Original Article

Classification of hepatic cavernous hemangioma or hepatocellular carcinoma using a convolutional neural network model

Yunbao Cao[1#], Jing Yu[2#], Hu Zhang[1], Jian Xiong[1], Zhonghua Luo[1]

[1]Department of Interventional Radiology, Tangdu Hospital, Fourth Military Medical University, Xi'an, China; [2]Department of Radiology, Xijing Hospital, Fourth Military Medical University, Xi'an, China

Contributions: (I) Conception and design: Z Luo; (II) Administrative support: Z Luo; (III) Provision of study materials or patients: Z Luo, H Zhang; (IV) Collection and assembly of data: Y Cao, J Yu; (V) Data analysis and interpretation: H Zhang, J Xiong; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

[#]These authors contributed equally to this work.

Correspondence to: Zhonghua Luo, MD. Department of Interventional Radiology, Tangdu Hospital, Fourth Military Medical University, Xi'an, China. Email: llhuaxian@163.com.

Background: Computed tomography (CT) is a common imaging technique for diagnosis of liver tumors. However, the intensity similarity on non-contrast CT images is small, making it difficult for radiologists to visually identify hepatic cavernous hemangioma (HCH) and hepatocellular carcinoma (HCC). Recently, convolutional neural networks (CNN) have been widely used in the study of medical image classification because more discriminative image features can be extracted than the human eye. Therefore, this study focused on developing a CNN model for identifying HCH and HCC.

Methods: This study is a retrospective study. A dataset consisting of 774 non-contrast CT images was collected from 50 patients with HCC or HCH, and the ground truth was given by three radiologists based on contrast-enhanced CT. Firstly, the non-contrast CT images dataset were randomly divided into a training set (n=559) and a test set (n=215). Then, we performed preprocessing of the non-contrast CT images using pseudo-color conversion, and the proposed CNN model developed using training set. Finally, the following indicators (accuracy, precision, recall) were used to quantitatively analyze the results.

Results: In the test set, the proposed CNN model achieved a high classification accuracy of 84.25%, precision of 81.36%, and recall of 82.18%.

Conclusions: The CNN model for identifying HCH and HCC improves the accuracy of diagnosis on non-contrast CT images.

Keywords: Liver tumor; convolutional neural network (CNN); computed tomography (CT); medical image classification

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Introduction

Clinically, hepatic cavernous hemangioma (HCH) and hepatocellular carcinoma (HCC) are common liver tumors (1). However, HCHs are usually stable and require only regular follow-up visits. HCC is a common malignant tumor worldwide (2), causing a heavy healthcare burden in many countries (3). Therefore, diagnosis and treatment of HCC or HCH are of particular importance (4).

Computed tomography (CT) examination is one of diagnosis tools for liver tumors (5). However, the imaging appearances of HCH and HCC on non-contrast CT images are similar, and it is difficult to distinguish them based on tumor morphological characteristics and intensity values. By intravenously injecting contrast media, radiologists diagnose liver tumors by observing the enhanced area of the

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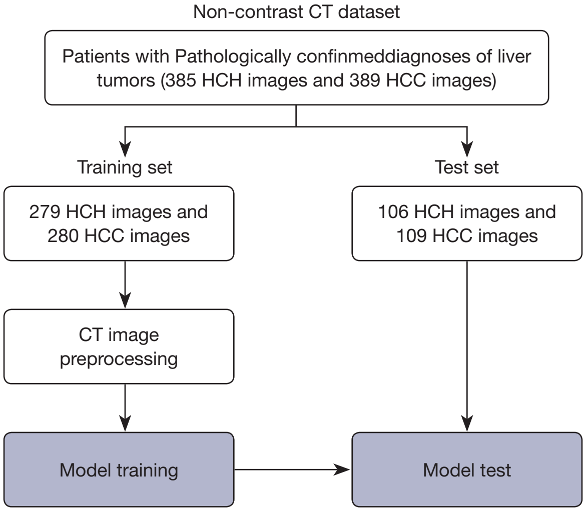

Figure 1 Flow diagram for deep learning model training and testing. CT, computed tomography; HCH, hepatic cavernous hemangioma; HCC, hepatocellular carcinoma.

tumor. However, the use of contrast medium may lead to acute kidney injury or other side effects (6).

Convolutional neural network (CNN) has been widely used to address many difficult medical problems because more discriminative image features can be extracted than the human eye (1,7-10). Such capabilities have been verified in brain tumor classification. However, the use of DL models to classify liver tumors on non-contrast CT images has not yet been reported. In this study, we proposed a CNN model that can classify liver tumors on non-contrast CT images. We present the following article in accordance with the STARD reporting checklist (available at https://jgo.amegroups.com/article/view/10.21037/jgo-22-197/rc).

Methods

This retrospective study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by institutional ethics committee of Institution for National Drug Clinical Trials, Tangdu Hospital (No. K202108-43) and individual consent for this retrospective analysis was waived. An overview of the model training and validation is illustrated in *Figure 1*.

Dataset

The liver tumor dataset consisted of 774 non-contrast CT images, which were collected from 50 patients with HCC or HCH, and the ground truth was given by three radiologists based on contrast-enhanced CT. All patients met the following criteria: (I) diagnosed HCC or HCH based on liver biopsy or clinical findings (based on clinical signs such as laboratory tests, imaging examinations); and (II) no contraindications to contrast medium and has undergone upper abdominal contrast-enhanced CT scans. The non-contrast CT images dataset were randomly divided into a training set (n=559) and a test set (n=215).

Image preprocessing

CT image preprocessing consisted of 2 steps. Firstly, we truncated the intensity value of all CT images to the range of [−100, 200] Hounsfield units (HU) to remove the irrelevant details. Each image in the training set was augmented by randomly rotation, translation, scaling, and intensity shifting to increase the number of training samples. Secondly, in order to increase the detailed information of the image, we performed a pseudo-color conversion to the CT image after the first step of preprocessing, as shown in *Figure 2*.

The total dataset was randomly divided into the training set (559 images) and test set (215 images). The training set was used to train the CNN model and the test set was used to test the accuracy of the model.

CNN model development

The CNN model was trained on a NVIDIA TITAN

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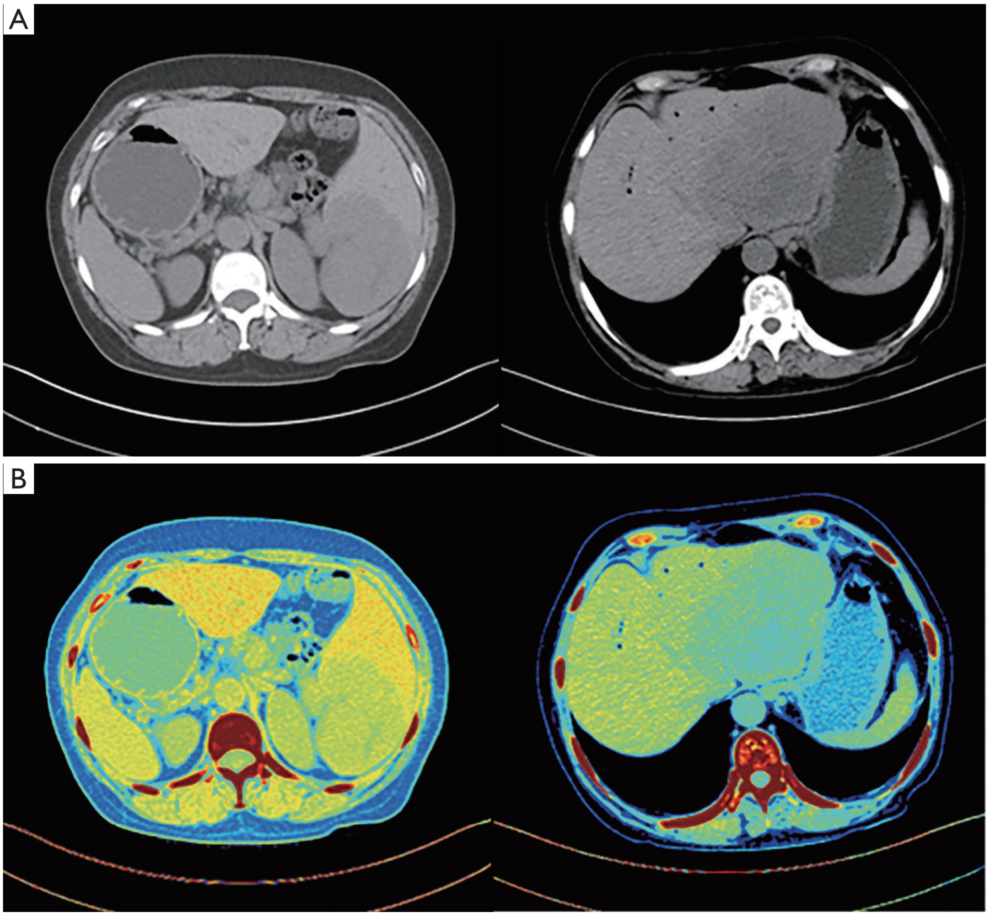

Figure 2 CT image preprocessing. (A) Truncation of the intensity values of all CT images to the range of [–100, 200] HU. (B) Pseudo-color conversion. CT, computed tomography; HU, Hounsfield units.

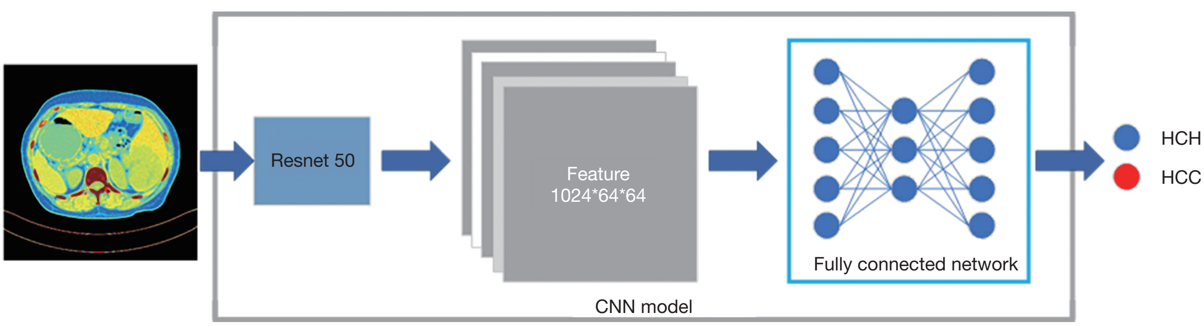

Figure 3 CNN model for liver tumor classification. CNN, convolutional neural network. HCH, hepatic cavernous hemangioma. HCC, hepatocellular carcinoma.

RTX GPU (NVIDIA, Suzhou, China) and the code was built using Python 3.6 and Pytorch 1.4. The architecture of our model is described in *Figure 3*. The model mainly consisted of Resnet-50 for image feature map extraction and fully connected layers for classification. The pre-trained Resnet-50 model was already trained on CT images from Liver Tumor Segmentation Challenge (https://competitions.codalab.org/competitions/17094). As we

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Table 1 Accuracy of classifying liver tumors into HCH/HCC using the deep learning model

Datasets	Accuracy (%)	Precision (%)	Recall (%)
Training dataset	95.02	96.10	97.14
Test dataset	84.25	81.36	82.18

HCH, hepatic cavernous hemangioma; HCC, hepatocellular carcinoma.

needed to train our CNN model to classify CT images into 2 classes (HCH and HCC), the output layer was set as a 2-class output layer. The following solver parameters were used for training: 200 iterations; learning rate, 0.0001; Adaptive Moment Estimation.

Statistics

The performance of the model was analyzed using precision, recall, and accuracy. The formulas are as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad [1]$$

$$\text{Recall} = \frac{TP}{TP + FN} \qquad [2]$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \qquad [3]$$

where, TP and TN represent true positive and true negative respectively, FP and FN represent false positive and false negative respectively. The closer the precision, recall, and accuracy are to 1, the more accurate the classification.

Results

The diagnostic accuracy of the proposed model is shown in *Table 1*. The final CNN demonstrated a training accuracy of 95.02% across the 2 tumor types. The test accuracy was 84.25% among individual lesions. For the training dataset, the model precision was 96.10%, with a recall of 97.14%. The model precision for the test dataset was 81.36%. The corresponding model recall for the test dataset was 82.18%.

Discussion

This study developed a CNN model for classifying liver tumors on non-contrast CT images, demonstrating high performance. The diagnosis results showed the potential of the CNN model to help radiologists classify HCH and HCC (model accuracy of 84.25%), which not only improves the accuracy of diagnosis on non-contrast CT images but also avoids the potential risks of contrast medium to patients.

Previous study has demonstrated that contrast-enhanced CT can accurately differentiate HCC from HCH (5). However, the use of contrast medium may lead to acute kidney injury or other side effects (6). Moving towards clinical implementation, non-contrast CT image-based tumor classification becomes increasingly challenging because of the intensity similarity. In this case, more discriminative image features must be learned. The CNN model is an effective algorithm which can discover more image information that may be invisible but is very important for image classification. As expected, the accuracy was higher with 2 classes (84.25%) when a radiologist cannot use non-contrast CT for classification.

This study faces the problem of insufficient data. In terms of network training, we expanded the data by rotating and horizontally flipping the original image. In terms of testing, we also need to conduct a wider range of tests on this basis to verify the stability and robustness of the model.

In summary, this study provides evidence for a CNN model for liver tumor classification that is effective in improving diagnostic accuracy when classifying HCC and HCH on non-contrast CT images. With the increasing clinical needs, the CNN model will be of great significance in the medical field.

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Footnote

Reporting Checklist: The authors have completed the STARD reporting checklist. Available at https://jgo.amegroups.com/article/view/10.21037/jgo-22-197/rc

Data Sharing Statement: Available at https://jgo.amegroups.com/article/view/10.21037/jgo-22-197/dss

Conflicts of Interest: All authors have completed the ICMJE

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uniform disclosure form (available at https://jgo.amegroups.com/article/view/10.21037/jgo-22-197/coif). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. This retrospective study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by Institution for National Drug Clinical Trials, Tangdu Hospital (No. K202108-43) and individual consent for this retrospective analysis was waived.

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