



Computer-aided diagnostic system with automated deep learning method based on the AutoGluon framework improved the diagnostic accuracy of early esophageal cancer

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Background: There have been studies on the application of computer-aided diagnosis (CAD) in the endoscopic diagnosis of early esophageal cancer (EEC), but there is still a significant gap from clinical application. We developed an endoscopic CAD system for EEC based on the AutoGluon framework, aiming to explore the feasibility of automatic deep learning (DL) in clinical application.

Methods: The endoscopic pictures of normal esophagus, esophagitis, and EEC were collected from The First Affiliated Hospital of Soochow University (September 2015 to December 2021) and the Norwegian HyperKvasir database. All images of non-cancerous esophageal lesions and EEC in this study were pathologically examined. There were three tasks: task A was normal *vs.* lesion classification under non-magnifying endoscopy (n=932 *vs.* 1,092); task B was non-cancer lesion *vs.* EEC classification under non-magnifying endoscopy (n=594 *vs.* 429); and task C was non-cancer lesion *vs.* EEC classification under magnifying endoscopy (n=505 *vs.* 824). In all classification tasks, we took 100 pictures as the verification set, and the rest comprised as the training set. The CAD system was established based on the AutoGluon framework. Diagnostic performance of the model was compared with that of endoscopists grouped according to years of experience (senior >15 years; junior <5 years). Model evaluation indicators included accuracy, recall rate, precision, F1 value, interpretation time, and the area under the receiver operating characteristic (ROC) curve (AUC).

Results: In tasks A and B, the accuracies of medium-performance CAD and high-performance CAD were lower than those of junior doctors and senior doctors. In task C, the medium-performance and high-performance CAD accuracies were close to those of junior doctors and senior doctors. The high-performance CAD model outperformed the junior doctors in both task A (0.850 *vs.* 0.830) and task C (0.840 *vs.* 0.830) in sensitivity comparison, but there was still a large gap between high-performance CAD models and doctors in sensitivity comparison. In task A, with the aid of CAD pre-interpretation, the accuracy of junior and senior physicians were significantly improved (from 0.880 to 0.915 and from 0.920 to 0.945, respectively); the time spent on film reading was significantly shortened (junior: from 11.3 to 8.7 s; senior: from 6.7 to 5.5 s). In task C, with the aid of CAD pre-interpretation, the accuracy of junior and senior physicians were significantly improved (from 0.850 to 0.865 and from 0.915 to 0.935, respectively); the reading time was significantly shortened (junior: from 9.5 to 7.7 s; senior: from 5.6 to 3.0 s).

Conclusions: The CAD system based on the AutoGluon framework can assist doctors to improve the diagnostic accuracy and reading time of EEC under endoscopy. This study reveals that automatic DL methods are promising in clinical application.

Keywords: Digestive endoscopy; early esophageal cancer (EEC); AutoGluon; automatic deep learning (automatic DL)

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Introduction

The incidence rate of esophageal malignant tumors is increasing year by year in China; meanwhile, most of them are diagnosed at an advanced stage (1-3). Early diagnosis and treatment of esophageal cancer can significantly prevent the progression of the disease, and some patients can even achieve a radical cure (4,5). Endoscopic examination is the main method for the diagnosis of early esophageal cancer (EEC), but it can easily lead to misdiagnosis due to the lack of specificity under endoscopy compared to other esophageal non-cancerous lesions (6). In recent years, artificial intelligence technology has been widely used in clinical diagnosis and treatment. There have been many reports of the application of artificial intelligence technology in the diagnosis and treatment of esophageal cancer in multiple related fields. Among them, the fusion of the deep learning (DL) method and digestive endoscopy

has significantly improved the detection rate and accuracy of EEC diagnosis, and can effectively reduce the adverse effects caused by differences in physician experience and equipment (7,8). However, the DL method poses a great challenge to the programming ability of medical staff and has become the biggest obstacle for front-line clinical doctors without programming experience to carry out artificial intelligence projects. In 2020, the Amazon Science Department (Seattle, WA, USA) released the AutoGluon automatic machine learning framework, which can carry out image classification DL tasks under simple code. This study intends to build a computer-aided diagnosis (CAD) system for EEC endoscopy under this framework, aiming to explore the feasibility of applying automatic DL in clinical computer vision tasks. We present this article in accordance with the TRIPOD reporting checklist (available at <https://jgo.amegroups.com/article/view/10.21037/jgo-24-158/rc>).

Methods

Data collection

This was a retrospective study collecting endoscopic images of normal esophagus, esophagitis, and EEC from the Digestive Endoscopy Center of The First Affiliated Hospital of Soochow University (September 2015 to December 2021) and the Norwegian HyperKvasir database, including white light imaging (WLI), narrow-band imaging (NBI), and narrow-band imaging combined with magnifying endoscopy (NBI-ME); the detailed flowchart is shown in *Figure 1*. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). This study was approved by the Ethics Committee of The First Affiliated Hospital of Soochow University (ethical approval number: [2022] No. 098). The requirement for informed consent was waived due to the retrospective nature of the study. In this study, EEC was defined as high-grade intraepithelial neoplasia of the esophagus or squamous cell carcinoma confined to the mucosal lining confirmed by endoscopic or surgical pathology. All images of non-

Highlight box

Key findings

- The computer-aided diagnosis (CAD) system based on the AutoGluon framework can assist doctors to improve the diagnostic accuracy and reading time of early esophageal cancer (EEC) under endoscopy.

What is known and what is new?

- The fusion of the deep learning method and digestive endoscopy has significantly improved the detection rate and accuracy of EEC diagnosis, and can effectively reduce the adverse effects caused by differences in physician experience and equipment.
- The CAD system based on the AutoGluon framework can help endoscopists to improve the detection rate of EEC and the accuracy of endoscopic diagnosis, and improve the efficiency of diagnosis.

What is the implication, and what should change now?

- The CAD system employed in this study exhibits superior accuracy and automation compared to other models, while also offering greater convenience and scalability. Its advantages are particularly pronounced for non-computer-proficient medical personnel.

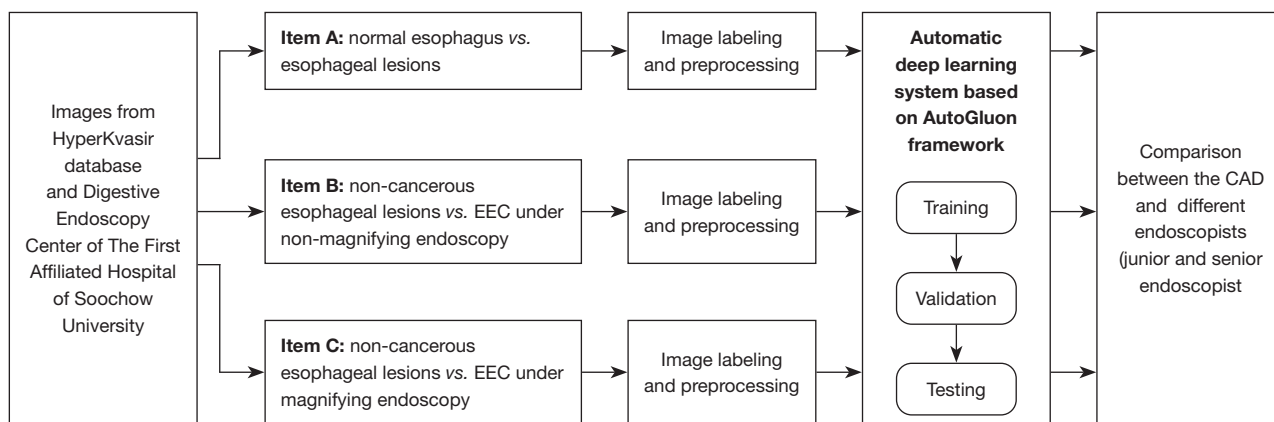


Figure 1 Research flow chart of the CAD system-assisted endoscopic diagnosis of EEC based on the AutoGlun framework. EEC, early esophageal cancer; CAD, computer-aided diagnosis.

Table 1 Classification, quantity, and source distribution of endoscopic images of each item

Task	Image type	Image classification and quantity	Image source	
			Endoscopy center	HK database
A	WLI and NBI	Normal group: 932	0	932
		Lesion groups: 1,092	429	663
B	WLI and NBI	Non-cancer group: 594	594	0
		EEC group: 429	429	0
C	NBI-ME	Non-cancer group: 505	505	0
		EEC group: 824	824	0

HK, HyperKvasir; WLI, white light imaging; NBI, narrow band imaging; EEC, early esophageal cancer; NBI-ME, narrow-band imaging combined with magnifying endoscopy.

cancerous esophageal lesions and EEC in this study were pathologically examined. Images which are blurred, out-of-focus, and unidentifiable, as well as images of esophageal submucosal lesions, advanced esophageal cancer, and other esophageal lesions were removed. All the screened endoscopic images of the esophagus were divided into three tasks for classification and summary as follows: task A: identification of normal esophagus and esophageal lesions (including non-cancerous esophageal lesions and EEC) under non-magnifying endoscopy; task B: identification of non-cancerous esophageal lesions and EEC under non-magnifying endoscopy; task C: identification of non-cancerous esophageal lesions and EEC under magnifying endoscopy. The classification, quantity, and source of endoscopic pictures of each item are detailed below (Table 1).

Image labeling and preprocessing

According to the manifestations of esophageal lesions under endoscopy and the pathological biopsy report, three senior physicians (that is, physicians with 15 years or more experience in digestive endoscopy) reviewed, classified, and labelled all pictures in the Endoscopy Center of The First Affiliated Hospital of Soochow University according to guidelines and requirements of Table 1. At the same time, according to the classification labels provided by the HyperKvasir database, we completed the classification and labeling of the database source pictures (Figure 2). Then, all involved pictures were preprocessed as follows: (I) a training set and verification set picture division: in project A, 100 normal group pictures and 100 lesion group pictures were randomly selected as the verification set, and the remaining

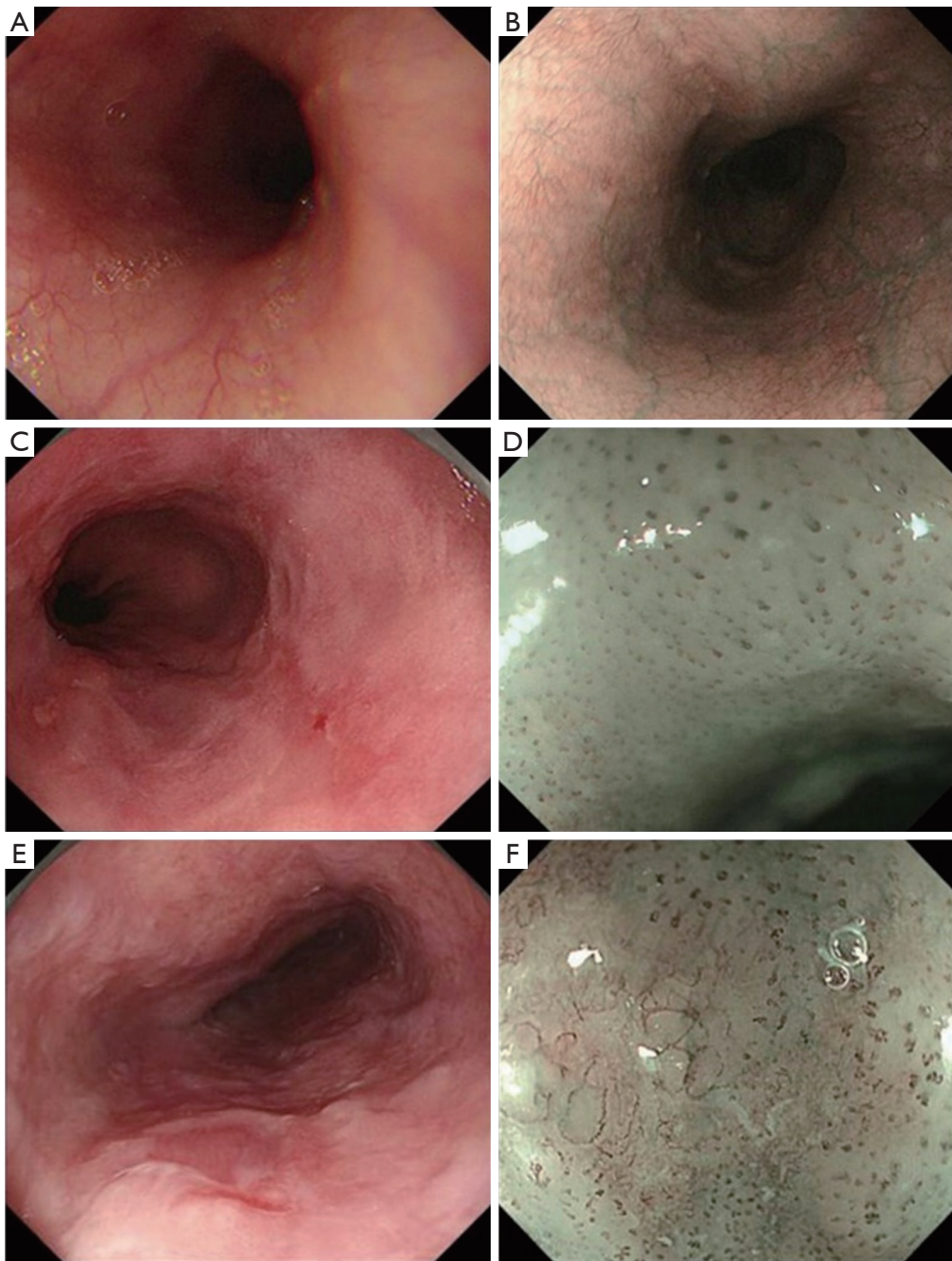


Figure 2 Classification and labeling of esophageal endoscopy pictures. (A) WLI image of the normal esophagus. (B) NBI image of the normal esophagus. (C) WLI image of the non-cancerous esophagus. (D) NBI-ME image of the non-cancerous esophagus. (E) WLI image of early esophageal cancer. (F) NBI-ME image of early esophageal cancer ME picture. WLI, white light imaging; NBI, narrow band imaging; NBI-ME, narrow-band imaging combined with magnifying endoscopy.

pictures comprised training set. In project B, 100 non-cancer group pictures and 100 EEC group pictures were randomly selected as the verification set, and the remaining pictures were used as the training set; in project C, 100 non-cancer group pictures and 100 EEC group pictures were randomly selected as the verification set, and the remaining pictures comprised the training set. (II) Picture size adjustment: the size of the original data picture were not the same, which might reduce the accuracy of the CAD system and increase the training time. All images were adjusted to 224×224 pixels. (III) Picture enhancement: the uneven sample size of the 2-category data in the training set could easily lead to bias in the model results, so the training set pictures for each project were enhanced. At the same time, the sample size of the training set increased after enhancement, which was conducive to model fitting. When enhancing, we used non-rigid image changes (flip up and down, flip left and right, rotate).

Establishment of the CAD system

The CAD system was established based on the AutoGluon framework; the steps were as follows: (I) load training data: according to the requirements of the architecture, we constructed a suitable data structure. The image data of the three tasks A, B, and C were loaded into the AutoGluon framework in the correct format; (II) the model architecture in the medium performance mode was ResNet50d, the model framework in the high-performance mode was Swin_base_patch4_window7_224, the training round was 50 rounds, and we constructed 32 training batches; the remaining parameters were replaced by the default parameters of the architecture. (III) Save the training model: we saved the high-performance and medium-performance models for each project, that was, the model with the highest accuracy in the test set.

Evaluation of the model

The CAD system was evaluated on the validation set data of each project. At the same time, two endoscopists were selected, determined as either junior or senior endoscopist (junior meant less than 5 years' experience in digestive endoscopy, and senior meant more than 15 years' experience in digestive endoscopy), and their interpretation results of the verification set data of each project were collected and used as a reference for model evaluation. The high-performance CAD-assisted endoscopist re-interpreted the

pictures of the verification set, which was arranged 4 weeks after the endoscopist independently interpreted them.

Data processing and statistical analysis

The following evaluation indicators were used for the classification results of each project model and junior or senior physicians: accuracy, recall, precision, F1-score, interpretation time, and test subjects. The area under the receiver operating characteristic (ROC) curve (AUC) was defined. The satisfactory level of sensitivity and specificity of CAD models was defined as exceeding 50%. The software used for data analysis was SPSS 23.0 (IBM Corp., Armonk, NY, USA).

Results

The CAD system had high classification accuracy in the three tasks, and the average classification accuracy of its high-performance mode was 0.845, which was slightly lower than that of the junior endoscopists (the average classification accuracy was 0.878). There was a certain gap in the classification accuracy of senior endoscopists (the average classification accuracy was 0.930). In the high-performance mode, the CAD system had the highest classification accuracy of 0.855 in the identification of non-cancerous esophageal lesions and EEC under non-magnifying endoscopy; the highest discrimination was achieved with an AUC of 0.876 (*Table 2*).

The high-performance CAD model outperformed the junior doctors in both task A (0.850 *vs.* 0.830) and task C (0.840 *vs.* 0.830) in sensitivity comparison. In the comparison of specificity, there was still a large gap between high-performance CAD models and even low-qualified doctors. Likewise, the F1 score and the AUC for high-performance CAD models were still lower than those of junior doctors (*Table 2*).

In terms of time, the interpretation time of each picture in the verification set of task A with medium performance (0.026 s) and high performance (0.037 s) was much lower than that of low-level (11.3 s) and high-level (6.7 s) endoscopists. The CAD interpretation time in task B and task C was much lower than that of junior and senior endoscopists (*Table 2*).

After being interpreted by the high-performance CAD system, the endoscopist interpreted the pictures of the verification set again according to the results. The results showed that: in task A, the accuracy of low-seniority and

Table 2 Performance of CAD system and endoscopist verification set

Task	Accuracy	Sensitivity	Specificity	Recall rate	Precision	F1 score	AUC	Time (s)
Task A: differentiate between normal esophagus and esophageal lesions (including non-cancerous esophageal lesions and EEC) under non-magnifying endoscopy								
Mid-performance CAD	0.790	0.810	0.770	0.810	0.779	0.794	0.813	0.026
High-performance CAD	0.845	0.850	0.840	0.850	0.842	0.846	0.864	0.037
Junior endoscopist	0.880	0.830	0.930	0.830	0.922	0.874	0.880	11.3
Senior endoscopist	0.920	0.900	0.940	0.900	0.938	0.918	0.920	6.7
High performance CAD + junior	0.915	0.880	0.950	0.880	0.946	0.912	0.915	8.7
High-performance CAD + seniority	0.945	0.920	0.970	0.920	0.968	0.944	0.945	5.5
Task B: differentiate non-cancerous esophageal lesions from EEC under non-magnifying endoscopy								
Mid-performance CAD	0.825	0.820	0.830	0.820	0.828	0.824	0.831	0.028
High-performance CAD	0.855	0.860	0.850	0.860	0.851	0.856	0.873	0.038
Junior endoscopist	0.905	0.890	0.920	0.890	0.918	0.904	0.905	7.9
Senior endoscopist	0.955	0.950	0.960	0.950	0.960	0.955	0.955	4.4
High-performance CAD + junior	0.905	0.880	0.930	0.880	0.926	0.903	0.905	6.3
High-performance CAD + seniority	0.960	0.960	0.960	0.960	0.960	0.960	0.960	3.8
Task C: differentiate non-cancerous esophageal lesions from EEC under magnifying endoscopy								
Mid-performance CAD	0.805	0.830	0.780	0.830	0.790	0.810	0.837	0.026
High-performance CAD	0.835	0.840	0.830	0.840	0.832	0.836	0.876	0.035
Junior endoscopist	0.850	0.830	0.870	0.830	0.865	0.847	0.850	9.5
Senior endoscopist	0.915	0.910	0.920	0.910	0.919	0.915	0.915	5.6
High-performance CAD + junior	0.865	0.860	0.870	0.860	0.869	0.864	0.865	7.7
High-performance CAD + seniority	0.935	0.930	0.940	0.930	0.939	0.935	0.935	3.0

Time: the average time for interpretation of each picture in the verification set. CAD, computer-aided diagnosis; AUC, area under the ROC curve; ROC, receiver operating characteristic; EEC, early esophageal cancer.

high-seniority physicians were significantly improved with the assistance of CAD pre-interpretation (from 0.880 to 0.915 and from 0.920 to 0.945, respectively); at the same time, the reading time was significantly shortened (low seniority: from 11.3 to 8.7 s; senior seniority: from 6.7 to 5.5 s). In task C, the same low-seniority and high-seniority physicians have significantly improved accuracy with the assistance of CAD pre-interpretation (from 0.850 to 0.865 and from 0.915 to 0.935, respectively), and the reading time was shortened (low-seniority: from 9.5 to 7.7 s; high-seniority: from 5.6 to 3.0 s) (*Table 2*).

Discussion

In recent years, with the advancement of artificial intelligence and DL technologies, there have been many reports of the application of artificial intelligence technology in the diagnosis and treatment of esophageal cancer in multiple related fields, including computed tomography (CT) imaging diagnosis, surgical pathological diagnosis, and the formulation of radiotherapy plans (9-12).

Significant progress has also been made in CAD in the field of EEC endoscopic diagnosis (13). Ohmori *et al.* collected endoscopic images of early squamous cell

carcinoma of the esophagus and used a 16-layer algorithm based on “Single Shot MultiBox Detector” to construct a DL model. The verification results confirmed that in terms of diagnostic performance, there was no significant difference between the DL system and experienced endoscopists (14). Li *et al.* obtained endoscopic images of early esophageal squamous cell carcinoma in China and developed a DL model using the backpropagation algorithm. The model demonstrated satisfactory sensitivity and specificity (15). de Groof *et al.* used 494,364 labeled endoscopic images of the esophagus to construct a classification model for EEC through the “Residual U-Net” model. The results showed that the diagnostic sensitivity and specificity of the model reached 0.90 and 0.88, respectively (16). Liu *et al.* utilized a dataset of 1,272 esophageal endoscopes from 748 patients to construct a convolutional neural network model consisting of two sub-networks, “O-steam” and “P-steam”. Extensive and detailed features were extracted from the sub-networks, resulting in improved diagnostic accuracy, sensitivity, and specificity compared to the traditional “LBP + SVM + HOG” model (17). In addition to the utilization of the aforementioned DL system in EEC research, ongoing investigations are being conducted on the application of various model building systems such as “Xception”, “NASNet Large”, “ResNet”, and “BigTransfer” in other domains of digestive endoscopy diagnosis (18-21). Remarkably satisfactory predictive outcomes have been achieved across all these endeavors.

However, the aforementioned DL models are associated with drawbacks such as intricate operations, high complexity, steep learning curves, manual debugging, and low accuracy. In response to this predicament, automatic learning amalgamates automation and machine learning disciplines to minimize human intervention and achieve automated machine learning; it has garnered increasing attention (22,23). Amazon has developed AutoGluon, an open-source code library for automatic machine learning that enables developers to build machine learning applications incorporating image, text, or tabular datasets. Compared with other machine learning programs, AutoGluon boasts the advantages of user-friendliness, scalability, and high accuracy (24-26). At present, good application effects have been achieved in multiple medically-related fields, such as the design and development of new drugs, government medical policy formulation, and more commonly assisting clinical physicians in evaluating patient prognosis and formulating appropriate diagnosis and treatment plans

(27-29). Seo *et al.* utilized the AutoGluon framework to facilitate personalized rehabilitation treatment for patients with cerebrovascular accidents, yielding favorable outcomes (30). Liu *et al.* employed the AutoGluon DL system to predict accidental carbon monoxide poisoning prevalence and aid government agencies in formulating pertinent public health policies (31). Additionally, there has been a report on coronavirus disease 2019 (COVID-19) virus epidemiology based on the AutoGluon framework (32). Currently, there is a lack of research on the application of AutoGluon architecture automatic machine learning for classification modeling in the field of CAD of digestive endoscopy.

This study collected esophageal endoscopy images from the Digestive Endoscopy Center of The First Affiliated Hospital of Soochow University and the Norwegian HyperKvasir database and used the AutoGluon framework to establish a CAD model of EEC under endoscopy. In this study, the CAD system demonstrated its ability to differentiate between normal and diseased esophagi under non-magnifying endoscopy with an accuracy of 84.9% in high-performance mode. Its lesion detection capability is comparable to that of low-qualified endoscopists (88.0%) and slightly lower than that of senior physicians (92.0%). For the detected esophageal lesions, both non-magnifying and magnifying endoscopy demonstrate high accuracy of the CAD system in distinguishing EEC from non-cancerous lesions, with rates reaching 85.5% and 83.5%, respectively. The assistance of CAD pre-interpretation by other endoscopists can significantly improve accuracy while reducing film reading time. Therefore, the CAD system based on the AutoGluon framework can help endoscopists to improve the detection rate of EEC and the accuracy of endoscopic diagnosis, and improve the efficiency of diagnosis. The CAD system employed in this study exhibits superior accuracy and automation compared to other models, while also offering greater convenience and scalability. Its advantages are particularly pronounced for non-computer-proficient medical personnel.

There are still some deficiencies in this study: (I) the sample size of the study is relatively small. In the later stage, it is necessary to accumulate samples from more sources, incorporate multi-center endoscopic data, and introduce external test verification to further improve the accuracy of the model. (II) The classification is relatively simple. In the future, it is necessary to carry out multimodal research in combination with EEC endoscopic findings. (III) It was limited to static pictures for auxiliary diagnosis. In the

later stage, it is planned to realize dynamic video-assisted diagnosis, realize real-time auxiliary diagnosis of EEC during the endoscopic examination, and meet clinical needs.

Conclusions

The CAD system based on the AutoGluon framework can assist doctors to improve the diagnostic accuracy and reading time of EEC under endoscopy. This study reveals that automatic DL methods are promising in clinical application.

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Footnote

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Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at <https://jgo.amegroups.com/article/view/10.21037/jgo-24-158/coif>). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). This study was approved by the Ethics Committee of The First Affiliated Hospital of Soochow University (ethical approval number: [2022] No. 098). The requirement for informed consent was waived due to the retrospective nature of the study.

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