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Effect of Imaging Parameters on Classification Accuracy of Large Intestine B-mode Images in Deep Learning

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1. Introduction

Ultrasound imaging is considered an effective means of diagnosing many diseases of the heart and liver due to its excellent temporal resolution, high image quality, and noninvasiveness. Therefore, research is being conducted to perform portable imaging[1], 3D imaging[2], and ultrafast imaging[3,4] in emergency medicine. Among these applications of ultrasound in the medical field, abdominal ultrasound examination is one of the effective methods to observe the condition of the colon. In a previous study, ultrasound examination of the descending colon of the large intestine was used to determine and classify stool characteristics, predict the timing of defecation, and diagnose disease[5]. However, ultrasonography requires skill, and it is difficult for anyone other than a medical professional to project a certain position. Therefore, in recent years, various applications of machine learning in ultrasonography have been proposed[6].

In recent years, CAD (Computer-Aided Diagnosis) has become a popular AI-based method of medical support. When performing ultrasound diagnosis, physicians do not necessarily deal only with ultrasound images of cases in which they have expertise, but also with a variety of cases. In some cases, they may be dealing with rare cases, which can be overlooked if the physician alone makes judgments based on ultrasound images. To prevent this oversight, an x-ray or MRI examination may be used in combination, but in clinical medicine, where the real-time nature of ultrasound diagnosis is required, on-the-spot judgment is necessary. By referring to the diagnosis made by the AI, physicians can make a diagnosis, allowing them to quickly make an accurate diagnosis from the ultrasound images. The use of deep learning to create this AI requires a huge dataset of medical images. However, there are several problems in creating medical ultrasound data sets. One of them is that the performance and parameters of different types of ultrasound equipment vary, resulting in differences in the images produced. There are a wide range of ultrasound equipment, from large stationary devices to portable devices, and it is not easy to create a data set that perfectly matches the parameters used by each device for imaging. It is not clear to what extent the use of data taken under different conditions (i.e., with different equipment and different parameters) as a data set affects the correct response rate in deep learning. Therefore, in this study, we compared the results of inference on colorectal ultrasound images taken under different conditions by creating a dataset of only each condition and training the model on it using deep learning, and by creating a dataset with a mixture of each dataset and training the model on it using deep learning. By comparing the results of the two datasets, we examine the extent to which the data sets are affected by the loss of uniformity.

2. Method

The ultrasound examination was conducted using iViz Air (FUJIFILM Medical Co., Ltd.) and viwphii-US (Socionext Inc.) convex probes.The frequency was set between 2 and 5 MHz, the gain was adjusted during the scan, and the depth (depth of field) was 15 cm for iViz Air and 14 cm for viewphii-US.

To create the dataset, abdominal ultrasound examinations were first performed on 11 male subjects in their 20's with the iViz Air, and the images were acquired. The same abdominal ultrasonography was also performed on five male subjects in their 20's using viewphii-US, and the images were acquired. Specifically, six types of images were obtained: (1) one showing the long axis of the descending colon, (2) one showing the short axis of the descending colon, (3) one tilted toward the umbilicus from the point where the colon is shown, (4) one tilted toward the back from the point where the colon is shown, (5) one slid toward the umbilicus from the point where the colon is shown, and (6) one slid toward the back from the point where the colon is shown. (6) a slide from the point where the large intestine was visible to the backside. These six types of videos were taken and image classification was performed with 10 subjects as training data and 1 subject as test data. Each of these 30-second videos was stored as approximately 700 still images. Examples of the ultrasound images of the descending colon used for training, taken with the iViz Air, are shown in **Fig. 1**, and those taken with the viewphii-US are shown in **Fig. 2**.

Fig. 1. Example of an ultrasound image of the descending colon taken with the iViz Air.

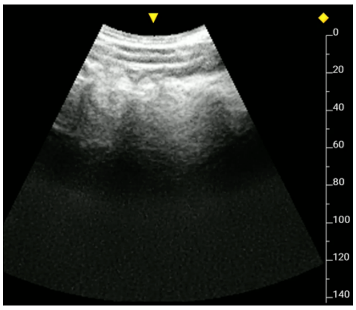

Fig. 2. Example of ultrasound image of the descending colon.

(1), (2) are annotated as having colon and (3), (4), (5), (6) are annotated as having no colon. These labeled images were used as the ResNet152 dataset.

3. Result

Figures 3 and 4 show the transition of the correct response rate and loss function for each epoch when training and inference are performed on the dataset taken using iViz Air and viewphii-US, respectively.

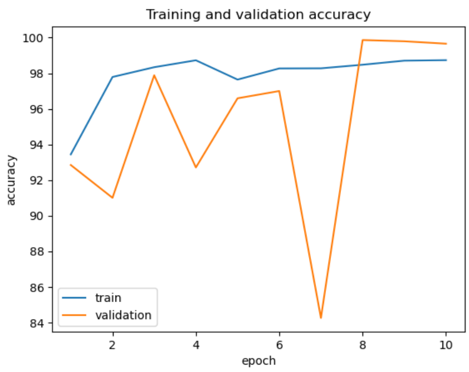

Fig. 3. Percentage of correct answers in the iViz Air dataset.

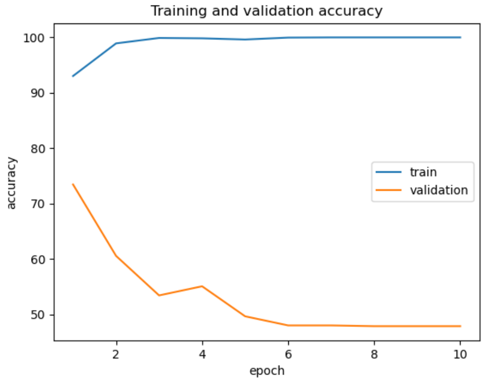

Fig. 4. Percentage of correct answers in the viewphii-US dataset.

4. Conclusion

For the data set taken with iViz Air, we classified the colon with a very high correct response rate, but for the data set taken with viewphii-US, the results were not highly accurate. This may be due to the fact that the data set captured by viewphii-US is for five people, less than half the amount of data captured by iViz Air.It is also possible that the video taken with viewphii-US did not accurately show the colon because the iViz Air had a higher level of filming skill. We are also considering increasing the number of datasets taken by viewphii-US and conducting another validation.In addition, we would like to conduct the same verification using a data set that combines data taken with iViz Air and data taken with viewphii-US.

Reference

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