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Review Article

The Role of Artificial Intelligence in Gastric Cancer: Surgical and Therapeutic Perspectives: A Comprehensive Review

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ABSTRACT

Stomach cancer has a high annual mortality rate worldwide necessitating early detection and accurate treatment. Even experienced specialists can make erroneous judgments based on several factors. Artificial intelligence (AI) technologies are being developed rapidly to assist in this field. Here, we aimed to determine how AI technology is used in gastric cancer diagnosis and analyze how it helps patients and surgeons. Early detection and correct treatment of early gastric cancer (EGC) can greatly increase survival rates. To determine this, it is important to accurately determine the diagnosis and depth of the lesion and the presence or absence of metastasis to the lymph nodes, and suggest an appropriate treatment method. The deep learning algorithm, which has learned gastric lesion endoscopyimages, morphological characteristics, and patient clinical information, detects gastric lesions with high accuracy, sensitivity, and specificity, and predicts morphological characteristics. Through this, AI assists the judgment of specialists to help select the correct treatment method among endoscopic procedures and radical resections and helps to predict the resection margins of lesions. Additionally, AI technology has increased the diagnostic rate of both relatively inexperienced and skilled endoscopic diagnosticians. However, there were limitations in the data used for learning, such as the amount of quantitatively insufficient data, retrospective study design, single-center design, and cases of non-various lesions. Nevertheless, this assisted endoscopic diagnosis technology that incorporates deep learning technology is sufficiently practical and future-oriented and can play an important role in suggesting accurate treatment plans to surgeons for resection of lesions in the treatment of EGC.

Keywords: Artificial intelligence; Stomach neoplasms; Diagnosis; Surgery; Endoscopy

INTRODUCTION

According to a 2020 survey, gastric cancer is ranked 5th among cancer incidence rates and 4th in mortality worldwide, ranking near the top every year. In the results of the 2018 sex-specific gastric cancer incidence survey, South Korea ranked first in both male and female categories [1]. Gastric cancer is a serious issue in Korea. Early detection and treatment of

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gastric cancer and intraepithelial tumors through esophagogastroduodenoscopy (EGD) have been shown to significantly reduce mortality.

In Korea, 74.07% of the 243 people diagnosed early showed early gastric cancer (EGC) results, and 55.30% of 132 people who were aware of symptoms and were screened showed EGC results. Thus, early examination, even if there is no pain or other symptoms, is important in preventing gastric cancer [2]. A Japanese study on the natural course of EGC without treatment found that if EGC was left untreated, the possibility of developing advanced gastric cancer within 3–4 years was over half. Furthermore, elderly patients are more likely to experience side effects such as perforation and aspiration pneumonia after endoscopic submucosal dissection (ESD). Therefore, it is important to perform regular checkups at a younger age and receive accurate treatment.

If accurate curative resection is not performed, the lymph node metastasis (LNM) rate is 5.3%–9.8%, leading to costly and time-consuming additional procedures [3]. Various methods, such as EGD, gastrointestinal angiography, and endoscopic ultrasonography (EUS), are being implemented for early detection. Gastric endoscopy is the most efficient method for diagnosing gastric cancer; however, it can be missed or misdiagnosed depending on various factors, such as the location of the lesion, the skill of the doctor, the shape of the EGC lesion, and the number of biopsies [2,4-7].

To compensate for this, various methods such as chromoendoscopy (CE), which scatters indigo carmine; narrowband endoscopy (NBI), which uses blue light instead of the existing white light endoscope (WLE); and magnifying endoscopy (ME) are also being used. However, this cannot be freed from other factors, such as the endoscopist's skill level, fatigue, and reading very precise images during a relatively short endoscopic procedure, which lasts approximately 5 minutes, further increasing the specialist's fatigue.

Alternatively, endoscopy-assisted diagnostic technologies using artificial intelligence (AI) deep learning are rapidly developing [8]. This technology can assist with endoscopy reading by utilizing the experience and knowledge accumulated by specialists to train AI. Moreover, predicting the horizontal boundary of the lesion and the depth of invasion can be helpful for correct treatment and surgery.

In this study, among the endoscopic-assisted diagnostic technologies using AI, we reviewed the prospects for EGC treatment, focusing on the technology for predicting the lesion boundary and depth of the EGC.

METHOD

Various academic papers were collected through electronic searches to identify the latest research trends and theoretical backgrounds related to the subject. A search was conducted using online academic databases, such as PubMed and Google Scholar. Search terms included 'AI,' 'deep learning,' 'EGC,' 'EGD,' 'ESD,' 'margin,' 'depth,' and 'therapy.' Among deep-learning algorithm technologies, titles, abstracts, and keywords were selected and reviewed for comparison with boundary display technologies. Research trends in academia are reviewed and compared (**Fig. 1**).

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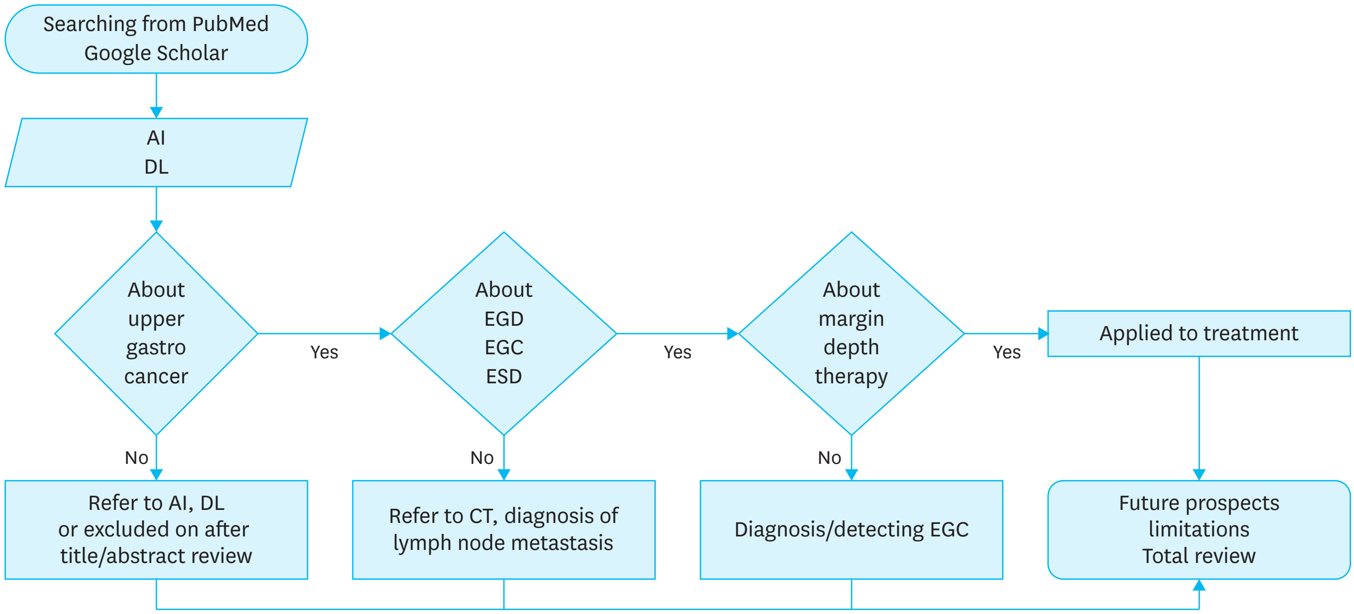

Fig. 1. Flowchart of the search strategy.
AI = artificial intelligence; DL = deep learning; EGD = esophagogastroduodenoscopy; EGC = early gastric cancer; ESD = endoscopic submucosal resection; CT = computed tomography.

MAIN SUBJECT

Deep learning in healthcare

Technology using AI has attracted attention in the medical field for many years. In Italy, in 1985, the Artificial Intelligence in Medicine conference was held for the first time to apply computer science to medicine and biology with the increasing recognition that a computer's computational power could be clinically useful [9]. AI and machine learning (ML) are used interchangeably. AI is a comprehensive concept in which computers imitate human knowledge and experience to act, reason, and make decisions with intelligence similar to humans. Algorithms are used to learn and draw conclusions inductively based on vast amounts of data. In ML, neural networks (NNs) mimic how the human brain interprets information and draws conclusions. This structure is suitable for application to complex and heterogeneous information in medical images. New images are arranged into categories through several stages of mathematical calculations. The trained NN derives the most appropriate result by combining and analyzing various factors such as symptoms, risk factors, and experimental results.

Deep learning (DL) is an advanced form of NN technology that excels at capturing complex and intricate correlations. Within DL, a specific type of NN designed for visual image analysis, inspired by the human optic nerve, is known as a convolutional neural network (CNN).

CNNs are particularly well-suited for tasks involving visual data. A CNN extracts features such as the line, color, contrast, and shape of an image and converts them into values that reflect nonlinear activation functions such as ReLU, Sigmoid, and tanh. It undergoes a subsampling process, such as pooling, followed by a selective process, such as reducing. Subsequently, each step is linked and classified into the most appropriate value using the softmax function (**Fig. 2**) [7,9,10].

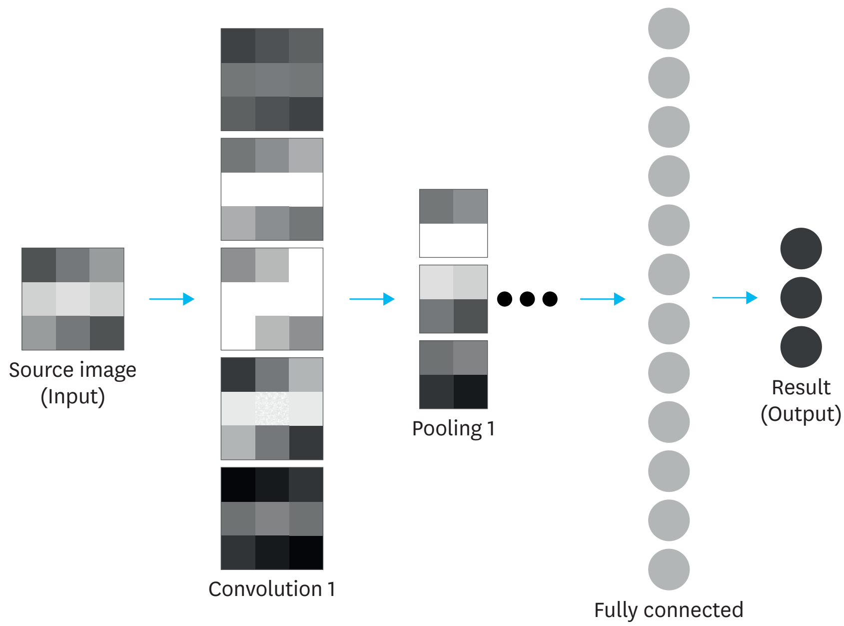

Fig. 2. Structure of a convolutional neural network.

AI technology for EGC detection

It is important to discover the lesion, accurately classify it using AI, and present the optimal treatment plan to the patient. Many studies have been conducted to discover and classify lesions by learning endoscopic images using deep-learning algorithms. These algorithms are being developed in various ways to detect and classify various gastric lesions under different diagnostic environmental conditions of WLE, ME-NBI, and CE; most of them show good performance. **Table 1** shows the results of studies on EGC detection.

In 2015, Miyaki et al. [11] from Japan studied a method for distinguishing between EGC and the tissue surrounding the lesion by utilizing images enlarged by endoscopy with blue-laser imaging. They attempted to quantitatively determine the characteristics of the surrounding tissue in EGC using a support vector machine-based analysis system. Cho et al. [12] created a model that distinguished lesions into 5 categories (gastric cancer, EGC, HGD, LGD, and non-neoplasms) in white light. It showed lower performance than the experts, but the difference was not statistically significant.

Ikenoyama et al. [13] compared the detection abilities of CNNs trained by different teams and experts [14]. They found that the sensitivity of CNN and experts was 58.4% and 31.9%, respectively, indicating a higher sensitivity of the CNN than that of experts; compared to the experts, most deep learning technologies perform similarly or comparably [13-15].

ESD as a solution for EGC

ESD, developed in Japan in 1990, is widely used for EGC treatment, with surgical excision being the standard treatment.

In 2016, the Japan Gastric Cancer Association published the guidelines for ESD and endoscopic mucosal resection (EMR). According to these guidelines, endoscopic resection is strongly recommended after EGC diagnosis when the possibility of LNM is extremely low and the size and location of the lesion allows for en bloc resection. By subdividing these

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Table 1. Technology status of early gastric cancer detecting technology using deep learning

Year	Authors	Lesion	Study design	Diagnostic method	Dataset capacity	AI technology	Outcomes (detection lesion)	Evaluation (compared to expert)
2015	Miyaki et al. [11]	EGC	Retrospective	BLI-ME	Patients: 95	SVM	Internal validation SVM output value cancer: 0.846±0.220	Useful
2019	Cho et al. [12]	Classification of lesion	Both prospective and retrospective	WLE	Retrospective Images: 5,017 Patients: 1,269 Prospective Images: 200 Patients: 200	Inception-ResNet-v2	Internal validation AUC Retrospective: 0.877 Prospective: 0.927 Average accuracy: 84.6%	Useful
2020	Lui et al. [15]	Gastric lesions	Retrospective	NBI	NBI images: 2,000	ResNet	Internal validation AUC: 0.91 Accuracy: 91.0% Sensitivity: 97.1% Specificity: 85.9%	Outperformed
2021	Ikenoyama et al. [13]	EGC	Retrospective	WLE, NBI	GC: 2,639 Images: 13,584	SSD	Internal validation CHN Sensitivity: 58.4% Specificity: 87.3% Expert Sensitivity: 31.9% Specificity: 97.2%	Useful
2022	Ishioka et al. [14]	EGC	Retrospective	WLE	Images Neoplastic: 150 Non-neoplastic: 165	Tango	Internal validation Tango/Expert Accuracy: 70.8%/67.4% Sensitivity: 84.7%/65.8%	Outperformed

EGC = early gastric cancer; BLI = blue laser imaging; SVM = support vector machine; ME = magnifying endoscopy; WLE = white light endoscopy; AUC = area under the receiver operating characteristic curve; NBI = narrow-band imaging; GC = gastric cancer.

into groups, the indication criteria for EGC are presented. According to the 2nd guideline published in 2020, ESD and EMR are recommended for intramucosal differentiated adenocarcinoma without ulcers of 2 cm or less, and intramucosal differentiation without ulcers of 2 cm or more; ESD is recommended for adenocarcinoma, intramucosal differentiated adenocarcinoma with an ulcer less than 3 cm, and undifferentiated intramucosal adenocarcinoma without an ulcer less than 2 cm. Furthermore, submucosal differentiated adenocarcinomas of 3 cm or less are curable through ESD, and radical resection is recommended in all other cases [16].

As such, ESD has a high cure rate for EGC, but there are situations in which the location of the lesion must be considered in addition to the histological and morphological features. The patient's condition and other diseases should also be considered. According to a domestic report, 40% of ESD surgeries are difficult to perform owing to the difficulty of endoscopic access. Despite these challenges, ESD remains an effective treatment option for EGC. Various technologies can be combined to overcome these challenges, and AI-assisted EGC cutting surface technology can help improve the accuracy of ESD surgery.

Role of AI in upper gastrointestinal tract therapy

The process and role of using AI for the detection and management of upper, small bowel, and lower GI cancers, such as esophageal squamous cells, Barrett's esophagus, and gastric neoplasia, defines and presents the expected value of AI. Gastrointestinal endoscopy is divided into 7 stages (pre-procedure, completion of procedure, identification of pathology, management of pathology, complications, patient experience, and post-procedure), and the stage where AI is currently most commonly applied is the "identification of pathology" stage.

In the upper gastrointestinal tract, AI can be used for the detection of gastric neoplasia and endoscopic prediction of submucosal invasion. In addition, the miss rate of gastric tumors is reported to be 10%, and the main causes are a decrease in proper training experience due to the low incidence of gastric cancer in Caucasians and incomplete examination due to subtle mucosal lesions. Endoscopy using AI can assist with this. In an offline study using video and still images, a sensitivity of 88% and a specificity of 89% were obtained. Thus, risk stratification and treatment plans can be established for gastric neoplastic lesions by estimating the lesion type and invasion depth.

Although endoscopic treatment, such as ESD, performed by a skilled endoscopist can determine early lesions and cure them, 20% of lesions are subject to judgment factors, such as color changes, redness, nodularity, interruption, convergence of gastric folds, and friability. Therefore, we assumed that the patient was not cured. Although the possibility of curative resection is difficult to judge, AI technology can provide a valid alternative to help select a complete treatment for gastric lesions (**Fig. 3**) [17].

Margin detection of EGC using AI

In endoscopy-assisted diagnosis technology using AI, distinguishing the boundary of the lesion is a necessary element to treat lesions more completely.

This is a necessary technology for the generalization and advancement of treatment techniques. In 2020, An et al. [18] developed an AI model to describe the interface of EGG under CE or WLE and compared its judgment results with those of endoscopy experts under ME-NBI. The results of the expert and AI models were displayed on the EGC images, and the degrees of overlap were compared. When the threshold was 0.6, accuracies of 85.7% and

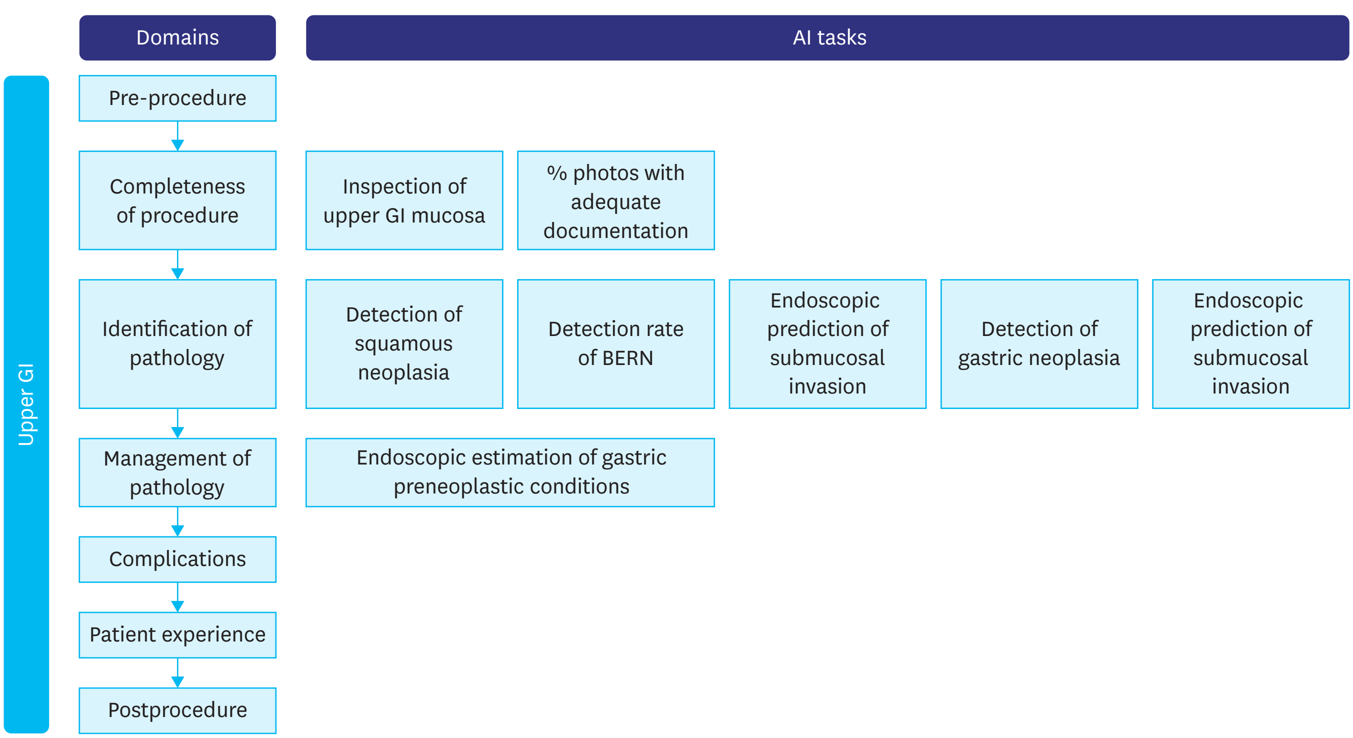

Fig. 3. Performance measurements for the use of AI in upper GI endoscopy and AI tasks.
AI = artificial intelligence; GI = gastrointestinal; BERN = Barrett's esophagus-related neoplasia.

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88.9% were obtained for the CE and WLE images, respectively. In the video data experiment, 100% accuracy was achieved when the threshold was 0.6. When comparing the actual pathological boundaries, there was no significant difference at 3.40±1.49 mm for AI and 3.32±2.32 for experts.

In 2021, Ling et al. [19] developed an AI model to determine the differentiation status of EGCs and describe their margins under ME-NBI. When the threshold was 0.8, the accuracy was 82.7% for differentiated EGC and 88.1% for undifferentiated EGC. The video also depicted the boundary in real time with good performance, but only in still frames. Liu et al. [20] and Hu et al. [21] and conducted research on the diagnosis of EGC and gastric neoplastic lesions using deep learning under ME-NBI.

The AI used by Hu et al. [21] learned the EGC image instead of separately learning information data about the lesion boundary and then used the Grad-CAM method to visualize the area that contributed the most to diagnosing the lesion.

Liu et al. [20] classified the boundary using the segmentation method with data labeled by the endoscopist and showed values of 0.776 precision, a recall coefficient of 0.983, and a Dice coefficient of 0.867 at a critical value of 0.5. What these 2 teams shared was that the results of the deep learning model were better than those of the endoscopist. Both junior and senior endoscopic diagnosticians showed higher diagnosis rates when using endoscopic-assisted diagnostic technology using AI (**Table 2**) [21].

Identification of EGC lesion invasion depth using AI

In addition to identifying the boundary for accurate treatment, it is important to check the infiltration depth, as the treatment varies depending on this [16]. It is also important to present the correct treatment to the patient at the diagnostic stage, before surgery.

Table 2. Technology status of early gastric cancer margin discrimination technology using deep learning

Year	Authors	Lesion	Study design	Diagnostic method	Dataset capacity	AI technology	Outcomes (resection margin)	Evaluation (compared to expert)
2020	An et al. [18]	EGC (resection margin)	Both prospective and retrospective	Trained: CE, WLE Evaluated: ME-NBI	Images: 1,244 Patients: 768 Videos: 10	U-Net++ (based VGG-16)	Internal validation CE: 85.7% WLE: 88.9%	Outperformed (similar to expert level)
2020	Hu et al. [21]	EGC	Retrospective	ME-NBI	Images: 1,777 Patients: 295	VGG-19	Not compared with experts	Outperformed
2021	Ling et al. [19]	EGC (differentiation status, margins)	Retrospective	ME-NBI	Internal (differentiated/ undifferentiated) patient: 90/42 image: 694/234 External patient: 53/34 image: 398/344 video: 2	VGG-16,	External (video) (differentiated/ undifferentiated) Accuracy: 82.7%/88.1%	Outperformed
2022	Liu et al. [20]	Superficial gastric neoplastic lesions (with margins)	Retrospective	ME-NBI	Gastric neoplastic lesions Images: 3,757 Patients: 392 Non-gastric neoplastic lesions Images: 2,420 Patients: 568	CNN (YOLO v3, EfficientNet B2, U-Net, VGG-16)	Internal validation Precision: 0.776 Recall coefficient: 0.983 Dice coefficient: 0.867	Outperformed (better than endoscopists)

EGC = early gastric cancer; CE = chromoendoscopy; WLE = white light endoscopy; ME = magnifying endoscopy; NBI = narrow-band imaging; VGG = Visual Geometry Group; CNN = convolutional neural network.

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EUS is currently a widely used technique for predicting the depth of invasion from the mucosal folds to the submucosa; however, it has additional time and financial constraints compared to endoscopy. In particular, EUS is more dependent on the operator than the endoscope, and low-quality EUS images increase the false diagnosis rate [22,23]. Moreover, EUS does not have a significant effect on determining the penetration depth compared with conventional endoscopy, and there are also reports that EUS tends to exaggerate the penetration depth. To determine the depth of invasion through endoscopy, factors such as remarkable redness, uneven surface, submucosal tumor-like margin elevation, and mucosal fold convergence are evaluated, with an accuracy of 82.5% to 96.5% [24-27]. This indicates that the depth of penetration can be predicted even with visual information that can be confirmed with the naked eye without using ultrasound and that the image can be learned and used by AI.

In 2019, Zhu et al. [23] conducted a study to diagnose the depth of invasion in gastric cancer using deep learning technology for the first time. This retrospective study compared coronary artery disease (CAD) and endoscopists, and the CAD accuracy, sensitivity, and specificity were 89.16%, 76.47%, and 95.56%, respectively. In addition, 4 research teams conducted a similar study that retrospectively diagnosed the depth of invasion of gastric lesions. Most of them showed a high accuracy of 89%–94% in WLE and showed similar or better diagnostic abilities than experienced endoscopists. There were no significant differences among WLE, NBI, and CE [22], and flat EGC tended to have poor detection accuracy [28].

In a prospective study conducted by Wu et al. [29] in China in 2022, endoscopy diagnostic technology using AI was verified by comparing an AI system called ENDOANGEL, developed by Wu et al. [30] in 2021, with 46 endoscopy experts. In this study, the technology for diagnosing gastric lesions and predicting the depth of invasion and degree of differentiation was tested using image data rather than images, which have been mainly used in previous studies. The accuracy, sensitivity, and specificity of ENDOANGEL were 78.57%, 70.00%, and 83.33%, respectively. This seems to be lower than the results tested in the existing image environment, but it showed excellent performance when compared with the endoscopists who participated in the study. In addition, the time taken to diagnose EGC, predict the depth of invasion, and judge the degree of differentiation was 0.160 hours for ENDOANGEL and 2.22 hours for endoscopists; AI shortened the diagnosis time considerably (**Table 3**).

Utilizing AI technology for lesion diagnosis using computed tomography (CT) images

Factors other than the boundary and depth of infiltration can be used to diagnose these lesions more accurately. The AJCC Cancer Staging Manual (8th edition) published by the American Joint Committee on Cancer presents a more detailed method for classifying lesions [31]. TNM staging is based on the depth of invasion of the primary tumor (T), lymph node metastasis (N), and metastasis (M). In general, the CT image of a lesion is visually judged by a radiologist to diagnose the degree of metastasis to the lymph nodes. Research is also underway to diagnose the degree of LNM by training AI to use CT images.

Jin et al. [32] and Li et al. [33] developed a deep-learning algorithm using 2D CT images.

The area under the receiver operating characteristic curve and median values were 0.82 and 0.876, respectively, which were very useful values, and the algorithm developed by Dong et al. [34] had a C-index value of 0.797 for external verification and 0.822 for international verification. The algorithm developed by Dong et al. [34] found LNM with 81.7% accuracy, which was missed even by radiologists when symptoms did not show well on CT.

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Table 3. Technology status of early gastric cancer invasion depth prediction technology using deep learning

Year	Authors	Lesion	Study design	Diagnostic method	Dataset capacity	AI technology	Outcomes (invasion depth)	Evaluation (compared to expert)
2019	Zhu et al. [23]	EGC (invasion depth)	Retrospective	WLE	Total Images:993	ResNet50	Internal validation AUC: 0.94 Accuracy: 89.16%/71.49% Sensitivity: 76.47%/87.80% Specificity: 95.56%/95.56% (CAD/Endoscopists)	Outperformed
2019	Yoon et al. [28]	EGC (diagnose and invasion depth)	Retrospective	WLE	Images EGC: 2,102 non-EGC: 9,834 (patient: 800)	VGG-16 ResNet-18	Internal validation AUC: 0.844 Accuracy: not compared Sensitivity: 81.7% Specificity: 75.4%	Useful (not compared to expert)
2020	Nagao et al. [22]	EGC (invasion depth)	Retrospective	WLE, CE, NBI (unused ME)	Images: 16,557 patient: 1,084	ResNet50	Internal validation AUC: 0.9590 Accuracy: 94.5%/94.3%/95.5% Sensitivity: 84.4%/75.0%/87.5% Specificity: 99.4%/100.0%/100.0%	Highly accurate (not compared to expert)
2022	Wu et al. [29]	Gastric neoplasm, EGC (diagnose and invasion depth, differentiation)	Prospective	WLE, ME	Video: 100	VGG-16 ResNet-50 U-net++	Internal validation EGC depth (ME) Accuracy: 78.57% Sensitivity: 70.00% Specificity: 83.33%	Outperformed
2022	Nam et al. [24]	BGU, EGC, AGC (detection, diagnose and invasion depth)	Retrospective	WLE	Images: 1,366 patient: 1,366	U-Net	Internal test AUC: 0.92 Accuracy: 89% Sensitivity: 94% Specificity: 82% External test AUC: 0.86 Accuracy: 79% Sensitivity: 77% Specificity: 89%	Outperformed

EGC = early gastric cancer; WLE = white light endoscopy; AUC = area under the receiver operating characteristic curve; CAD = computer-aided design; VGG = Visual Geometry Group; CE = chromoendoscopy; NBI = narrow-band imaging; ME = magnifying endoscopy; BGU = benign gastric ulcer; AGC = advanced gastric cancer.

Jin et al. [32] combined the patients' clinical characteristics with a deep learning algorithm trained on CT images and compared the predicted values of 11 lymph node metastases but did not obtain significant results. However, the depth of lesion invasion is an important factor in predicting the presence of LNM. There is a disadvantage in that information on the exact depth of invasion cannot be obtained after surgery [33,34].

In addition to predicting LNM, studies have applied CT data to deep learning technology to predict patient survival and prognosis. Zhang predicted the survival rate of patients with gastric cancer by applying a CT image to a deep learning model and showed higher results than Clinical and Radiomics with a C-index of 0.78. Additionally, she said that the TNM staging system, which was widely used previously, had a disadvantage in that it could not present optimized treatment information for each patient, and that DL technology could compensate for this.

Jiang et al. [35] studied whether the prognosis of disease-free survival and overall survival could be differentiated by integrating not only CT images but also clinicopathological factors and concluded that they were not related. However, she stated that CT image-based deep learning techniques could be useful in predicting the survival of patients with gastric cancer (**Table 4**) [36].

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Table 4. Therapeutic use of deep learning technology trained on CT data

Year	Authors	Lesion	Study design	Diagnostic method	Dataset capacity	AI technology	Outcomes (median survival time)	Evaluation
2020	Dong et al. [34]	Lymph node metastasis	Retrospective	CT	patient: 730	DL (Multivariable linear regression analysis)	C-index External validation: 0.797 International validation: 0.822	Outperformed
2020	Li et al. [33]	Lymph node metastasis	Retrospective	CT	Patient: 204	DCNN	AUC: 0.82	Outperformed
2021	Jin et al. [32]	Lymph node metastasis	Retrospective	CT	Patient: 1,699	ResNet-18	Externational validation median AUC: 0.876 Accuracy: nearly 90% Sensitivity: 0.743 Specificity: 0.936	Useful
2020	Zhang et al. [36]	Risk prediction of overall survival	Retrospective	CT	Patient: 640	ResNet	C-index DL(internal) vs Clinical(external) vs Radiomics	Outperformed than clinical radiomics
2021	Jiang et al. [35]	Predict prognosis	Retrospective	CT	Patient: 1,615	S-Net	Externational validation C-index DFS: 0.719 OS: 0.724	Useful than TNM staging system

CT = computed tomography; DL = deep learning; DCNN = deep convolutional neural network; AUC = area under the receiver operating characteristic curve; DFS = disease-free survival; OS = overall survival.

CONCLUSION

Summary and limitations

Among the endoscopy-assisted diagnostic technologies using AI, we examined technologies that detect lesions and predict their boundary and penetration depth. Most of them showed the same level of diagnosis and determination of the interface and penetration depth as endoscopists; when these techniques were used together, the interface diagnosis rate of not only the unskilled but also the expert increased. Additionally, it showed the possibility of a more accurate treatment using CT images to determine LNM, patient survival rate, and prognosis. Endoscopic-assisted diagnosis technology using AI is sufficiently practical and can be used as an appropriate assistive technology by surgeons during ESD.

However, this method has some limitations. First, in the studies that detected boundaries, most were diagnosed only in the ME-NBI environment. Usually, an endoscopic diagnosis is performed in the WLE state, and when a physician suspects a lesion, ME-NBI must be used. Therefore, when this technology is used in the medical field, it may be difficult to apply it to assist doctors in the first exploration of lesions [21]. The second reason is the insufficient amount of available data. In most cases, AI is trained on a small amount of insufficient image data extracted from a single center. Additionally, because only patients who underwent resection were selected and studied retrospectively, only lesions that were easy to resect were included. The study by Hu et al. [21] yielded poor diagnostic results for mixed lesions [18]. In addition, images of low quality, bleeding, and mucus were excluded from the learning, and in some studies, only images extracted from one type of endoscopic device were used [20]. In an actual clinical environment, there are variables, such as centers in various countries and environments, various types and versions of endoscopic devices, and factors that interfere with the endoscopic view according to the condition of the patient's upper gastrointestinal tract. This aspect should be improved by learning more images and prospective studies. Third, the detection accuracy according to the presence or absence of accompanying inflammatory changes, such as atrophic gastritis and intestinal metaplasia of the mucous membrane, was not analyzed. Stomach neoplasia is usually accompanied by other symptoms. This could be supplemented by learning additional non-EGC image data [28].

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Future perspective

The trend brought about by deep learning technology in the medical world is expected to have a significant impact on the human quality of life. This is not limited to patients but includes both endoscopic diagnosis outside the operating room and surgery inside the operating room. Techniques for diagnosing lesions of the upper and lower gastrointestinal tracts, from the esophagus to the large intestine, are rapidly developing, and there is little time left before they can be applied to the treatment of many patients. Among them, endoscopy-assisted diagnostic technology using AI to discover and diagnose EGC has shown rapid development worldwide with good results. In addition, technology for determining the resection margin and depth of invasion of the lesion, which is the next step for practical clinical application, is being rapidly developed. As a result, the advantages that endoscopists and surgeons can obtain are as follows: First, both low- and high-skilled specialists can reduce the rate of misdiagnosis. Although diagnosing EGC requires a specialist's experience and skill, it is important to know that variables always exist, such as when the patient's clinical data are insufficient or the medical environment, such as medical facilities and personnel, is insufficient to make an accurate diagnosis, or the doctor is careless owing to the difference in condition on the day of diagnosis. AI technology, which makes auxiliary diagnoses with objective judgment regardless of the environment, can help reduce false diagnosis rates. Secondly, if sufficient data are collected, it can help doctors in special situations where medical education and experience are difficult, in poor countries, and among multiracial patients. Third, it could reduce work fatigue among physicians.

Although technologies for more accurate diagnosis of cancer, such as ME-NBI, have been developed, they require higher skills and cause more fatigue. AI-assisted diagnostic endoscopy can reduce doctors' fatigue and reduce endoscopy and procedure time in the diagnosis process.

The first advantage for patients is that a more suitable treatment is possible.

Side effects and bleeding can be minimized by using surgical resection margins suitable for a wide variety of lesion types. Second, in places with low medical standards (poor countries, countries with severe religious and gender discrimination, and places in Korea with poor medical facilities), patients will receive more objective and improved treatment. Third, this proves the transparency of the treatment process. The transparency of treatment results can be visually provided to patients to increase their understanding and induce cooperation to maximize treatment effects.

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