# **Development of Real-Time Detection System for Ultrasound Images of the Descending Colon Region Using Deep Learning**

Deep Learning を使用した下行結腸部位超音波画像のリアルタイム検出システムの開発

Ryota Kabata<sup>1‡</sup>, Jun Orihara<sup>1</sup>, Junko Yotsuya<sup>2</sup>, and Masayuki Tanabe<sup>3</sup> (<sup>1</sup> Grad. School Sci Technol, Kumamoto Univ. <sup>2</sup>Dept. Medicine, Fukui Univ.; <sup>3</sup>Fac. Adv. Sci. Tech., Kumamoto Univ.)

椛田涼太 <sup>1‡</sup>, 折原純 <sup>1</sup>, 四谷淳子 <sup>2</sup>, 田邉将之 <sup>3</sup>(<sup>1</sup>熊本大院 自然科学, <sup>2</sup>福井大 医, <sup>3</sup>熊本大院 先 端科学)

# 1. Introduction

In 2007, Japan became a super-aging society, which is defined as a society where the percentage of the population over 65 years old accounts for 21 % of the total population. Even now, the number of people who need nursing care is increasing, while there is a shortage of workers to provide nursing care [1]. Among the various types of care, bowel care is a major issue for both the care recipient and the caregiver [2].

Bowel care is a heavy work for caregivers as well as greatly damaging the self-esteem of the care recipient. In concrete terms, diapers should be checked and changed frequently while estimating the timing of defecation based on the past defecation schedule.In case of constipation, judging from the position and amount of stool stored in the large intestine, measures such as removal of stool, laxatives, and enemas are taken. Until now, questioning and palpation have been the most common methods of care for constipation. Monitoring by ultrasonography of the colon area has been proposed as a more accurate way to determine the condition.

Medical ultrasound imaging equipment is inexpensive compared to other medical equipment and can visualize the inside of the body in a noninvasive manner, and is widely used in diagnostic imaging systems and ultrasonic urine gravitometers. However, the reading of ultrasound images requires skill. This has been a bottleneck to the widespread use of diagnostic ultrasound systems.

Analysis of ultrasound images has been performed to assist in the reading of ultrasound images of the colon by humans [3]. We attempted to obtain information such as fecal hardness and the presence of gas by processing images of a single axis of the descending colon of the large intestine while considering the acoustic characteristics [4]. We also tried image classification using that information and support vector machine, and obtained better results than CNN trained on a small data set [5]. In a previous study, we used a CNN to classify ultrasound images using the presence or absence of the colon as a class [6]. The number of images was about 14,000 training data and about 1,400 test data. As a result, an average accuracy of 99 % was obtained for the long axis of the descending colon.

However, previous studies have not examined the actual real-time use of colorectal classification, and it is assumed that 20 to 30 fps would be sufficient for point-of-care use.

The two specific processes to be applied to a single ultrasound image are: discrimination of the presence or absence of the large intestine, and if the large intestine is visible, further discrimination of the stool characteristics stored in the large intestine.

In this study, we first classify the presence or absence of the colon using deep learning, and then evaluate the accuracy and processing time. To evaluate the accuracy, we will use sensitivity, specificity, fit rate, and F value. To evaluate the processing time, the frame rate is calculated from the time required for inference of one image.

## 2. Method

Eleven male subjects in their twenties were subjected to abdominal ultrasonography, and their videos were acquired. Ten subjects were used as training data and one subject as test data, and image classification was performed using them. Each of these 30-second videos was saved as approximately 700 still images. An example of ultrasound image of the descending colon is shown in **Fig. 1**.

These images were labeled as to whether they showed the colon or not. The labeled images were used as a data set for GoogLeNet [7].

mtanabe@cs.kumamoto-u.ac.jp



Fig. 1. Example of ultrasound image of the descending colon.

### 3. Results

**Figure 2** illustrates the evaluation indices of the classification of the longitudinal axis of the colon when the subjects of the test data were changed. Most of indices, sensitivity, specificity, fit rate, and F-measures, were 100 %. In addition, the inference of one image was performed 10 times. As a result, the average processing speed for one image was 89 fps.



Fig. 2. Change in evaluation index of classification of colorectal long axis when changing the test data subjects.

#### 4. Conclusion

Using deep learning, the colorectal region was automatically detected from the ultrasound image, and the accuracy and the time taken for the calculation were measured. The results showed very high values for each index except for one subject. The low value of one subject may have been due to the fact that he was not accustomed to video recording and was not able to capture the colon properly. However, a bias toward young and healthy males cannot be excluded from the results of this experiment. In the future, more data of diverse ages, genders, and health conditions will be obtained to clarify this concern.

In terms of computation time, it took an average of 11.1 ms to discriminate the presence or absence of the colon for one image. The calculated frame rate was 89 fps. As a next step, the computational time will also be measured for the process of discriminating the nature of stool stored inside the colon.

## References

- 1. Ministry of Health: Labour and Welfare:Report on the status of long-term care insurance business in FY 2008, Retrieved August 3, 2021.
- 2. Y. Kikuchi, J. Minai and S. Shimanouchi: Bulletin of International University of Health and Welfare, **15**(2) (2010), 13–23.
- S. Liu, Y. Wang, X. Yang, B. Lei, L. Liu, S. X. Li, D. Nia and T. Wang: Engineering, 5(2) (2019), 261–275.
- 4. M. Tanabe, and J. Matsuo: Japan patent P6592836, (2009).
- 5. M. Tanabe, K. Tomihara, J. Yotsuya: Ultrasound TECHNO, **31**(2) (2019), 64–71.
- K. Ryota, T. Sugino, J. Orihara, M. Tanabe and J. Yotsuya: 41th Symp. Ultrasonic Electronics, (2020) 2Pb5-1.
- C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich: Proc. CVPR, 2015. DOI: 10.1109/CVPR.2015.7298594.