]. The program was tested on 1118 test images containing an array of adenocarcinoma, squamous cell carcinoma, and no carcinoma. Esophageal cancer was detected with a sensitivity of 98%. However, there were quite a few false positives with a positive predictive value of only 40%. Most of the false positives were due to shadowing and identification of normal structures as cancerous. The next year, Tokai et al. took the same CNN and used an additional 1751 test images with information about invasion depth to see if the system could accurately predict the depth of invasion of esophageal SCC. The depth of invasion determines the extent of treatment. According to Japanese guidelines, lesions reaching muscular mucosa (T1a) or infiltrating the submucosa up to 200μm (T1b-SM1) have a very low likelihood of nodal metastases and are amendable to endoscopic resection, whereas those infiltrating the submucosa past 200μm (T1b-SM2) are treated with esophagectomy. The system was tested along with 13 expert endoscopists against 291 retrospectively obtained images of ESCC of different invasion depths. The AI system identified 95.5% of ESCC within the test images and was able to accurately predict the invasion depth with a sensitivity of 84.1% and an accuracy of 80.6% [17]. The system accuracy was better than 12 out of the 13 experts, showing its potential diagnostic ability.

Detection of Helicobacter pylori (H. pylori) infection

H. pylori infection is a known risk factor for developing gastric cancer. However, diagnosis on endoscopy can be challenging. Watanabe et al. illustrated this point by testing endoscopists ability to diagnose *H. pylori*. Six endoscopists of varying experience were given a series of retrospectively obtained images of *H. pylori*-infected and uninfected patients.

They found that the diagnostic yield for identifying *H. pylori*-infected patients was 62.1%. They also discovered that the less experienced the endoscopist was, the lower their diagnostic yield was, thus demonstrating the potential for CAD in recognizing *H. pylori-infected* patients [18]. In 2017 Shichijo et al. developed a CNN-based CAD to identify *H. pylori* infections using regular WLE. They retrospectively obtained 32,208 images of *H. pylori*-positive (735 patients) and negative (1015 patients) from which their CNN was constructed. The system, as well 23 endoscopists with varying levels of experience, was asked to classify a separate retrospectively obtained data set of endoscopic images as either *H. pylori*-infected or *H. pylori*-uninfected. The CAD system had a sensitivity, specificity, and accuracy of 88.9%, 87.4%, and 87.7%, respectively. As a whole, the endoscopists obtained sensitivity, specificity, and accuracy of 79%, 83.2%, and 82.4%, with the more experienced endoscopists performing better than less experienced endoscopists [19]. Around the same time, Itoh et al. also created a CNN utilizing 149 prospectively obtained images from a single endoscopist to train the system. The CAD system was then tested on an additional 30 images that had been obtained at the same time but that were not used for the development of the CNN. The system was able to identify *H. pylori*-infected patients with a sensitivity and specificity of 86.7% and 86.7%, which was a slight improvement from previous studies [20]. While these CNN-based CAD systems do show promise in aiding the endoscopist in the endoscopic identification of *H. pylori* infection, they have yet to be used in a real-time, live fashion, which limits their current feasible use.

Colonic Polyp Detection

Colonic polyp detection has also been an area of active AI research. The rate of colonic polyp detection should be consistent within a given population; however, studies have shown the detection rates among endoscopists vary greatly. It

is also estimated that every 1% increase in adenoma detection rate will decrease the adenocarcinoma rate by 3–6% [21], which is why polyp detection is fertile ground for AI utilization. In 2003, Karkanis et al. created a selection algorithm based on feature extraction to identify colonic polyps on colonoscopy images. The system showed the feasibility of computer-aided diagnosis, reaching a specificity of 97% and a sensitivity of 90%. However the system was tested on still images limiting its clinical use [22]. In 2013, Glòria Fernández-Esparrch developed a computer-aided diagnosis model that analyzed colonoscopy videos and produced an overlying energy map correlating with the likelihood of a polyp being present. Tested on 24 videos, the system had a sensitivity of 70.4% and a specificity of 72.4% for polyp detection [23]. Urban et al. aimed to improve upon this performance in 2018, developing a state-of-the-art learning CNN. The system was trained first on millions of labeled natural images contained on the ImageNet learning database. Once this baseline training had been complete, the system was then fine-tuned on 8641 hand-labeled images from screening colonoscopies from over 2000 patients [21]. Testing commenced on 1300 still images, where it achieved an accuracy of 96.4% with an Area Under the Curve (AUC) of 0.974. Not only did the system show good accuracy, but it was also able to analyze 98 images per second, making real-time use feasible. This was tested by running the system over 9 full colonoscopy recordings in which 28 total polyps had been removed at the original colonoscopy. The video of the colonoscopies was first reviewed by three experts, who identified 36 unique polyps. The CNN system was then tested on the videos and was able to identify all 36 polyps as well as an additional nine polyps that were missed by the experts. Of the 9 additional polyps that were identified three of them were deemed high likelihood of being an actual polyp while the other 6 were considered low likelihood. While this system showed promising result, it still was not tested in a live clinical situation. In 2019 Klare et al. performed a prospective study, testing a developed automated polyp detection software utilizing AI which had previ-

ously been validated in ex vivo applications. The software was designed to identify and mark polypoid structures in real-time endoscopy. The system works by utilizing a frame-grabber device to capture the colonoscopy video stream. The images are then cropped by the software neglecting unnecessary image data such as the black frame. A weighted combination of color, structure, textures, and motion information is used to identify regions of interest that may represent a polyp. The system gives feedback to the endoscopist by encircling the area of interest with circles displayed on an HD screen. To test the feasibility of use during real-time colonoscopy, the system was applied to 55 real-time colonoscopies. The endoscopist was unable to see the screen that displayed the computer-aided diagnosis system. A researcher was able to see the real-time unbiased endoscopy screen next to the diagnostic system computer screen. The endoscopist would give vocal cues to when a polyp was identified. The researcher would then correlate this information with the information provided by the system. A total of 73 polyps were identified by the endoscopist, 40 neoplastic, 36 adenomas, and 1 intramucosal carcinoma. The CAD system identified 55 of the 73 polyps (75.3%), and 31 of the 40 neoplastic polyps [24]. The system also indicated an average of 6 false positive images per procedure. No polyps were identified by the system prior to being detected by the endoscopist. On logistic regression analysis the system struggled to identify flat-shaped and small polyps. While the system did not perform as well as the expert endoscopist, this study did show the potential utility of real-time computer-aided diagnosis of colonic polyps, especially with deep learning models that continue to improve their performance over time.

Detection of Inflammatory Conditions

Ulcerative colitis (UC) and Crohn's disease are conditions that can be difficult to diagnose, differentiate from each other, and stratify severity of disease. Ozawa et al. applied AI

to this problem by creating a CNN-based CAD system intended to identify the severity of ulcerative colitis. The motivation for creating the CAD was the amount of interobserver variability that existed among endoscopist when classifying the severity of disease, which was greater among nonexperts. This can affect clinical decisions, such as starting patients on expensive biological medication. They trained their CNN image recognition system using 26,304 colonoscopy images from 841 patients with UC. They then tested the system on a separate set of 3981 images, tasking the system to identify the images as Mayo grades of inflammation. The system was able to correctly classify 73% of the Mayo 0 images, 70% of the Mayo 1 images, and 63% of the Mayo 2–3 images [25]. In 2018 Maeda also developed a machine learning-based CAD utilizing endocytoscopic images to try to predict histological healing of UC. They argued that there is an incremental benefit of achieving histological healing of UC beyond just endoscopic mucosal healing, as ongoing histological inflammation increases the risk of exacerbation and dysplasia. The CAD was trained on 12,900 endocytoscopic images with known, biopsy proven histological grades of healing. It was then validated on 525 retrospectively obtained images, where the histology was also known from biopsy. The system had an overall diagnostic sensitivity, specificity, and accuracy of being able to predict ongoing histologic inflammation of 74%, 97%, and 91% respectively [26]. While the sensitivity is too low to do away with physical biopsies, as systems improve it could reduce the need and cost of several biopsies within each area of UC. Celiac disease is another relatively common inflammatory disorder that is immune-mediated. The gold standard for diagnosis is endoscopy and biopsy; however, there is interobserver variability with this approach as well. Celiac disease is another disease which can be difficult to diagnose by the unexperienced endoscopist. Wimmer et al. strived to create a CNN that would accurately identify celiac disease using CAD. They trained models already in existence that had been previously trained on large image data sets of the natural world. They then fine-tuned them to be able to

identify images of celiac disease using modified immersion technique with traditional WLE as well as under NBI. Modified immersion technique is a technique that consists of closeup views of the wall of the duodenum under clear water to enhance the image of the duodenal villi. The system was able to achieve an accuracy of 90.5% in diagnosing celiac disease from the endoscopic images alone [27]. There has yet to be a computer-aided diagnostic system for celiac or IBD that has been tested in real-time conditions, which limit their applicability to clinical practice.

As we make technological advances in medicine in terms of smaller and more precise equipment, we have also used imaging and navigation with the help of AI for procedural planning and guidance. Though this application is not gastroenterology related, it is one of the new applications of AI in therapeutics, not just diagnostics. Figure 45.2 shows the Auris Bronchoscope to target small lung lesions for biopsy which are not accessible through conventional bronchoscopy. The Auris Bronchoscopy uses an outer sheath and an inner bronchoscope with a 4-way steering control, electromagnetic navigation guidance, and continuous peripheral visualization for procedural navigation and biopsy [29]. The Auris Bronchoscope uses the MONARCH Platform which combines electromagnetic tracking, optical pattern recognition, and robotic kinematic data to help locate the bronchoscope during the procedure and provide positional data for the scope in relation to the target lesion. In 2019, a post-marketing multicenter study using the Monarch Auris robotic platform in 165 patients showed successful navigation to 88.6% of the lung nodules with 70.7% of the nodules located in the outer third of the lung [30].

AI—Limitations and Challenges

Despite the significant advances made in medicine over the last several decades, there continue to be large and increasingly complex problems that arise. This is partly because of

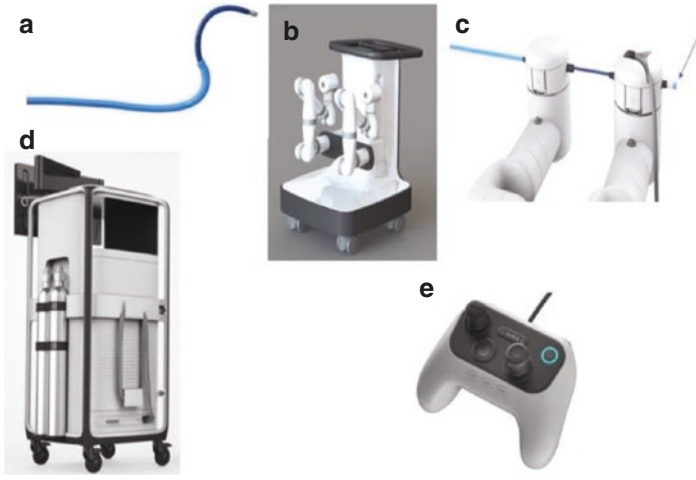

FIGURE 45.2 The Auris Bronchoscope is formed by an inner scope and the outer sheath. (**a**) The bronchoscope includes a camera that provides the operative perspective, an integrated light source in the handle, and a 2.1 mm inner diameter working channel for the passing of manually controlled tools. (**b**) The Auris Cart with the robotic arms. (**c**) Attachment of the bronchoscope to the robotic arms with the proximal valve for saline, air, or instrument insertion (arrow). (**d**) The tower with the monitor for endoscopic and electromagnetic navigation display. (**e**) The controller. From Murgu, S.D. Robotic assisted-bronchoscopy: technical tips and lessons learned from the initial experience with sampling peripheral lung lesions. *BMC Pulm Med* **19**, 89 (2019) [28] http://creativecommons.org/licenses/by/4.0/

the phenomenon of "we did not know what we did not know," as we become aware of more and more layers of complexity in each disease process. What adds to this challenge is the decreasing tolerance (appropriately) of failure and error. With massive amounts of data becoming available, there is an opportunity to use artificial intelligence to make things better for our patients, clinicians, health systems, and society overall.

Recently, the Food and Drug Administration (FDA) approved one of the first AI systems for clinical use in oph-

thalmology for interpretation of diabetic retinopathy funduscopic images [31]. AI can be instrumental in computer-assisted diagnosis (CAD) in multiple fields but especially endoscopy. It can assist in quality control of procedures being performed as well as performance improvement of novice (and even expert) endoscopists. It can help make diagnoses more quickly and potentially more accurately, especially with premalignant lesions [32]. It can also potentially help in disease localization and therapeutics in the future using preoperative image guidance. With the vast and rapid advances in computing power, the role of artificial intelligence in clinical medicine should have been ubiquitous. The fact that it is not is due to several challenges and limitations.

Many of the AI systems used in endoscopy so far have used limited datasets. They rely on high-quality endoscopic images to train the datasets for recognition, excluding lower quality images like those with some mucus or bile on them. This does not always follow real-world conditions, potentially falsely increasing accuracy in the initial single center studies. This could cause overfitting of the models and falsely increase detection accuracy [3]. The artificial intelligence neural network training will need to include live, unprocessed videos to simulate real-world conditions. Just like humans, the more training and feedback the AI gets, the better it can get.

The involvement of AI in diagnostics and clinical medicine will have nonclinical implications as well. These include assumption of responsibility for errors, ethical concerns, and medico-legal risks. There is also the risk of amplification of this error by a faulty algorithm. Instead of a single error by a single physician, the application of the AI broadly could result in a vast number of errors [33]. Currently, there is a relative lack of standards and regulations to evaluate efficacy and safety of AI systems in clinical medicine [34]. These regulatory and legislative issues will need to be addressed by involving all the stakeholders including clinicians, technology experts, industry and regulatory bodies among others. Payors like insurance companies and/or the government will also need to be involved to address reimbursements for the added initial cost that AI incorporation may introduce.

Recently, Watson for Oncology, IBM Watson Health's AI algorithm, was used by several hospitals around the world for treatment recommendations for cancer patients. Some of the recommendations were found to be faulty such as recommending use of bevacizumab in a patient with bleeding, which is a contraindication [33]. The algorithm was based on a small number of theoretical cases with limited input from oncologists [33, 35]. This example highlights potential problems with current algorithms and also provides opportunities for future improvements. This has regulatory implications and significant work has yet to be done on that front. As mentioned earlier, because of the potential for amplification of these errors, the algorithms need to be based on as large a dataset as possible with ongoing machine and deep learning. There needs to be detailed simulation, validation, frequent audit, and periodic prospective evaluation of the algorithm. This would need to go beyond the current FDA requirements for medical algorithm approval [33, 36]. There may also be regulatory need to make algorithms more accessible so they can withstand scientific scrutiny as well, but it can be challenging to balance intellectual property rights with transparency. There also is a need to address data security and privacy. With global teams of hackers already pervasive and involved in data breaches and ransom, significant software security measures will need to be taken to maintain data privacy and also to avoid a malicious hack of algorithms that can result in erroneous or dangerous recommendations from the AI.

Conclusion

Will AI ever replace clinicians? Though there are fields like radiology and pathology that initially seem more at risk, physicians will still be needed to process the information and come up with a treatment plan for the foreseeable future. AI will be used to analyze, process, and find patterns in massive sets of data that observe and detect things that are not humanly possible [33]. It can do so accurately, efficiently, repeatedly, and reliably. What seems difficult to replace is the

advantages of an actual person to communicate with the patient and their family with empathy and sympathy, to read the nonverbal cues of a stressed patient, and to provide the ever-important human touch to comfort the patient [31].

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