Small Bowel Capsule Endoscopy

Small bowel capsule endoscopy (SBCE) is one of the most useful methods for diagnosing small bowel lesions. When a pill-like capsule endoscope is swallowed, the camera of the capsule endoscope captures the small bowel mucosa. Although it is a noninvasive endoscopy, it has the disadvantage of long reading time. To solve this problem, artificial intelligence (AI) algorithms for SBCE reading are being actively studied. The main goal is to quickly and accurately detect small bowel lesions using an AI algorithm trained on images of lesions. This content briefly summarizes the use of AI algorithms for SBCE reading.

1. Introduction

Small bowel capsule endoscopy (SBCE) was first performed in humans in 2000 [1]. Since then, it has become the first modality in the diagnosis of various small bowel diseases such as obscure gastrointestinal (GI) bleeding, Crohn's disease, small bowel tumor or polyposis syndrome, and celiac disease [2][3][4]. With the advancement of technology, the function of capsule endoscopy, such as battery life and optical performance, have improved [5][6]. However, the long reading time (often more than 1 h) of SBCE has yet to be solved. The length of the small bowel is known to be about 6–8 m [7]. The battery time is about 8 to 12 h and about 50,000 to 100,000 images are captured during an SBCE examination [2][8]. The European Society of Gastrointestinal Endoscopy (ESGE) guidelines recommended a reading rate at a maximum of 10 frames per second in a single view mode [9]. However, reading capsule images for a long time is inevitably boring and burdensome for the clinician. There is also a risk of error resulting from eyestrain.

Therefore, several options have been proposed to reduce the burden of SBCE reading for the clinician. The ESGE guidelines suggest the use of skilled nurses or technicians for pre-reporting [9]. However, this needs additional manpower. Software tools have also been developed to aid in SBCE reading. There have been studies on the suspected bleeding indicator (SBI), which detected obscure GI bleeding, i.e., the most common indication of SBCE [10]. In addition, one study reported that the "QuickView mode", which shows the selected image in the viewer software, reduced the reading time compared to the conventional reading by a clinician (e.g., in short, conventional reading) [11]. However, these reading tools have a limitation in that they are less accurate than conventional reading [11][12]. Currently, lesion detection using an AI algorithm has emerged as a way to save reading time while maintaining the accuracy of lesion detection compared to conventional reading [13].

2. Application of Artificial Intelligence (AI) into the Reading of Small Bowel Capsule Endoscopy (SBCE)

Since 2010, deep learning and convolutional neural network (CNN) algorithms have been used in medicine. Currently, the CNN algorithm is being used as the dominant AI algorithm in the field of medical image reading [13]. As previously mentioned, it takes a lot of time and effort to read a capsule endoscopy. However, among tens of thousands of SBCE images, lesions appear only in a few [14]. To solve this problem, it is essential that reading software can accurately detect small bowel lesions. Therefore, the need for lesion detection using an AI algorithm has increased in SBCE reading.

2.1. Automatic Detection of Small Bowel Lesions

In 2016, a study was published that focused on bleeding detection using an AI (especially CNN) algorithm in SBCE images [15]. Since then, many studies have been published that use an AI algorithm to read SBCE images to detect of various small bowel lesions, including inflammatory lesions (such as erosions and ulcers) [16][17][18][19], vascular lesions (such as bleeding and angioectasia) [20][21][22], and protruding lesions [23]. In these studies, high sensitivity and specificity for lesion detection were confirmed and the feasibility of an AI algorithm for SBCE reading was demonstrated.

However, in a clinical SBCE video, various lesions were shown to exist at the same time or in several places throughout the video. Therefore, studies are needed to develop and verify AI algorithms that can locate various small bowel lesions for use in clinical practice. In one large scale study [24], 158,235 images that contained two normal variants and eight abnormal lesions were used to train an AI algorithm. Then, the validation of an AI algorithm was performed with images not included in the training set. Compared to the conventional reading, the AI-assisted reading showed higher sensitivity and specificity for lesion detection (sensitivity of 99.9% and specificity of 99.9% in AI-assisted reading vs. sensitivity of 74.6% and specificity of 76.9% in conventional reading). The reading time was also reduced by about 94% in the AI-assisted reading compared to that in the conventional reading (96.6 min in conventional reading to 5.9 min in AI-assisted reading). In a multicenter study [25], 66,028 images containing normal mucosa and various lesions were used to train an AI algorithm. The overall accuracy of lesion detection was 98% when reading was performed using an AI algorithm. This showed a higher accuracy compared to that of 89% in "QuickView mode", which was used as a control. In particular, for protruding lesions, the detection accuracy of an AI algorithm significantly improved over the "QuickView mode" (99% vs. 80%). In another study [26], 7556 images containing hemorrhagic lesions and ulcerative lesions (i.e., the most common lesions in SBCE images) were used to train an AI algorithm. A lesion detection accuracy of 96.83% and a sensitivity of 97.6% were confirmed when SBCE reading was performed using an AI algorithm. In another AI-assisted reading study [27], 60,000 images of significant and insignificant lesions were divided by binary classification and used to train an AI algorithm. In total, 20 SBCE cases were externally validated by experts and trainees using conventional reading and AI-assisted reading, respectively. In the external validation test for all 20 SBCE cases, the overall lesion detection rate increased from 29.5% with conventional reading to 63.1% with AI-assisted reading. Moreover, when AI-assisted reading was applied to trainees, the total reading time for 20 SBCE cases reduced by 64% compared to the conventional reading (1621 min with the conventional reading vs. 587 min with AI-assisted reading). In a study that used 39,963 images containing normal and various lesions for training an AI algorithm, area under the curve (AUC) values for detecting inflammatory lesions, vascular lesions, and tumorous lesions were all 0.95 or higher [28] (**Table 1**).

Table 1. Summary of automatic detection of various lesions by using an AI algorithm for reading of small bowel capsule endoscopy.

Author (CNN System)	Lesion Categories (Trained Images) Validation and/or Test (Images)	Results
Ding et al. [24] (ResNet)	**2 normal variants** lymphangiectasia, lymphatic follicular hyperplasia **8 abnormal lesions** inflammation, ulcer, bleeding, polyp vascular disease, protruding lesion, diverticulum, parasite (Total 158,235 trained images) 5000 cases (113,268,334 images)	1. Overall sensitivity 99%. 2. Overall specificity 100%. 3. Shorter reading times than conventional reading. ($p < 0.001$)
Aoki et al. [25] (SSD + ResNET50)	Mucosal breaks (5360 images) Angioectasia (2237 images) Protruding lesions (30,584 images) Blood content (6503 images) 379 cases (5,050,226 images)	1. Detection rate was 100%, 97%, 99% and 100% for each lesion.
Otani et al. [28] (RetinaNet)	Erosions and ulcers (398 images) Vascular lesions (538 images) Tumors (4590 images) 29 cases (14,867 images) in external validation	1. AUC 0.996 at inflamed 2. AUC 0.950 at vascular 3. AUC 0.950 at tumors
Park et al. [27] (Inception-Resnet-V2)	Inflamed mucosa Atypical vascularity, or bleeding (Total 60,000 images) 20 cases (210,100 images) in external validation	1. Overall AUC 0.998. 2. Shorter the reading time for trainees ($p = 0.029$)

Author (CNN System)	Lesion Categories (Trained Images) Validation and/or Test (Images)	Results
Hwang et al. [26] (VGGNet and Grad-CAM)	Hemorrhagic lesions Ulcerative lesions (Total 3778 images [1])	1. Overall AUC 0.9957 2. Sensitivity 96.95% 3. Specificity 97.13%
	162 cases (5760 images)	

[1] 30,224 augmented (×8) image was used for training dataset.

To date, several studies using an AI algorithm for SBCE reading focused on detecting lesions. For automatic lesion detection in selected and single still images, an AI algorithm showed high accuracies. However, studies on AI-assisted reading for images obtained from a of full-length capsule endoscopy are still lacking. In one study [29], 20 full-length SBCE videos, including erosions and ulcers, were read using an AI algorithm. The AI-assisted reading shortened the reading time while maintaining the detection rate compared to the conventional reading. However, this study had a limitation that an AI algorithm did not: it read multiple lesions, such as vascular lesions and protruding lesions. A recent multicenter study [25] was conducted on the detection of various lesions using an AI algorithm at the full-length SBCE video level. This study showed a high detection rate in per-patient analysis, but per-lesion analysis could not be carried out. In addition, it is absolutely necessary to confirm the actual performance of an AI algorithm through a prospective study.

2.2. Automatic Classification of Small Bowel Cleanliness

Although the stomach and colon can be cleaned by suction and washing in a wire endoscopy, bowel cleansing cannot be actively performed in a SBCE. Proper small bowel preparation affects the quality control and lesion detection of SBCE. Therefore, adequate bowel cleanliness is important during the SBCE examination [30][31]. Although small bowel cleanliness scales have been developed [32][33], they also cannot objectively represent the whole small bowel cleanliness. It has also been shown that the intra-observer reproducibility was low when classifying small bowel cleanliness [34]. To increase the intra-observer reproducibility and assess the bowel cleanliness as an objective indicator, several studies have been conducted to evaluate small bowel cleanliness using an AI algorithm.

In one study [35], 55,293 images were classified into dirty and clean images according to a 4-level scale and used to train an AI algorithm. In total, 30 SBCE cases were tested with an AI algorithm and the accuracy of the small bowel cleanliness assessment was confirmed to be 95.2%. In another study [36], 600 normal small bowel images were classified into adequate and inadequate cleanliness according to a 10-point scale and used to train with an AI algorithm. Adequacy evaluation of small bowel cleanliness showed a sensitivity of 90.3%, a specificity of 83.3%, and an accuracy of 89.7% when an AI algorithm was tested using 156 SBCE cases. In a recent study [37], an AI algorithm was trained using 71,191 images that classified bowel cleanliness according to a five-step scoring method. Then, an automated scoring of small bowel cleanliness was conducted by using a trained AI algorithm. The average cleanliness score was 4.0 for the adequate group and 2.9 for the inadequate group ($p < 0.001$). When the cut-off value of cleanliness score was 3.25, the AUC of small bowel cleanliness was found to be 0.977.

2.3. Automatic Compartmentalization of Small Bowel

The main indication of SBCE obscures GI bleeding [2][3]. Therefore, in most cases, upper endoscopy and colonoscopy are performed before SBCE [38]. In other words, the area from oral cavity to second portion of duodenum was already confirmed by wire endoscopy. However, when reading the SBCE in clinical practice, one must first examine the images where the capsule stays in the stomach. During a SBCE, the mean gastric transit time is about 50 min [39]. However, in about 6% of SBCE cases, the capsule stays in the stomach for more than 90 min (delayed gastric transit) or fails the duodenal transit [40]. Therefore, even if the time when capsule passes through the pylorus is accurately identified, the clinician can reduce some of the reading time. In a recent study using OMOM capsule endoscopy device (Jinshan, Chongqing, China) [41], the first duodenal images were used to train an AI algorithm to identify the duodenal transition of the capsule. AUC of 0.984, sensitivity of 97.8%, and specificity of 96.0% were confirmed in the duodenum transit of the capsule. The difference between the actual transit time and the AI determined transit time was mostly within 8 min. The completion of the SBCE study is related to the quality of the SBCE [30]. Therefore, additional research is needed to confirm the cecal transition of the capsule using an AI algorithm.

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