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Deep learning-based classification of rectal fecal retention and analysis of fecal properties using ultrasound images in older adult patients

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Abstract

Aim: The present study aimed to analyze the use of machine learning in ultrasound (US)-based fecal retention assessment.

Methods: The accuracy of deep learning techniques and conventional US methods for the evaluation of fecal properties was compared. The presence or absence of rectal feces was analyzed in 42 patients. Eleven patients without rectal fecal retention on US images were excluded from the analysis; thus, fecal properties were analyzed in 31 patients. Deep learning was used to classify the transverse US images into three types: absence of feces, hyperechoic area, and strong hyperechoic area in the rectum.

Results: Of the 42 patients, 31 tested positive for the presence of rectal feces, zero were false positive, zero were false negative, and 11 were negative, indicating a sensitivity of 100% and a specificity of 100% for the detection of rectal feces in the rectum. Of the 31 positive patients, 14 had hard stools and 17 had other types. Hard stool was detected by US findings in 100% of the patients (14/14), whereas deep learning-based classification detected hard stool in 85.7% of the patients (12/14). Other stool types were detected by US findings in 88.2% of the patients (15/17), while deep learning-based classification also detected other stool types in 88.2% of the patients (15/17).

Conclusions: The results showed that US findings and deep learning-based classification can detect rectal fecal retention in older adult patients and distinguish between the types of fecal retention.

KEYWORDS
constipation, deep learning, fecal property, older adult, rectum, ultrasonography

1 | INTRODUCTION

Chronic constipation is a common problem in older adult people, with some studies reporting symptoms in up to 50% of nursing home residents (Bosshard, Dreher, Schnegg, & Bula, 2004; Zanocchi et al., 2008). However, consensus is lacking on the definition of constipation that combines what the older adults perceive as constipation and what physicians traditionally view as constipation (Tariq, 2007). Older adult people may not complain of subjective symptoms or may have difficulty with communication. Hence, the assessment of chronic constipation by nursing staff is imperative; when it does occur, efforts should focus on initiating appropriate care and treatment to manage the condition, diet and lifestyle, and drug therapy options. However, Japan has the highest prevalence of potentially inappropriate medication management in patients with chronic constipation (Niwata, Yamada, & Ikegami, 2006) because its healthcare providers tend to provide excessive medication to prevent fecal impaction (De Hert et al., 2011). Accordingly, the precise assessment of fecal retention in the colon and rectum is crucial.

Although typically recommended diagnostic tests for constipation include plain abdominal radiography, barium enema, colonoscopy, defecography, abdominal computed tomography, and magnetic resonance imaging (Rao, Ozturk, & Laine, 2005; Remes-Troche & Rao, 2006; Seltzer, 2012), these procedures might provide inadequate information and involve radiation exposure; moreover, they are unsuitable for follow-up testing, are expensive, and lack standardization. Conversely, conventional ultrasonography (US) can be broadly applied in clinical practice because of its low cost, high safety, high speed, and nonionizing radiation (Berger, Tabbers, Kurver, Boluyt, & Benninga, 2012; Perniola et al., 2008). Several recent studies reported using a pelvic sonography technique to diagnose constipation by measuring the rectal diameter in children; US images revealed a fecal mass in the rectum as a crescent-shaped acoustic shadow (Di Pace et al., 2010; Joensson, Siggaard, Rittig, Hagstroem, & Djurhuus, 2008; Karaman et al., 2010). Moreover, rectal US can be used concomitantly to assess fecal retention in adults combined with a physical follow-up examination to assess constipation (Yabunaka et al., 2015; Yabunaka et al., 2018; Yabunaka, Nakagami, Komagata, & Sanada, 2017). US can also be used to visualize rectal fecal retention as constipation patterns. In 74.4% of patients, US detected a continued reflection with acoustic shadow in rectal patterns, indicating fecal retention in the rectum (Tanaka et al., 2018).

When US is used to assess fecal retention in the rectum for point-of-care examinations, healthcare providers depend on the skill and technique of the US technician to properly reach this diagnosis. In particular, in conventional approaches, clinicians may rely too heavily on the US technician's skill in image interpretation, which may lead to poor outcomes (Burlina, Billings, Joshi, & Albayda, 2017). In recent years, nurses have reportedly used US to confirm rectal fecal retention (Matsumoto et al., 2018; Matsumoto, Yabunaka, et al., 2020; Matsumoto, Yoshida, et al., 2020; Tanaka et al., 2018), which suggests that nurses may, through training, acquire skills for obtaining US images. However, problems regarding skills in interpreting US images remain. To overcome this challenge, we focused on deep learning methods, in which image features are learned automatically from the data. Recent algorithmic advances have led to dramatic improvements in general purpose image classification.

The aim of this study was to develop a tool by which clinicians can use US images to assess fecal retention in the rectum by deep learning methods. The accuracy of fecal property evaluations was compared between clinicians who used deep learning techniques and experienced sonographers.

2 | MATERIALS AND METHODS

2.1 | Development of deep learning-based classification system

2.1.1 | Fully convolutional network

Deep learning is a powerful machine learning technique that can approximate complicated mapping of input/output space without special preprocessing. A convolutional neural network (CNN) is a deep learning model commonly used in the field of image recognition. CNN determines the best performance in various tasks such as object detection and semantic segmentation (Russakovsky et al., 2015). A fully convolutional network (FCN) (Lin et al., 2014) is a typical semantic segmentation method based on a CNN that consists of an encoder that extracts the image feature and a decoder that estimates the label map from the extracted feature. For fecal evaluation, we used an FCN to segment areas of transverse rectal images. Considering the data shortage, we used a VGG16-like CNN pretrained by general images as the encoder (Simonyan & Zisserman, 2015), while the decoder was composed of FCN-8 as introduced in the paper. The number of channels in each convolutional layer of the VGG16-like CNN was one-fourth of that of the VGG16. The above procedure was performed with reference to a previous study (Matsumoto et al., 2019).

2.1.2 | Training datasets

The training data were collected from an acute care hospital in Japan by a certified sonographer. Study approval was obtained from the Institutional Review Board. The sonographer plotted rectal US images from outpatients as the training data. The training and evaluation data were collected by different operators in different hospitals. The training data were labeled based on the opinions of two certified sonographers to detect a strong hyperechoic area, hyperechoic area, and acoustic shadow. The total number of data was 97.

2.1.3 | Implementation

Input US images were resized to 512 × 384 pixels and randomly subjected to brightness change, contrast change, and horizontal flip. We used a stochastic gradient descent with momentum for 200 epochs and adjusted the hyperparameters by a random search. Learning rates were initialized to 1e-4 and divided by 10 for every 50 epochs. Our source codes were written based on Keras, and our experiments were run on a single NVIDIA GTX 1080Ti.

2.2 | Evaluation of deep learning-based classification system

2.2.1 | Patients and settings

The data collection was conducted at two Japanese long-term care facilities from May to August 2017. Patients aged ≥65 years with oral intake and an expected hospitalization ≥1 week were included in this study. Patients with a history of colorectal or diarrhea-causing diseases (e.g., enteritis) and those in whom US was difficult to perform were excluded.

2.2.2 | US scanning technique

The purpose and protocol of the study were explained to the patients and their immediate families or extended relatives to obtain informed consent. To obtain the rectal US image just before defecation as much as possible, US was performed once daily while the patient was in bed, after the initial defecation, and until just before the next defecation. Therefore, the number of times US was performed depended on how frequently the patient defecated. Among US images taken at the closest date and time before the next defecation, a single rectal transverse image was selected from each patient for analysis. Normally, using US to check for stool retention in the rectum requires only approximately 5 to 10 seconds at a time, but in this study, it was necessary to acquire and store more accurate images as data. Therefore, acquiring US images took approximately 30 seconds. The patients and nurses were asked to report when defecation occurred. A researcher checked the feces using the Bristol Stool Form Scale immediately after defecation (Chumpitazi et al., 2016). A hand-held ultrasonic device (SonoSite iViz®☐; FUJIFILM-SonoSite, Tokyo, Japan) with a curved array (1–5 MHz) transducer was used. Gain and image depth were adjusted as necessary. The rectum of each patient was scanned using a systematic scanning method (Yabunaka et al., 2018) by a research nurse trained in US.

2.2.3 | Application of deep learning-based classification system

All rectal US images were processed by our developed tool. Figure 1 displays the images with yellow representing the hyperechoic area, red representing the strong hyperechoic area, and green representing the acoustic shadow. In a previous study, we determined that US images with a strong hyperechoic area and acoustic shading were indicative of hard stool in the rectum; thus, shading in the hyperechoic area was indicative of stool in the rectum (Yabunaka et al., 2018).

2.2.4 | Data analysis

First, the transverse US images of rectal feces were assessed by a certified sonographer according to the following visual evidence: (a) the presence of a hyperechoic area (representative of fecal retention) and (b) absence of hyperechoic area (representing absence of fecal retention). US images with poor quality were excluded. After that, the deep learning-based classification tool was used, and US images were classified according to the same visual evidence. The visual evaluation was conducted by a certified sonographer with more than 20 years experience. Two independent certified sonographers evaluated the US images. All images were evaluated under blinded conditions. The relationships between the visual evaluation and presence/absence were assessed by Cohen's kappa statistic to establish agreement between the two certified sonographers.

Second, fecal materials discharged during defecation were classified as hard stool (types 1 or 2 stool according to the Bristol Stool Form Scale) or other types (types 3 to 7 stool according to the Bristol Stool Form Scale). Then, with the sonographer's assessment serving as a reference, the sensitivity and specificity of the deep learning-based classification tool were calculated with and without stool accumulation and with or without hard stool. SPSS for Windows version 22.0 software (IBM, Armonk, NY, USA) was used to conduct the statistical analyses.

2.2.5 | Ethics

Written informed consent was obtained from all participants prior to study enrollment in line with the tenets of

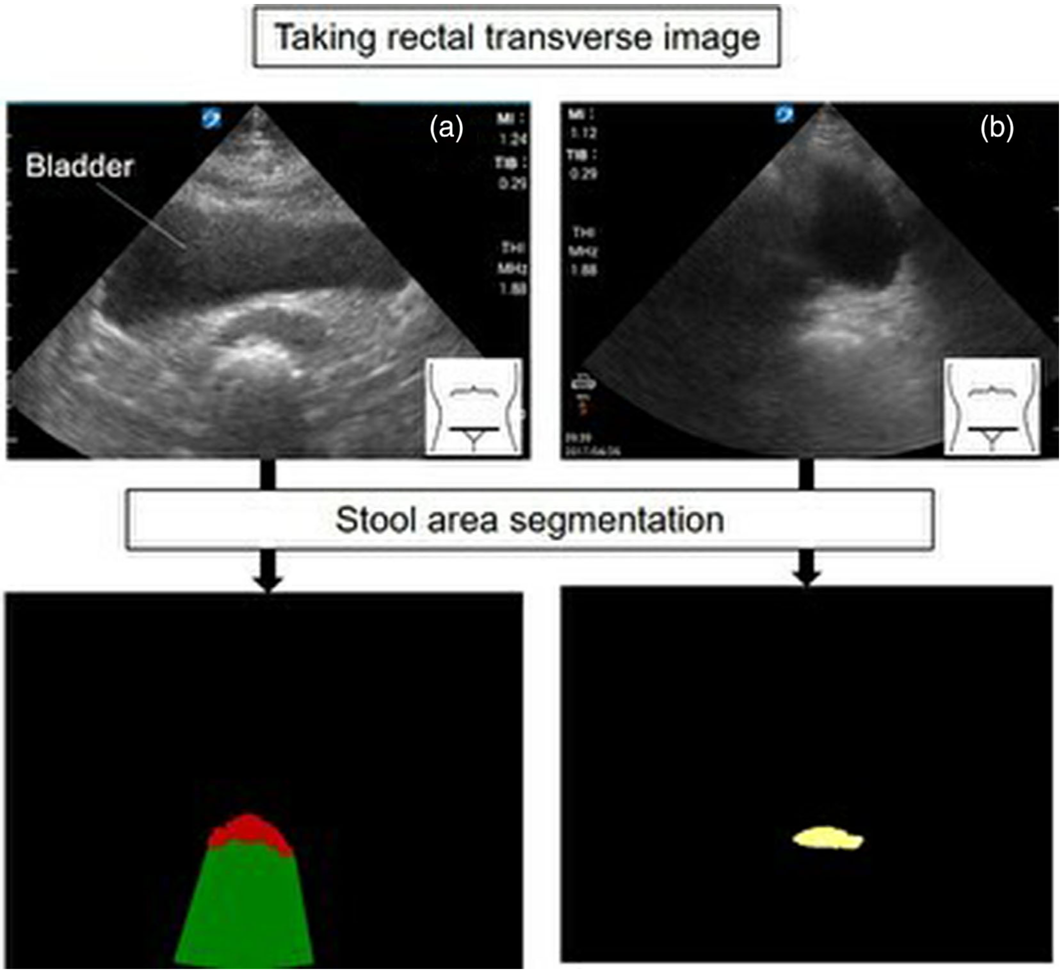

FIGURE 1 An example of training data. The users obtain a transverse image, and the subsequent processing is automated. Stool area segmentation is provided by a deep learning algorithm. (a) The strong hyperechoic area is the original image; the red area represents the strong high echoic area, and green area represents the echoic shadow. (b) The hyperechoic area is the original image; the yellow area represents the high echoic area without the acoustic shadow

TABLE 1 Patient characteristics

	Presence or absence of rectal feces analysis (n = 42)	Analysis of fecal properties (n = 31)
Age, mean ± *SD*	86.0 ± 8.1	86.9 ± 7.3
Women, n (%)	24 (57%)	16 (52%)
Body mass index, mean ± *SD*	19.5 ± 3.9	19.6 ± 4.3

the World Medical Association Declaration of Helsinki. This study was approved by the Research Ethics Committee of The University of Tokyo (No11521-4).

3 | RESULTS

Table 1 summarizes the patients' characteristics. Among the 84 eligible patients, 42 were excluded from analysis (40 in whom defecation could not be confirmed and two for whom image quality was insufficient); therefore, the presence or absence of rectal feces was analyzed in 42 patients. Eleven patients without rectal fecal retention according to the US images were excluded from the analysis; thus, the fecal properties analysis consisted of data for 31 patients (Figure 2). Deep learning was used to classify the transverse US images into three types: absence of feces, a hyperechoic area, and a strong hyperechoic area in the rectum (Figure 3).

Table 2 shows the agreement of the presence or absence of rectal feces. Of the 42 analyzed patients,

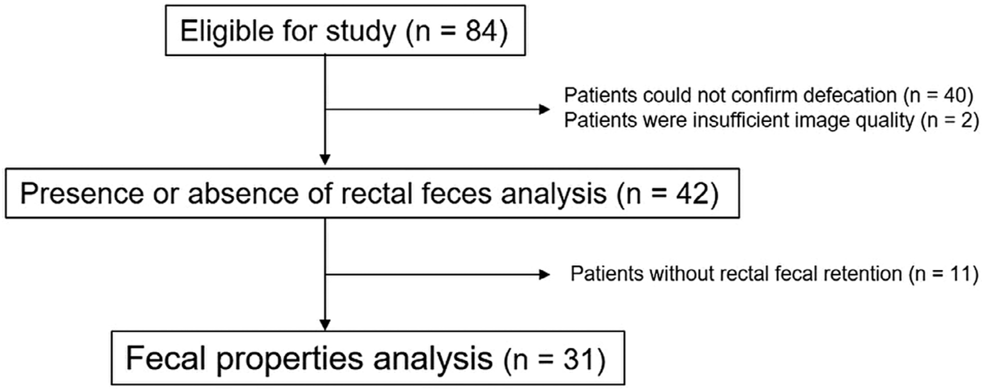

FIGURE 2 Flow of the data

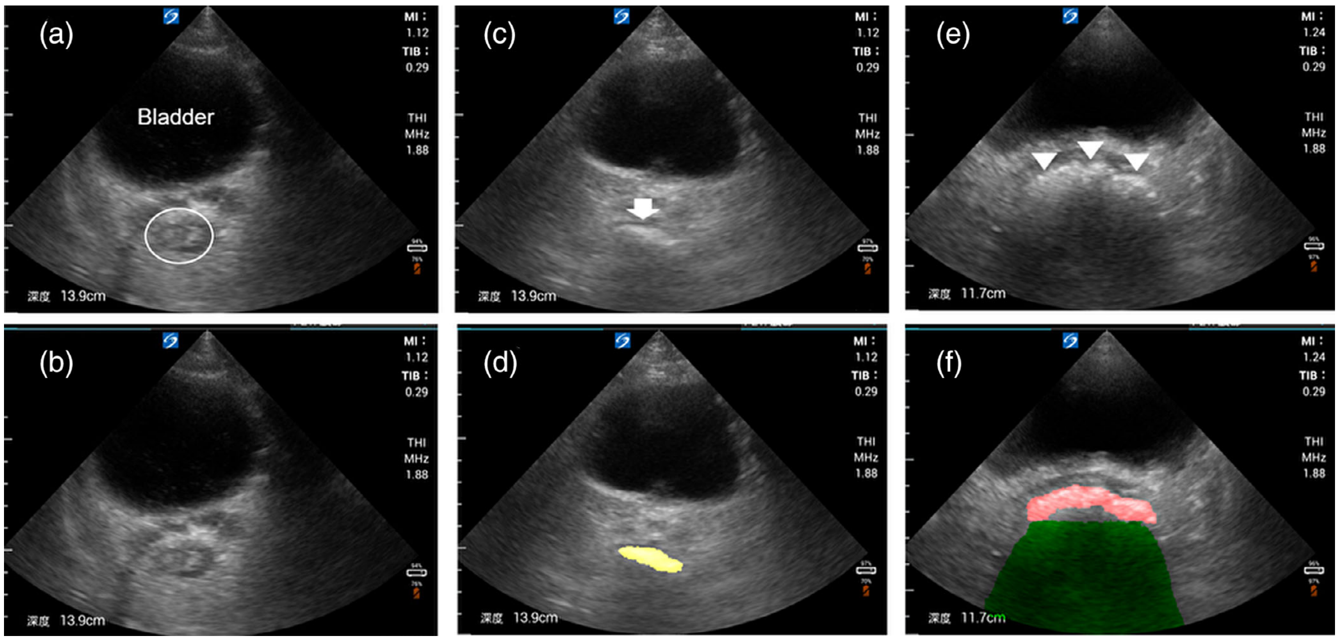

FIGURE 3 Classification of deep learning transvers ultrasound (US) images in rectum. Absence of feces: (a) US image showing no recognizable high echo area (circle); (b) no signal detected by a deep learning algorithm. Hyperechoic area: (c) US image showing a recognizable high echo area (arrow); (d) yellow area represents the high echoic area without the acoustic shadow according to a deep learning algorithm. Strong hyperechoic area: (e) US image showing a recognizable strong high echo area (arrowheads); (f) red area represents the strong high echoic area and green represents the acoustic shadow according to a deep learning algorithm

31 tested positive for the presence of rectal feces, none were false positive or false negative, and 11 were negative, indicating a sensitivity of 100% and a specificity of 100% for the detection of feces in the rectum. Table 3 shows the agreement of fecal properties. Of the 31 patients with rectal feces, fecal properties were classified as hard stool in 14 patients and other in 17 patients based on the Bristol Stool Form Scale. Of patients with hard stool, US detected 100% of patients (14/14), whereas deep learning-based classification detected 85.7% of patients (12/14). Of patients with other types of stool, US detected 88.2% of patients (15/17), whereas deep learning-based classification detected 88.2% of patients (15/17). Cohen's kappa statistic for the visual evaluation and presence/absence agreed at an inter-rater reliability of $\kappa = 0.95$.

4 | DISCUSSION

In the present study, US and the deep learning techniques had high rates of detecting the presence or absence of rectal feces (100% sensitivity and 100% specificity) and fecal properties in the rectum (hard stool detection: US detected 100%, deep learning techniques detected 85.7%). The deep learning-based classification

TABLE 2 Analysis of the presence or absence of rectal feces (n = 42)

		Sonographer	
		Presence[a]	**Absence**[b]
Dl	Presence[a]	31	0
	Absence[b]	0	11

[a]Presence: presence of hyperechoic area.
[b]Absence: absence of hyperechoic area.
DL, deep learning-based classification.

TABLE 3 Analysis of fecal properties (n = 31)

		Fecal properties	
		Hard stool[a] **(n = 14)**	**Others**[b] **(n = 17)**
Sonographer	(+)	14	2
	(−)	0	15
Dl	(+)	12	2
	(−)	2	15

[a]Hard stool: Bristol Stool Form Scale score of 1 or 2.
[b]Others: Bristol Stool Form Scale score of 3–7.
DL, deep learning-based classification.
Note: (+): presence of hyperechoic area with acoustic shadow; (−): absence of hyperechoic area with acoustic shadow.

tool that we created (Tanaka et al., 2018) identified fecal retention and fecal properties in the rectum.

A previous study reported that hard stool was discharged in 92.9% of older adults who had US findings of a crescent-shaped strong hyperechoic area with an acoustic shadow (Tanaka et al., 2018). In this study, red in the strong hyperechoic area and green in the acoustic shadow hyperechoic area represented hard stools. However, two of the hard stool cases were false negatives according to the deep learning method. False negative cases (hard stool classified as normal stool) occurred because of the narrow hyperechoic area and underestimation of the acoustic shadow. Both deep learning and US identified two false cases of other types of stool. False positive cases (normal stool classified as hard stool) were evaluated as hard stool because of the wide hyperechoic area and overestimation of the acoustic shadow. Thus, deep learning-based classification of rectal feces requires further improvement in the future.

In healthy adults, rectal fecal retention was observed only when they had a desire to defecate (Halls, 1965). The results of our study support those of our previous work, in which the images of 74.4% of older Japanese patients with physical and cognitive impairments showed a continued reflection with acoustic shadow, indicating fecal retention in the rectum (Tanaka et al., 2018). In addition, older adults with physical or cognitive impairment tended to have a higher rectal perception threshold than younger people (Whelan, Judd, Preedy, & Taylor, 2008). Therefore, the abnormal patterns of fecal distribution may cause older people to feel uncomfortable due to continuous fecal retention in the rectum. Thus, defecation care based on US findings is necessary, such as confirming fecal retention by US and giving priority to promptly discharge feces in cases of fecal retention.

In previous studies, the use of machine learning to classify US images helped with the development of diagnostic support tools such as the automatic identification of breast lesions and myositis (Burlina et al., 2017; Han et al., 2017). However, in these studies, automatic identification was not performed in real time. Conversely, we hope to use this tool to evaluate rectal feces retention at the bedside, particularly by visiting nurses in home care settings. Nursing care requires easy assessment procedures in real time using a minimal US device. In the future, with the use of US for defecation care in home care settings, feces in the rectum must be identified with high accuracy based on the quality of the hand-held US image, and the result must be displayed on the US device screen in real time. Such a tool will help nurses perform US assessments of rectal feces retention without the need for special techniques.

This study has some limitations. First, the study population was small. Future studies with large numbers of older adult subjects are required to further examine the use of US for determining the fecal retention status. Second, additional consideration must be given to the reliance on the skill and technique of the US operator. Third, there was patient age and body mass index bias because this study targeted Japan's older adult population. Finally, this study focused on rectal feces and did not observe other parts of the colon. However, when assessing constipation type, other parts of the colon (e.g., descending) must be observed. Future studies must increase the number of patients and further evaluate the accuracy of deep learning techniques.

5 | CONCLUSION

This study considered the development of machine learning methods for automatically classifying fecal retention and properties in the rectum on US imaging. We showed that these techniques can detect rectal fecal retention in older adult patients and distinguish between types of fecal retention among them.

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CONFLICT OF INTERESTS

Masaru Matsumoto and Yuka Miura belong to a social collaboration department that receives funding from Fujifilm Corporation. Takuya Tsutaoka belongs to Fujifilm Corporation. Mikako Yoshida belonged to a social collaboration department that receives funding from Fujifilm Corporation.

AUTHORS' CONTRIBUTIONS

All the authors contributed to the conception and design of this study. M.M., T.T. and S.T. carried out the data collection and analysis. M.M., T.T. and G.N. drafted the manuscript. J.S., S.O., H.O. and H.S. critically reviewed the manuscript and supervised the whole study process. All the authors read and approved the final version of the manuscript.

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