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Review Article

Application and future perspectives of gastric cancer technology based on artificial intelligence

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Abstract

Gastric cancer is among the most common cancers and the second-leading cause of death globally. A variety of artificial intelligence (AI) applications have been developed to facilitate the image-based diagnosis of gastric cancer through pathological analysis, endoscopy, and computerized tomography. This article provides an overview of these AI applications as well as suggestions pertaining to future developments in this field and their application in clinical practice.

Keywords: *Artificial intelligence, Gastric cancer, Image-based diagnosis*

Introduction

Gastric cancer is among the most common cancers and the second-leading cause of death globally. In the early stages, most gastric tumors are detected and differentiated from other stomach-related diseases through endoscopic observation of the gastrointestinal tract. Gastric lesions can be broadly classified into advanced gastric cancer, early gastric cancer (EGC), and gastric precursor disease. There is strong evidence indicating that the early detection of gastric cancers improves the chance of survival [1,2]; however, gastric cancer is generally only diagnosed in advanced stages, due to latent nonspecific symptoms and a lack of experience among imaging technicians and physicians. Even highly-qualified specialists cannot avoid misdiagnoses. The only way to effectively deal with the early atypical symptoms of gastric cancer and its late invasive behavior is through advanced screening.

Artificial intelligence (AI) has attracted widespread attention for its ability to deduce subtle solutions to otherwise intractable problems by mimicking the cognitive functions of the human brain (learning and problem-solving) while leveraging the immense data processing power of modern computers [3]. AI has been applied in the field of gastroenterology to facilitate clinical diagnosis and decision-making based on medical imaging data. One subset of artificial intelligence referred to as machine learning (ML) uses computer algorithms to search for optimal solutions or make predictions based on the experience derived from real-world training data [4]. A number of machine learning algorithms, including random forests, support vector machines (SVMs), and neural networks, have been employed in the field of medicine. Note, however, that ML methods require the use of additional algorithms for the selection of important features as inputs. At present, the field of ML is dominated by deep learning (DL) algorithms, which use multiple convolution layers to extract higher-level features from raw input for computation, analysis, and recognition.

Application of AI to diagnosis of gastric cancer

Most of the input data for DL models is obtained through endoscopy and pathological sections [5-20]. The diagnostic performance of several AI models has been shown to match or even exceed that of human experts.

AI-assisted diagnosis in endoscopy

AI methods have been used in the early detection of gastric cancer [7-10] as well as precancerous lesions [11]. Table 1 lists recent works using AI in the diagnosis of gastric cancer based on endoscopic images. Liu *et al.* [5] combined diagonalized principal component analysis with traditional algorithms to reduce the dimensionality of endoscopic images for the early detection of gastric cancer. Ali *et al.* [6] proposed a new texture extraction method (Gabor-based grayscale co-occurrence matrix) to detect abnormalities in chromoendoscopy sequences for use in conjunction with SVM classifiers to detect gastric cancer. Luo *et al.* [7] developed an AI-based diagnostic system for the real-time detection of upper gastrointestinal tumors. Sakai *et al*. [8] developed a highly-accurate detection model based on a convolutional neural network (CNN). Yoon *et al.* [9]

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Table 1: Applications of artificial intelligence in endoscopy

Reference	Country	Study population	Number of images	Year	Methods	Results
Liu *et al*. [5]	China	Hospital	400	2016	JDPCA	AUCs (0.9532), accuracy (90.75%)
Ali *et al*. [6]	Pakistan	Public images dataset	176	2018	G2LCM	AUCs (0.91), accuracy (87%)
Luo *et al*. [7]	China	Hospital	1,036,469	2019	GRAIDS	Accuracy (97.7%)
Sakai *et al*. [8]	Japan	Hospital	29,037	2018	CNN	Accuracy (87.6%)
Yoon *et al*. [9]	Korea	Hospital	11,539	2019	VGG	AUCs (0.981 for detection) and AUCs (0.851 for depth prediction)
Zhu *et al*. [10]	China	Hospital	993	2019	CNN-CAD system	AUCs (0.94), accuracy (89.16%)
Guimarães *et al*. [11]	Germany	Medical center	270	2020	DL	AUCs (0.98), accuracy (93%)
Miyaki *et al*. [12]	Japan	Hospital	100	2015	SVM	Average (0.846±0.220)
Liu *et al*. [13]	China	Hospital	1120 M-NBI images/3068 images	2018	Deep CNN	Top accuracy (98.5%)
Bergholt *et al*. [15]	Singapore	Hospital	1063 *in vivo* Raman spectra	2011	ACO-LDA	Sensitivity (94.6%), specificity (94.6%)
Duraipandian *et al*. [16]	Singapore	Hospital	2748 *in vivo* Raman spectra	2012	PLS-DA	Accuracy (85.6%), specificity (86.2%)

CNN: Convolutional neural network, M-NBI: Magnifying narrow-band imaging, AUCs: Area under the curves, G2LCM: Gabor-based gray-level co-occurrence matrix, GRAIDS: Grading of Recommendations, Assessment, Development, and Evaluation, VGG: Visual geometry group, CAD: Computer-aided diagnosis, DL: Deep learning, SVM: Support vector machine, ACO-LDA: Ant colony optimization algorithm-linear discriminant analysis, PLS-DA: Partial least squares discriminant analysis, JDPCA: Joint diagonalisation principal component analysis

used a DL model for the prediction and detection of EGCs and listed the factors of importance to AI-assisted diagnosis. Zhu *et al*. [10] constructed a CNN-based detection system to determine the invasion depth of EGCs, achieving specificity and accuracy beyond what can be achieved using the area under the curve (AUC) approach. The DL model in [11] outperformed endoscopists in diagnosing atrophic gastritis with a diagnostic accuracy of 93% and an AUC of 0.98. Advances in magnifying narrow-band imaging (M-NBI) have greatly improved the early diagnosis of gastric cancer [12]. Researchers have developed an SVM system based on magnifying endoscopy and blue laser images for the identification of gastric cancer. Liu *et al.* [13] used transfer learning to fine-tune deep CNN features to classify gastric mucosal lesions in M-NBI images. Unfortunately, M-NBI is still unable to diagnose lesions that are invisible to the naked eye [14]. Raman endoscopy appears to have considerable potential for the early diagnosis of gastric cancer, due to its ability to display the surface and subsurface cellular structures point-by-point. Bergholt *et al*. [15] combined real-time Raman endoscopy with an AI-based algorithm to differentiate tumor tissue from normal gastric tissue. Duraipandian *et al.* [16] designed an automated Raman spectroscopy diagnostic framework (the partial least squares discriminant analysis algorithm), which achieved a diagnostic accuracy of 85.6% in the detection of gastric cancers. Most recent studies on conventional endoscopy have reported detection accuracy of 69% to 79% [17]. Note also that endoscopic procedures are heavily dependent on human operators, many of whom must deal with a heavy workload, leading to a high incidence of missed or misdiagnoses.

AI-assisted diagnosis based on pathological findings

The morphological characteristics of malignant cells can also be characterized through the histopathological analysis of biopsy specimens. This information can then be used as input for a learning module tasked with the identification of lesions [18-20]. Using a CNN architecture, Sharma *et al*. [18] achieved an accuracy of 0.6990 in cancer classification and 0.8144 in necrosis detection based on the analysis of pathological images. Leon *et al*. [19] proposed two deep CNN-based models for the respective analysis of local and global morphological features for use in detecting instances of gastric cancer. In experiments, they achieved notable accuracy of 89.72%. Iizuka *et al.* [20] trained a CNN and a recurrent neural network to differentiate among gastric adenocarcinoma, adenoma, and nontumors. When tested on three independent biopsy histopathology whole slide image test sets, their models achieved an accuracy of 0.97 in the classification of gastric adenocarcinoma.

Researchers are also making strides in overcoming difficulties in the automatic segmentation of lesion regions. Qu *et al*. [21] presented a novel approach to improving the classification performance of deep neural networks using a novel intermediate dataset with a stepwise fine-tuning scheme. Sun *et al*. [22] demonstrated a DL model for image segmentation, which achieved mean accuracy of 91.60% and a mean intersection over the union of 82.65%. Note that there has been a recent shift toward the development of DL models specifically to deal with the analysis of pathological samples. Many of these applications have achieved good results, particularly in enhancing the efficiency of image segmentation and reducing the time required to formulate a substantive diagnosis [Table 2].

AI-assisted diagnosis in computed tomography

Computed tomography (CT) is widely used in the clinical diagnosis of gastric cancer, due to its noninvasiveness and convenience [23,24]. Nonetheless, the diagnostic accuracy depends largely on the clinical experience of the attending

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Table 2: Applications of artificial intelligence to the analysis of pathological samples

Reference	Country	Study population	Number of images	Year	Methods	Results
Sharma *et al*. [18]	Germany	Hospital	454	2017	CNN	Accuracy (0.6990 for cancer classification), accuracy (0.8144 for necrosis detection)
Leon *et al*. [19]	Colombia	Department of pathology	40	2019	Deep CNN	Accuracy (89.72%)
Iizuka *et al*. [20]	Japan	Hospital, TCGA	1746 biopsy histopathology WSIs	2020	CNN	AUCs (0.98), accuracy (95.6%)
Qu *et al*. [21]	Japan	Hospital	9720 images/19,440 images	2018	DL	AUCs (0.965)
Sun *et al*. [22]	China	Hospital	500	2019	DL	IoU (0.8265), accuracy (91.60%)

CNN: Convolutional neural network, TCGA: The Cancer Genome Atlas, DL: Deep learning, AUCs: Area under the curves, IoU: Intersection over union, WSIs: Whole slide images

Table 3: Applications of artificial intelligence to computed tomography images

Reference	Country	Study population	Number of images	Year	Methods	Results (%)
Li *et al*. [25]	China	Hospital	38 lymph node datasets	2012	ML	Accuracy (96.33)
Li *et al*. [26]	China	Hospital	26 cases	2015	KNN	Accuracy (76.92)
Gao *et al*. [27]	China	Hospital	32,495	2019	FR-CNN	AUCs (0.9541)
Huang *et al*. [28]	China	Hospital	-	2020	Deep CNN	Sensitivity (75), specificity (75)

CNN: Convolutional neural network, ML: Machine learning, KNN: K-nearest neighbors, FR-CNN: Faster R-CNN

radiologist, many of whom are laboring under a heavy workload. Several ML and DL models have been developed to facilitate the extraction of valuable information from CT images [Table 3]. Using an ML architecture for the analysis of CT images, Li *et al.* [25] achieved an accuracy of 0.9633 in the classification of gastric cancer. In another work, Li *et al*. [26] used the K-nearest neighbor algorithm to facilitate the interpretation of CT images. Gao *et al*. [27] used a highly-accurate automatic detection model based on FR-CNN to enhance diagnostic capabilities, achieving an AUC of 0.9541. Huang *et al*. [28] used a CNN model to perform preoperative diagnostic analysis of peritoneal metastases in advanced cases of gastric cancer.

Future challenges

Researchers have had considerable success in the application of AI to the diagnostic analysis of medical images; however, a number of challenges must be overcome to enable the application of these methods in real-world clinical settings. The robustness of any AI model depends on the large volume of well-annotated data for training, validation, and testing. Considerable volumes of data are constantly being generated; however, much of that data is not labeled or annotated, such that it is inapplicable to the training of algorithms. Researchers must develop systems by which to expand the availability of high-quality data for use in the ongoing development and optimization of AI diagnostic systems. One approach is to build large-scale open-access databases, which will require the sharing of data by hospitals and other facilities. Another hindrance to the development of robust algorithms is the difficulty of interpreting AI results, due to the "black box" operations of ML/DL algorithms, which tends to hinder acceptance by clinicians. Fortunately, researchers are moving forward in the development of data visualization schemes to elucidate the decision-making process.

The computing power and learning capacity of AI models can be used to alleviate the workloads of clinicians; however, ethical and safety issues necessitate the evaluation of AI predictions by clinicians. Thus, it is unlikely that AI will replace clinicians in the foreseeable future.

Conclusions

This review article outlines the current state and future development trajectory of AI-assisted diagnosis of gastric cancer. Despite the fact that this research remains in its infancy, existing systems have demonstrated performance superior to that of conventional statistical methods. Further advances will require enormous volumes of well-annotated data and methods by which to comprehend AI decision-making processes. When these difficulties have been addressed, it is likely that AI will revolutionize the diagnosis of gastric cancer.

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Conflicts of interest

There are no conflicts of interest.

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