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A study on optimal input image conditions for each type of tumor in convolutional neural network for classifying ultrasound images of liver tumors

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1. Introduction

In recent years, artificial intelligence (AI) technology has made great advances and is now being used in many fields. Many AI technologies have been also put into practical use in medical devices, and many AI technologies are currently being researched and developed. We have also been developing AI to support ultrasound image diagnosis, [1-4]. In general, the quantity and quality of training data are important in AI development, and large amounts of high-quality data are required to develop highly accurate AI.

In ultrasound imaging diagnosis, not only information about the inside of the tumor but also information about the area around the tumor is important. For example, when diagnosing liver tumors, the state of fibrosis around the tumor is important diagnostic information. Therefore, we previously conducted research on how much information around the tumor should be used to achieve the highest accuracy in convolutional neural networks (CNNs), which classify and detect liver tumors from ultrasound images, [5,6]. As a result, we reported that the accuracy of liver tumor ultrasound image classification was highest when the maximum diameter of the liver tumor was 60% of the CNN input image size, [5]. On the other hand, in liver tumor detection, we reported that the detection accuracy was highest when the maximum diameter of the liver tumor was 90% of the ground truth region size, [6]. These results indicate that little information about the area surrounding liver tumors is required for detection, whereas more information about the area surrounding liver tumors is required for liver tumor classification. In this previous study of liver tumor classification, the number of data was small, so no clear trends were observed in the accuracy for each type of liver tumor (cyst, hemangioma, hepatocellular carcinoma (HCC), metastatic liver cancer (Meta)). It is thought that the amount of information around the tumor required for diagnosis differs depending on the type of liver tumor.

Therefore, in this study, we will increase the amount of data and verify how much information around the tumor should be used to achieve the highest accuracy for each liver tumor type. Until now, we have been developing AI to improve accuracy for liver tumors as a whole, but because accuracy for malignant tumors is more important in clinical practice, the results of this study will make it possible to develop AI with higher accuracy for malignant tumors.

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2. Method

2.1. Data

In this study, we used ultrasound image data of liver tumors collected from 11 hospitals under the leadership of the Japan Society of Ultrasound in Medicine with support from AMED. The data shown in **Table I** were used in this report. These data were collected by February 16, 2020.

Table I Data used in this study

Tumor type	Number of cases	Number of images
Cyst	1,225	3,580
Hemangioma	964	2,726
HCC	604	2,759
Meta	605	3,149
Total	3,398	12,214

2.2. Convolutional neural network

In this study, we used a VGG19, [7]-based CNN with an input image size of 128 × 128 × 1 and four outputs to classify liver tumor ultrasound images into four classes: cyst, hemangioma, HCC, and Meta. We chose this CNN because it had the best accuracy when comparing various input image sizes and various CNNs. On the other hand, in our previous studies, the amount of data was small, so a CNN with a small input image size of 64 × 64 × 1 and a shallow network depth was used, [5].

2.3. ROI cropping

To verify how much information about the area around the liver tumor should be included in the ROI image (CNN input image) to maximize accuracy, we used *D/L*, calculated by dividing the maximum diameter of the tumor (*D*) by the size of

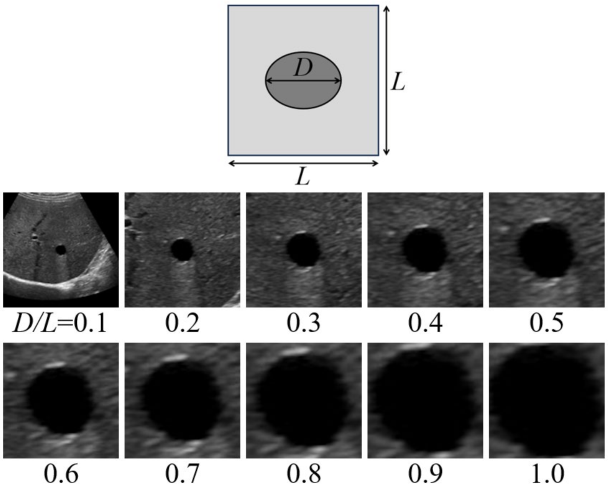

Fig. 1 ROI cropping index *D/L* and examples of ROI images cropped at each *D/L*.

the square ROI (*L*), as in our previous studies. As shown in **Figure 1**, the value of D/L was changed from 0.1 to 1.0 in 0.1 intervals to create training data for each ROI cropping condition. The images cropped for each D/L value were resized to the input image size of our CNN.

2.4. Validation and Data augmentation

We used k-fold cross-validation (k=10) as the validation method. We also added left-right inverted images as training data, doubling the amount of training data. However, in the evaluation, only the original ROI images were used as test data. We evaluated the accuracy in cases and evaluated this accuracy for each type of liver tumor.

3. Result

The results of evaluating the accuracy for each liver tumor type by changing the *D/L* value are shown in **Figure 2**. From this result, the accuracy was highest for cysts and hemangiomas when *D/L*=0.6. This result is consistent with the result of all liver tumors in our previous study. This may be because in our previous study, the amount of data for cyst and hemangioma was greater than that for HCC and Meta. On the other hand, for HCC, the accuracy was highest when D/L was 0.5 and 0.6, and for Meta, the accuracy was highest when D/L was 0.4. In ultrasound images, HCC and Meta have very similar image characteristics. On the other hand, around the tumor, fibrosis is often observed in HCC, whereas fibrosis is rarely observed in Meta. Therefore, we think that the diagnosis of HCC and Meta achieved higher accuracy by using more information around the tumor.

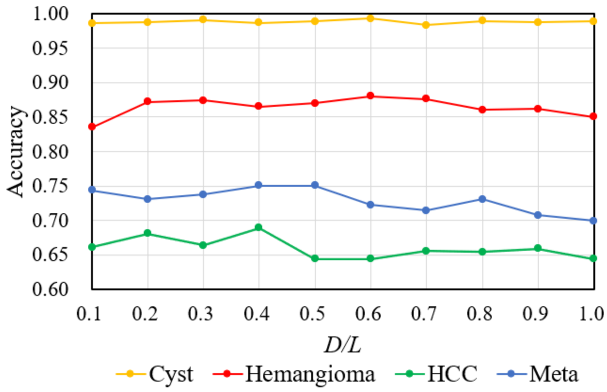

Fig. 2 Accuracy at each D/L for each type of liver tumor.

4. Conclusion

In this study, we examined how much information about the area surrounding the liver tumor should be included in the input image of CNN for each type of liver tumor to maximize accuracy. As a result, we found that for malignant tumors such as HCC and Meta, accuracy is improved by including more information about the area around the tumor in the input image of the CNN than for benign tumors such as cysts and hemangiomas. Therefore, based on the results of this study, we plan to develop AI to assist in ultrasound imaging diagnosis of liver tumors with improved diagnostic accuracy for malignant tumors.

Acknowledgment

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