CT Image Segmentation of Liver Tumor Based on Improved Convolution Neural Network

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ABSTRACT

In this paper, an improved cross entropy loss function CNN structure is proposed to segment images, and a group of original three-phase images of liver tumors are input into the network for training. Finally, the dice coefficient (DSC) of the segmentation results of this method is 96%, the accuracy is 86% and the recall rate is 89%. The results show that the improved cross entropy loss function CNN structure is more conducive to the segmentation of liver tumors, with a higher accuracy. Meanwhile, it is proved that the algorithm converges when the correlation conditions are satisfied.

KEYWORDS
Image segmentation, Convolution neural network, Loss function, three-phase CT image.

INTRODUCTION

The liver plays an important role in urea synthesis and metabolism in human beings, but the liver is also one of the most common sites of tumor and the resection is the main method for the treatment of liver tumors. The segmentation result of liver tumor image is an important basis for resection is the main method for the treatment of liver tumors resection. With the rapid development of computer technology, the computer aided diagnosis technology based on medical imaging has made rapid development. It separates the suspected lesions from the normal anatomical background, so as to help doctors improve the work efficiency and the accuracy of diagnosis. Today CT image has been widely used in radiology department because of its high resolution and reasonable charge pricing. Therefore, how to use modern information technology to segment CT images of liver tumors efficiently and automatically has become an important research direction.

With the further development of research work, CT image segmentation gradually changes from two-dimensional to three-dimensional research, and the loss function for neural network is also gradually improved. In 2016, Li Wen[1] proposed a CT image liver tumor segmentation method based on deep convolution neural network, and the logarithm likelihood function is used as the loss function. Compared with the traditional machine learning algorithm, the image...
features of convolution neural network autonomous learning are more effective and divisible, which is beneficial to tumor segmentation. In same year, Ben-Cohen[2] proposed a Fully Convolution Network segmentation method for CT image liver tumor segmentation, Peijun Hu[3] proposed an automatic segmentation framework based on three-dimensional convolution neural network and global optimization surface evolution. The logarithm likelihood function is also used in it. In 2017, Eli Gibson[4] defined a CNN architecture comprising fully-convolutional deep residual networks with multi-resolution loss function. However, there exists sample imbalance in liver tumor images, and the cross-entropy loss function has some defects in dealing with sample imbalance. In 2018, Kai Hu[5] proposed an improved cross entropy loss function for retinal vascular segmentation of color fundus images. The recall rate increased from 75.23% to 75.52%, which indicates that the improved cross entropy loss function is suitable for unbalanced retinal vessels. Fu, YB[6] proposed a depth learning model for automatic segmentation of liver, kidney, stomach, intestine and duodenum in three-dimensional MR images. The model includes a voxel direction label prediction CNN and a correction network composed of two subnetworks.

At the same time, the study of CT images of liver tumors is also transferring from single phase data to multi-phase data, which can extract and utilize three-dimensional information as much as possible. Ji Zhiyuan[7] proposed a classification problem of liver tumors based on multi-phase three-dimensional CT images. Peng Gu[8] designed an 8-layer convolution neural network combined with a neural network for comprehensive evaluation to segment three-dimensional breast ultrasound images into four main tissues: skin, fibrogland tissue, mass and adipose tissue, and achieved good segmentation results. The above provides a new idea for our research.

DATA PREPARATION

BACKGROUND KNOWLEDGE OF CT IMAGES OF LIVER TUMORS

The plain scanning phase refers to the period without contrast agent injection, the arterial phase(ART) is within 30-40 seconds after contrast agent injection, the portal vein phase(PV) is within 70-80 seconds after contrast agent injection, and the delayed phase(DL) is 3-5 minutes after contrast agent injection. CT images of typical liver tumors in phase iii of ART, PV and DL are shown in Figure 1:

![Figure 1. Medical imaging of liver tumors in ART, PV and DL](image_url)
DATA ACQUISITION

The liver CT image data in this paper are from The Cancer Genome Atlas Program (TCGA)\cite{10}. This joint effort between the National Cancer Institute and the National Human Genome Research Institute began in 2006, bringing together researchers from diverse disciplines and multiple institutions. In this paper, the CT images of liver tumors in this database (TCGA-LIHC) are selected as samples for training in the network.

Figure 2. CT image training sample of liver tumor.

Figure 3. Convolution Neural Network structure of Pixel Classification.

| Layers | Input size | Kernel size | Stride length | Output size |
|--------|------------|-------------|---------------|-------------|
| Conv 1 | 128×128×1 | 7×7×36      | 1             | 122×122×36 |
| Pool 1 | 122×122×36| 2×2×36      | 2             | 61×61×36   |
| Conv 2 | 61×61×36  | 5×5×36      | 1             | 56×56×36   |
| Pool 2 | 56×56×36  | 2×2×64      | 2             | 28×28×64   |
| Conv 3 | 28×28×64  | 3×3×64      | 1             | 24×24×64   |
| Pool 3 | 24×24×64  | 3×3×64      | 3             | 8×8×64     |
| FC     | 4096 × 1  | –           | –             | 1024 × 1   |
| Softmax| 1024 × 1  | –           | –             | 2 × 1      |

TABLE I. CNN STRUCTURE PARAMETER TABLE FOR PIXEL CLASSIFICATION.
DATA PROCESSING

The downloaded image is Dicom file type. The picture sample is read by Python to convert the original gray image into a meaningful array of CNNs numbers. Create true tags and store them as segmented tags for training input images. The image block is divided into training set and test set, and the pixels in the training set image block are marked according to the true value label, which is used for network training. The segmentation effect is evaluated by using the test set.

METHOD

In this paper, the neural network architecture adopts the network structure of double network in reference\cite{8} to process the third phase image data of liver tumor CT image.

NETWORK DESIGN

The original three phase image data are used as input, and an 8-layer CNN (CNN-I) is used for network training. The region of interest (ROI) of tumor data is obtained from the original image and label information according to the original image and label information. The CNN schema and detailed configuration parameters are shown in Table II and Figure 3. The input image size is selected as 128*128 through the pre-experiment.

After the forward propagation of the network, the original data is output to the probability value of tumor or non-tumor by sigmoid classification function, and the two probability values of the output array indicate the probability tags of tumor and non-tumor. The index of the maximum element determines the central pixel in the image block. The size and layer number of each core were determined in the pre-experiment. In order to capture the nonlinear mapping between input and output, all convolution layers and fully connected layers are activated by sigmoid function.

In order to determine the final classification of target pixels in the above CNN output array, the second small classification CNN (CNN-II) is used for comprehensive evaluation. Six neurons (generated by 3 CNN) were inputted into the second CNN and connected to the output two neurons, the full junction layer and the softmax layer through the convolution layer, and the probability values of the two categories were finally obtained. The specific configuration parameters are shown in Figure 4. The prediction class of the target pixel can be obtained by using this small network.
THE IMPROVED CROSS-ENTROPY LOSS FUNCTION

The cross entropy loss function can not only simplify the computation of the network, but also effectively overcome the problem of slow convergence of the sigmoid function. Because there are a lot of interference terms in CT images of liver tumors, if the loss function does not consider the problem of sample balance, the learning process will tend to segment most of the non-tumor tissues. Therefore, we use the class equilibrium cross entropy loss function to improve the original loss function as follows.

\[
L(\alpha, b) = -\sum_{j \in T} \beta \times \log(\sigma(y_j)) + \alpha(1 - \beta) \times \log(1 - \sigma(y_j))
\]

where \(y_j\) and \(Y_j\) represent tumor and non-tumor pixels, respectively. The weights \(\beta\) and \(\alpha\) are used for the balance class, and \(\beta\) is represented by the ratio of tumor pixels to all pixels. \(\alpha\) is a superparameter and we set it to 2.5 in the experiment. \(\sigma(y_j)\) represents the probability that the sigmoid function is active at pixel \(j\).

PROOF OF CONVERGENCE OF FULL CONNECTION LAYER OF NEURAL NETWORK

Assuming that the number of neural units in the input layer and the hidden layer is \(Q \times P\). The essence of liver tumor image segmentation is the binary classification of image pixels, so the number of neurons in the output layer is 2. The training sample set is recorded as \(\{\xi^j, O^j\}_{j=1}^J \subset \mathbb{R}^Q \times \mathbb{R}^Q, O^j = (o^j_1, o^j_2)^T\), where \(o^j_i \in (0,1), t = 1, 2\). The weight matrix between the output layer and the hidden layer is recorded as \(V = (V_o)_{o \in P} \), where \(V_o^p = (v_{o,p,1}, v_{o,p,2}, ..., v_{o,p,P})^T \in \mathbb{R}^P, p = 1, 2, ..., P\). The connection right matrix between the hidden layer and the output layer is denoted as \(W = (w_{p})_{p \in P} \), where \(w_{p} = (w_{p,1}, w_{p,2}, ..., w_{p,P})^T \in \mathbb{R}^P, t = 1, 2\). Set \(g : \mathbb{R} \rightarrow P\) as nonlinear smooth activation function of each node in hidden layer, \(\sigma(x) = \frac{1}{1 + e^{-x}}, x \in \mathbb{R}\) is activation function for each node in the output layer.

After the sample \(\xi^j \in \mathbb{R}^Q\) is input into the network, the actual output of the network is

\[
\hat{z}^j_t = f(w^j \cdot G(V \cdot \xi^j)), t = 1, 2, j = 1, 2, ..., J.
\]
\( W^n, V^n \) denote the weight matrix after the training of the \( n \)th cycle in the network training.

\( \eta_n \) denotes the learning rate of the \( n \)th training. \( \eta_n \) varies according to the following rules: For an arbitrary initial value \( \eta_0 > 0 \),

\[
\frac{1}{\eta_n} = \frac{1}{\eta_{n-1}} + \epsilon \quad n = 1, 2, ...,
\]

When the improved cross entropy loss function is used in the process of network training, we have

\[
E(W, V) = \sum_{j=1}^{J} \sum_{p=1}^{P} \left[ \beta \ln(f(w_j \cdot G(V \cdot \xi^j))) + \alpha(1-\beta) \ln(1-f(w_j \cdot G(V \cdot \xi^j))] \right)
\]

The gradient function of the weight matrix \( W, V \) corresponding to the fully connected layer is

\[
E_{w}(W, V) = \sum_{j=1}^{J} \sum_{p=1}^{P} \left[ (\alpha \ln f(x) + (1-\alpha) \ln(1-f(x))) \right]
\]

When existing an \( C_i > 0 \) satisfied the following conditions:

(1) \( |g^{(k)}(x)| \leq C_i, k = 0, 1, 2 \quad x \in R \)

(2) \( |h_j^{(k)}(x)| \leq C_i, k = 0, 1, 2 \quad x \in R \quad 1 \leq j \leq J \quad t = 1, 2 \)

where \( h_j(x) = -\sum_{p=1}^{P} [O_p \ln f(x) + \alpha(1-O_p) \ln(1-f(x))] \]

(3) \( \|w^n\| \leq C_i, t = 1, 2, n = 1, 2, ...; \quad \|v^p\| \leq C_i, p \leq P, n = 1, 2, ... \)

the fully connection layer weight matrix of convolution neural networks is converged\(^{[11]}\).

For any given initial weight matrices \( W^0 \in M_{f \times P}, \ V^0 \in M_{P \times q}, \ (W^n, V^n) \) is generated by a reverse propagation algorithm based on improved cross-entropy function criterion. Then when the learning rate \( \eta_n^{new} \) is little enough, there exists \( N_0 > 0 \), which let every \( n > N \) has

\[
E(W^{new}, V^{new}) \leq E(W^n, V^n)
\]
And there also exists $E^* > 0$, so that $\lim_{n \to \infty} E(W^*, V^*) = E^*$ can be established.

Proof For any $t = 1, 2, j = 1, 2, ..., J$ and $n = 1, 2, ..., n_1$, we have

$$
\ln f(w^n_t \cdot G(V^n, \xi_t^j)) - \ln f(w^{n_1} \cdot G(V^{n_1}, \xi^j)) = (f(w^n_t \cdot G(V^n, \xi_t^j)) - f(w^{n_1} \cdot G(V^{n_1}, \xi^j)) + \frac{1}{2} (f(u_{t,j})(1 - f(u_{t,j}))(w^{n_1} - w^n_t \cdot G(V^n, \xi_t^j))
$$

where $u_{t,j} = \theta_{t,j} w^{n_1} \cdot G(V^{n_1}, \xi^j) + \alpha(1 - \theta_{t,j}) w^n_t \cdot G(V^n, \xi_t^j), \theta_{t,j} \in (0,1)

$\nu_{t,j} = \partial_{\xi_t^j} w^{n_1} \cdot G(V^{n_1}, \xi^j) + \alpha(1 - \partial_{\xi_t^j} w^n_t \cdot G(V^n, \xi_t^j), \theta_{t,j} \in (0,1)$

We can also get the conclusion in the same way that

$$
g(v^n_p \cdot \xi^j) - g(v^{n_1}_p \cdot \xi^j) = g'(v^n_p \cdot \xi^j)(\Delta v^n_p \cdot \xi^j) + \frac{1}{2} g''(v^n_p \cdot \xi^j)(\Delta v^n_p \cdot \xi^j)^2
$$

where $l_{p,j} = (\theta_{p,j} v^{n_1}_p + (1 - \theta_{p,j}) v^n_p) \cdot \xi^j, \theta_{p,j} \in (0,1), p = 1, 2, ..., P$

Then

$$
w^n_t \cdot G(V^n, \xi_t^j) - G(V^n, \xi_t^j) = \sum_{p=1}^{P} w^n_p (g(v^n_p \cdot \xi^j) - g(v^n_p \cdot \xi^j))
$$

$$
= \sum_{p=1}^{P} w^n_p (g'(v^n_p \cdot \xi^j)(\Delta v^n_p \cdot \xi^j) + \frac{1}{2} g''(v^n_p \cdot \xi^j)(\Delta v^n_p \cdot \xi^j)^2)
$$

And

$$
\sum_{p=1}^{P} \sum_{j=1}^{J} (f(w^n_p \cdot G(V^n, \xi^j)) - \alpha(1 - \theta_{t,j}) \cdot (G(V^{n_1}, \xi^j) - G(V^n, \xi_t^j))
$$

$$
= \frac{1}{\alpha} \sum_{p=1}^{P} \sum_{j=1}^{J} \Delta v^n_p \cdot G(V^n, \xi^j) + \frac{1}{2} \sum_{p=1}^{P} \sum_{j=1}^{J} \sum_{j=1}^{J} (f(w^n_p \cdot G(V^n, \xi^j)) - \beta \cdot w^n_p \cdot G(V^n, \xi_t^j))
$$

For any $t = 1, 2, j = 1, 2, ..., J$ and $n = 1, 2, ..., n_1$

$$
w^{n_1} \cdot G(V^{n_1}, \xi^j) - w^n_t \cdot G(V^n, \xi_t^j) = \Delta w^n_t \cdot (G(V^{n_1}, \xi^j) - G(V^n, \xi_t^j)) + \Delta w^n_t \cdot G(V^n, \xi_t^j)
$$

So we have the conclusion as follow
\[
E(W^{out}, V^{out}) - E(W^*, V^*)
\]
\[
= \sum_{j=1}^{J} \sum_{i=1}^{I} \left[ -\beta \ln f(w^{out}_i \cdot G(V^{out}_j, \xi_j)) - \alpha (1-\beta) \ln f(1-w^{out}_i \cdot G(V^{out}_j, \xi_j)) \right] \\
- \sum_{j=1}^{J} \sum_{i=1}^{I} \left[ -\beta \ln f(w_i \cdot G(V^*, \xi_j)) - \alpha (1-\beta) \ln f(1-w_i \cdot G(V^*, \xi_j)) \right] \\
= \sum_{j=1}^{J} \sum_{i=1}^{I} \left[ \alpha f(w^{out}_i \cdot G(V^{out}_j, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)] \right] \\
+ (1-\alpha) \beta f(w_i \cdot G(V^*, \xi_j)) - 1] [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
= \sum_{j=1}^{J} \sum_{i=1}^{I} \left[ \frac{\beta}{2} f(u_{ij}) (1-f(u_{ij}))[w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)] \right]^2
\]
\[
+ \frac{\alpha (1-\beta)}{2} f(v_{ij}) (1-f(v_{ij}))[w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)] \right]^2
\]

Where \( \alpha \) is a constant that is greater than 1, so \( 1-\alpha < 0 \), and \( 0 < \beta < 1 \),
0 < \( f(w_i \cdot G(V^*, \xi_j)) \) < 1,
then
\[
(1-\alpha) \beta f(w \cdot G(V^*, \xi_j)) - 1 > 0
\]
So for any \( j = 1, 2, ..., J \)
if \( w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j) \leq 0 \), then
\[
\alpha f(w^{out}_i \cdot G(V^{out}_j, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
+ (1-\alpha) \beta f(w_i \cdot G(V^*, \xi_j)) - 1] [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
\leq \alpha f(w_i \cdot G(V^*, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
if \( w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j) > 0 \), then
\[
\alpha f(w^{out}_i \cdot G(V^{out}_j, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
+ (1-\alpha) \beta f(w_i \cdot G(V^*, \xi_j)) - 1] [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
\leq \alpha f(w_i \cdot G(V^*, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
+ (1-\alpha) (1-\beta) f(w_i \cdot G(V^*, \xi_j)) [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
\[
\leq \alpha f(w_i \cdot G(V^*, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)]
\]
Summarize the above conclusions, we have
\[
E(W^{out}, V^{out}) - E(W^*, V^*)
\]
\[
\leq \sum_{j=1}^{J} \sum_{i=1}^{I} \left[ \alpha f(w^{out}_i \cdot G(V^{out}_j, \xi_j)) - \beta [w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)] \right]
\]
\[
+ \frac{\beta}{2} f(u_{ij}) (1-f(u_{ij}))[w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)] \right]^2
\]
\[
+ \frac{\alpha (1-\beta)}{2} f(v_{ij}) (1-f(v_{ij}))[w^{out}_i \cdot G(V^{out}_j, \xi_j) - w_i \cdot G(V^*, \xi_j)] \right]^2
\]
\[
= \frac{1}{l_{in}} \left( \sum_{j=1}^{J} \sum_{i=1}^{I} \Delta v_{ij}^2 + \sum_{j=1}^{J} \sum_{i=1}^{I} \Delta w_{ij}^2 \right) + \delta_1 + \delta_2 + \delta_3
\]

Where
\[ \eta_n^{\text{new}} = \eta_n(a + b \exp \left( - \frac{1}{\sum_{j=1}^{p} \sum_{t=1}^{T} |f(w_j \cdot G(V^t \cdot \xi^t))| - \beta} \right)) \]

\[ \Delta w_n^p = -\eta_n^{\text{new}} E_n(W^n, V^n) \]

\[ u_{n,j} = \theta_{n,j} w_{n,j}^{p+1} \cdot G(V^{n+1} \cdot \xi^j) + (1 - \theta_{n,j}) w_{n,j}^p \cdot G(V^p \cdot \xi^j), \theta_{n,j} \in (0,1) \]

\[ v_{n,j} = \vartheta_{n,j} w_{n,j}^{p+1} \cdot G(V^{n+1} \cdot \xi^j) + (1 - \vartheta_{n,j}) w_{n,j}^p \cdot G(V^p \cdot \xi^j), \vartheta_{n,j} \in (0,1) \]

\[ \delta_1 = \sum_{j=1}^{p} \sum_{t=1}^{T} (f(w_j \cdot G(V^t \cdot \xi^j)) - \beta) \Delta w_n^p \cdot (G(V^{n+1} \cdot \xi^j) - G(V^p \cdot \xi^j)) \]

\[ \delta_2 = \frac{1}{2} \sum_{j=1}^{p} \sum_{t=1}^{T} (f(w_j \cdot G(V^t \cdot \xi^j)) - \beta) w_n^p \cdot g''(l_{p,j})(\Delta w_n^p \cdot \xi^j)^2 \]

\[ \delta_3 = \sum_{j=1}^{p} \sum_{t=1}^{T} \frac{\beta}{2} (f(u_j)(1 - f(u_j))(w_{n,j}^{p+1} \cdot G(V^{n+1} \cdot \xi^j) - w_{n,j}^p \cdot G(V^p \cdot \xi^j)) \]

\[ + \frac{1 - \beta}{2} (f(v_j)(1 - f(v_j))(w_{n,j}^{p+1} \cdot G(V^{n+1} \cdot \xi^j) - w_{n,j}^p \cdot G(V^p \cdot \xi^j)) \]

From Cauchy-Schwarz Inequality, we have

\[ \delta_1 \leq C_1 \sum_{j=1}^{p} \sum_{t=1}^{T} \| \Delta w_n^p \| \cdot \| G(V^{n+1} \cdot \xi^j) - G(V^p \cdot \xi^j) \| \]

\[ \leq C_2 \sum_{j=1}^{p} \sum_{t=1}^{T} (\| \Delta w_n^p \|^2 + \| G(V^{n+1} \cdot \xi^j) - G(V^p \cdot \xi^j) \|^2) \]

\[ \leq \max \left( C_2 J, C_3 J \right) \cdot \sum_{j=1}^{p} \| \Delta w_n^p \|^2 \]

\[ \delta_2 \leq 2\alpha C_1 J \sum_{j=1}^{p} \| \xi^j \|^2 \sum_{p=1}^{P} \| \Delta w_n^p \|^2, \quad \delta_3 \leq 4C_1 C_2 J \sum_{j=1}^{p} \| \Delta w_n^p \|^2 + \alpha \sum_{p=1}^{P} \| \Delta w_n^p \|^2 \]

So

\[ E(W^{n+1}, V^{n+1}) - E(W^n, V^n) \leq \frac{1}{\eta_n} \left( \alpha \sum_{j=1}^{p} \| \Delta w_n^p \|^2 + \sum_{j=1}^{p} \| \Delta w_n^p \|^2 \right) + C_2 \sum_{j=1}^{p} \| \Delta w_n^p \|^2 + \alpha \sum_{p=1}^{P} \| \Delta w_n^p \|^2 \]

Then there must exist \( N_0 \) satisfies the inequality

\[ 0 < \eta_n^{\text{new}} < \frac{1}{C} \]

when \( n > N_0 \) if the learning rate is little enough. Then

\[ E(W^{n+1}, V^{n+1}) \leq E(W^n, V^n) \]

The sequence of error functions is monotone decreasing. With the condition that \( E(W^n, V^n) \geq 0, n=1,2,\ldots \) So there exists \( E^* \geq 0 \) that satisfies

\[ \lim_{n \to \infty} E(W^n, V^n) = E^* \]

To sum up, it is proved that the improved cross entropy loss function is applicable to the network, and the algorithm is converged in a condition.
EXPERIMENTAL RESULTS AND ANALYSIS

EXPERIMENTAL SETUP

In this paper, the CT image of the liver tumor is classified by two CNN networks to realize the image segmentation. The input image is a CT image of three different phases which size is 128*128, including the arterial phase, the portal vein phase and the delayed phase. After preprocessing, the parameters in the network are trained by minimizing the improved cross-entropy loss function. The predicted pixel categories of the three phase image blocks are calculated in CNN-I, in which the parameters are trained from the data from different phases.

![Figure 5. CT image of liver tumor after pretreatment.](image)

Then the output pixel class is comprehensively analyzed as the input of CNN-II, and the final output pixel classification is obtained.

EVALUATING INDICATOR

The performance evaluation index of classification task can be described mainly by confusion matrix. The true positive (TP), false positive (FP), true negative (TN) and false negative (FN) represent the four categories predicted by the sample and predicted by the mode. And the sum of TP, FP, TN and FN numbers is equal to the number of samples.

| Reality   | Prediction Result |
|-----------|-------------------|
| positive  |                  |
| negative  |                  |

With the definition of Table II, there are some evaluating indicator about the experimental results:
accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad \text{precision} = \frac{TP}{TP + FP}
\text{recall rate} = \frac{TP}{TP + FN} \quad F1\text{-measure} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}

There are great defects in using accuracy as an evaluation index in the case of imbalance between positive and negative samples. The precision measures how likely the model is to predict the correct positive class, and the recall rate measures the extent to which the correct positive class predicted by the model includes a true positive sample. The F1-measure is the harmonic mean value of the precision rate and the recall rate. When the precision rate and recall rate are both high, the F1-measure will also be high. In this paper, the accuracy rate and recall rate are used as evaluation indexes to quantitatively evaluate the results of the automatic segmentation method.

EXPERIMENTAL RESULT

In the experiment, the CT image is divided into training set and test set, and the network is trained by the corresponding correct segmentation label of the training set. As shown in Figure 6, with the increase of the number of iterations in training samples, the error rate of sample classification decreases, and the network model tends to be stable. The test set is automatically segmented by using the trained neural network to evaluate the segmentation performance.

Figure 6. Diagram of the Variation of Training Error with the Number of Samples.

Figure 7. Schematic Diagram of Liver Tumor Image Segmentation.
TABLE III. COMPARISON OF THE RESULTS OF DIFFERENT LIVER TUMOR SEGMENTATION METHODS.

| Reference Documentation | Image Type | DSC   | Precision | Recall Rate |
|-------------------------|------------|-------|-----------|-------------|
| Li Wen\(^{[5]}\)       | CT         | 0.8361| 0.8522    | 0.8458      |
| Ben-Cohen.\(^{[6]}\)   | CT         | 0.8900| ———      | 0.8600      |
| Ji Zhiyuan\(^{[7]}\)   | CT         | ———  | 0.8300    | ———         |
| Esther Dura\(^{[8]}\)  | MR         | 0.898 | ———      | 0.898       |
| Fu, YB\(^{[9]}\)      | CT         | 0.953 | ———      | ———         |
| Improved algorithm in this paper | CT     | 0.9600| 0.8600    | 0.8900      |

We obtain the trained parameters to test through the training set input network, and the input test set to obtain the segmented tumor image. The black mark in the Figure 7 shows the location of the tumor that is automatically segmented by the liver tumor.

We used the improved convolutional neural network to segment liver tumors, and the final DC coefficient reached 96%. In terms of accuracy, the calculated value reached 86%. In terms of recall rate, 89%. Compared with other tumor segmentation methods, the result is shown in Table III.

CONCLUSION

In this paper, an automatic segmentation method for CT images of liver tumors based on improved convolution neural network algorithm is proposed. The experimental results show that its quantitative evaluation results are better than those of traditional neural network, and the precision rate and recall rate are 86% and 89% respectively. Therefore, the automatic segmentation method proposed in this paper can provide an objective reference for radiologists to segment liver CT images and a new idea for further research to improve the loss function and use three-phase image training, which is helpful to the rapid development of automatic diagnosis and evaluation of liver tumors.

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