Editorial Commentary

Deep learning application in the oesophageal endoscopy

Shigeru Kiryu[1], Hiroyuki Akai[2], Koichiro Yasaka[2]

[1]Department of Radiology, International University of Health, School of medicine, Narita, Japan; [2]Department of Radiology, The Institute of Medical Science, The University of Tokyo, Tokyo, Japan

Correspondence to: Shigeru Kiryu, MD, PhD. Department of Radiology, International University of Health, School of medicine, 4-3, Kouzunomori, Narita, Chiba 286-8686, Japan. Email: skiryu1@gmail.com.

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This editorial is in response to the article on deep learning application in oesophageal endoscopy by Nakagawa *et al.* (1). The role of deep learning in the classifying invasion depth of oesophageal carcinoma and the future aspect of deep learning in endoscopy are described.

Artificial intelligence (AI) has attracted attention in many fields, not only medicine. Deep learning with a convolutional neural network (CNN) has been a primary strategy in recent advances in AI. Conventional machine-learning requires advanced knowledge of specific imaging features, while CNN uses imaging features extracted via the convolutional process to learn automatically (2). Deep CNN has been developed to handle images for self-driving car technology, facial recognition, and other uses. In medicine, deep CNN has had major impacts on radiology and pathology that deal with images from early stage of AI researches (3,4). Deep CNN has also been used in gastrointestinal endoscopy, and studies have examined the detection of Helicobacter pylori gastritis (5) and gastric cancer (6), and the classification of polyps at colonoscopy (7,8).

Oesophageal cancer is the sixth leading cause of cancer-related death (9). Although the main treatment of oesophageal cancer is oesophagectomy, the procedure is invasive, and the physical burden on patients is enormous (10,11). Endoscopic resection is effective for early oesophageal cancer, but it is crucial to determine the indications precisely because oesophageal wall extension of the lesion increases the likelihood of metastasis (11). Oesophageal cancer invading from the epithelium to 200 μm into the submucosa (EP-SM1) has a low risk of metastasis, whereas deeper oesophageal cancer (SM2/3) has a higher risk (12,13). Therefore, the indication for oesophageal resection is up to SM1, and it is required to differentiate EP-SM1 from SM2/3. However, endoscopy is an operator-dependent examination and the diagnosis of oesophageal wall invasion by humans is not thought to be sufficient.

To improve the diagnostic evaluation of oesophageal wall invasion using endoscopy, Nakagawa *et al.* applied a deep learning technique based on CNN (1). They acquired 14,338 endoscopic images (8,660 non-magnified and 5,678 magnified endoscopic images) from 804 superficial oesophageal squamous cell carcinomas with pathological proof of cancer invasion depth as a training dataset and 914 endoscopic images (405 non-magnified and 509 magnified endoscopic images) from 155 patients as a validation dataset.

The images were converted into joint photographic experts group (JPEG) format and resized to 300 × 300 pixels. The training dataset was fed to the deep learning process using the Single Shot MultiBox Detector CNN architecture to create a model to differentiate EP-SM1 and SM2/3. The trained deep CNN model was applied to the validation dataset and its diagnostic performance was assessed. The authors also compared the performance of their deep CNN model with that of 16 board-certified specialists. In this unique study, they found that the deep CNN model and experienced endoscopists had comparable diagnostic ability, with a sensitivity of 90.1% and 89.8%, specificity of 95.8% and 88.3%, and accuracy of 91.0% and 89.6%, respectively, in the validation dataset. The deep CNN model took 29 s to assess the validation dataset, whereas it took an average of 115 min for the endoscopists.

In this retrospective study, a Single Shot MultiBox Detector was used to detect lesions in endoscopic images. Therefore, the lesion does not need to be cropped manually, which is an excellent way to avoid operator-bias. The purpose of this study was to classify the wall invasion of oesophageal cancer; however, the detection of lesions during the examination is also a vital role for deep learning because endoscopy is performed within a limited time. Other researchers have assessed the ability of CNN to detect lesions in endoscopic images (14-16). It would of interest to determine whether the present method can detect lesions in a similar dataset.

Endoscopists diagnose oesophageal cancer wall invasion based on specific endoscopic findings, such as protrusion, depression, and hardness (1). CNN makes the diagnosis by extracting image features. In other hand, although some research has clarified which anatomical structures CNN uses for the diagnosis (17-19), it is difficult to define the imaging features that CNN focused on, such as the pattern of texture and heterogeneity in the lesion. CNN has the potential to surpass human diagnosis and may make diagnoses using imaging findings that humans may not consider (20). Therefore, it is important to clarify what imaging features CNN focuses on during the diagnostic process because this may contribute to the development of medical knowledge.

In recent years, radiomics research has been developed to evaluate image features, such as texture and heterogeneity, which are difficult to represent with general indicators such as size and signal value. Radiomics studies using computed tomography (CT) and positron emission tomography, and magnetic resonance imaging (MRI) have also been conducted in gastrointestinal tract, and are used to predict the prognosis and therapeutic response of lesions (21). Radiomics research has the potential to reveal which image features CNN focuses on; for now, however, the radiomics features that CNN focuses on are in a black box.

In this study, endoscopic images were converted to JPEG format and resized to 300 × 300 pixels; thus, images smaller than original were processed by deep CNN. Because the deep CNN algorithm consists of several layers and handles a lot of parameters during the training phase, it is necessary to reduce the data size of the input image. With advances in hardware and programming of the algorithm, CNN may extract diagnostically more useful imaging features from higher-quality original images, and its diagnostic performance may improve.

This study examined both magnified and non-magnified endoscopic images. The diagnosis of cancer invasion depth using non-magnified endoscopic images is based on subjective imaging findings, which cause interobserver variability. The deep CNN diagnostic performance of magnified endoscopic images was no better than that of non-magnified endoscopic images in this study, and the authors attributed this to the small training dataset. The size of the training dataset strongly correlates with the diagnostic performance of the AI model, and a larger dataset is desired. The use of publicly available datasets or collaborative collections of datasets at multiple facilities could increase the size of training datasets (22). Recently, a generative adversarial network (GAN) has been applied to increase the dataset (22). Given a training set, GAN learns to generate new data and creates fake images indistinguishable from real images. Using GAN may solve the problem of training dataset size.

In conclusion, Nakagawa *et al*. showed the usefulness AI in the diagnosis of cancer oesophageal wall invasion using endoscopic images. The problem of inter-observer variability, which often occurs with endoscopic diagnosis, was not seen with AI, and an accurate diagnosis was possible. In clinical endoscopy, it is necessary to make a diagnosis quickly, unlike with modalities such as CT and MRI. By overcoming this limitation, AI can play a more important role in endoscopic diagnosis.

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