Improved classification accuracy of liver tumors by ultrasound image deep learning model with hepatitis virus infection information

肝炎ウィルス感染情報を加えた深層学習による超音波肝腫瘍画像の分類精度改善の試み

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1. Introduction

The world's prevalence of liver cancer in 2015 was the sixth highest in the world, and it was shown that the death from liver cancer was the fourth highest after lung cancer, colorectal cancer, and stomach cancer[1]. Ultrasonography(US) is one of the modalities used in the diagnosis of liver cancer. Among the OECD member countries, Japan has the largest number of CTs and MRIs, but the number of radiologists is at the bottom[2]. Radiologists have to make many diagnostic imaging, and reading more than 6 images per hour significantly increases the error rate[3]. In recent years, in the field of medical diagnostic imaging, research on computer-aided diagnosis (CAD) using deep learning methods has been actively conducted[4-6]. A large database is required to improve the diagnostic accuracy of deep learning.Therefore, the Japan Society of Ultrasound Medicine(JSUM) has also created an ultrasound image database of liver tumors, breast tumors, and heart diseases. In this study, we aim to establish a method for improving the diagnostic accuracy of liver tumor on US images.

In the classification of liver fibrosis using CT images by deep learning, the classification accuracy is improved by adding gender and age as additional information[7].However, studies have not yet been conducted to classify US images of liver tumor by deep learning using images and additional information. Therefore, we tried to improve the classification accuracy of liver tumor US images by adding hepatitis virus infection information to deep learning.

2. Method

The liver tumor US data used in this study was collected with the approval of the Ethics Committee in AMED project of the JSUM. This data consists of 1,384 training data, 154 validation data, and 171 test data. 171 test data include 75 cyst images, 26

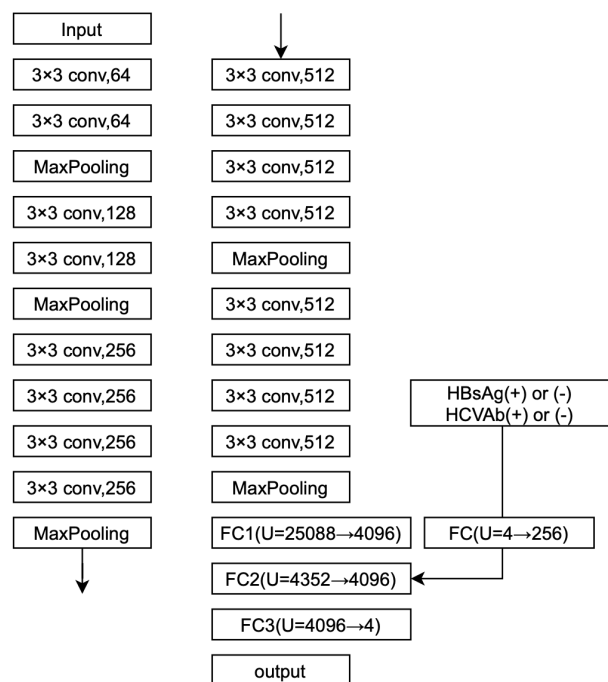d.hatamoto@shiz-med-sci.ac.jp

Fig.1 The structure of our CNN. Conv; convolutional layer. FC; fully connected layer. U; unit.

hepatocellular carcinoma (HCC) images, 52 hepatic hemangioma images, and 18 metastatic liver cancer images.

The deep learning method used in this study is a convolutional neural network (CNN) based on VGG net [8]. The infection information added to CNN is the positive or negative of hepatitis B surface antigen (HBsAg) and hepatitis C virus antibody (HCVAb). Infection information for each image is a combination of positive and negative of HBsAg and HCVAb, and there are 4 patterns.

Infection information for each image was entered in the second layer of the fully connected layer of CNN (Fig.1). In our CNN, the input image size is 224×224, and output is 4 classes (liver cyst, hepatic hemangioma, hepatocellular carcinoma, metastatic liver cancer).

3. Result

The addition of infection information increased the accuracy of HCC classification. This result is consistent with our expectations, as hepatitis is likely to cause HCC. In a network with only image input, the amount of data in each class was imbalanced, so it tended to be estimated as Cyst and hemangiomas. By adding infection information, the network has become stronger tendency to estimate to Cyst. It is probable that the effect of data imbalance was stronger because the addition of infection information made it easier to classify into HCC. In the future, improving the data imbalance by increasing the amount of data through data expansion may solve the problem.

4. Conclusion

As a result of adding infection information, the classification accuracy of HCC has improved, but the network has become tendency to estimate to Cyst. This problem may be remedied by reducing data inequality through data augmentation.

Acknowledgment

Table. 1 Classification results

(A) CNN

	Predict			
True	Cyst	Hemangioma	HCC	Meta
Cyst	63	10	2	0
Hemangioma	3	37	6	6
HCC	3	15	3	5
Meta	2	8	3	5

(B) CNN+infection information

	Predict			
True	Cyst	Hemangioma	HCC	Meta
Cyst	73	1	0	1
Hemangioma	7	32	7	6
HCC	5	10	9	2
Meta	6	4	3	5

Table. 2 Classification accuracy

(A) CNN

Tumor type	Precision	Recall	F1-Score
Cyst	0.89	0.84	0.86
Hemangioma	0.53	0.71	0.61
HCC	0.21	0.12	0.15
Meta	0.31	0.28	0.29

(B) CNN+infection information

Tumor type	Precision	Recall	F1-Score
Cyst	0.80	0.97	0.88
Hemangioma	0.68	0.62	0.65
HCC	0.47	0.35	0.40
Meta	0.36	0.28	0.31

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