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# Automatic Liver Segmentation in CT Images Using Hopfield Neural Networks

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***Abstract*— Liver cancer is one of the most common types of cancer worldwide. Unfortunately, the symptoms appear in the late stages of the disease. Therefore, early diagnosis is important to detect the disease and prevent its development. In light of this, we propose an automatic system for segmenting the liver region in chest CT images. The segmentation results will be used as the ground for a Computer-Aided Diagnosis (CAD) system for the early detection of liver cancer, which will increase the chances of patient survival. In this study, we used Hopfield Neural Networks (HNN) as a segmentation method for the liver organ. We applied this method on 19,163 CT images. The HNN succeeded in extracting the liver region and the Dice coefficient of the liver segmentation results reached 81.7%.**

***Keywords*— *Liver Cancer, Computed Tomography, Image Segmentation, Hopfield Neural Network.***

## I. Introduction

Liver cancer is one of the most widespread types of cancer worldwide. More than half of all people diagnosed with primary liver cancer have cirrhosis, an illness that causes permanent liver damage and liver failure. Globally, 841,080 new cases of liver cancer were diagnosed in 2018 alone, along with nearly 782,000 deaths [1]. In fact, liver cancer is considered a silent disease because most patients do not present with signs and symptoms in the early stages. Significantly, the symptoms typically appear in the late stages of the disease when the chances of survival are low. Hence, early diagnosis is essential for the detection of the disease and to prevent its progression.

Many techniques are available to diagnose liver cancer, including Ultrasound, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). MRI and CT scans can detect liver cancer at an early stage. However, CT is the most used imaging method among oncologists and radiologists for liver cancer detection and staging [2].

In medical image analysis, segmentation is an essential processing step. Segmentation is a procedure of partitioning an image into expressive subregions with the same attribution. In a matter of fact, segmenting liver tissues is important for cancer diagnosis, treatment, and following the response to treatment, and it is a key assessment for many treatment chances. Over the last 30 years, a lot of methods have been proposed for automated, semi-automated, and interactive segmentation liver region [3]. In this work, we propose a method to segment the liver organ from abdominal CT images using a Hopfield Neural Network (HNN).

## II. Problem Statement

Fully-automated segmentation of the liver is still problematic due to different acquisition procedures, different contrast-agents, different levels of contrast enhancement, and different scanner resolutions, all of which lead to unsteady intensity differences between liver tissue and lesion tissue [3].

Lately, some researchers have showed the ability of Hopfield algorithms in distinguished projects and reported on significant developments [4]. As well, HNNs have been associated with promising performance in medical image processing [5], [6].

For this reason, we encouraged to use a HNN to segment the liver area based on an analysis of chest CT images. In our work, we employed the HNN algorithm as a segmentation method for the liver area because HNN is sensitive to any differences in intensity. Furthermore, the HNN algorithm can differentiate between liver tissues and the other organ tissues that are present in CT chest images.

## III. Hopfield Neural Networks

A Hopfield Neural Network (HNN) [7] is a single-layer feedback neural network. It is a type of recurrent neural network. HNNs is categorized as an unsupervised learning, which means that the network classifies the features without supervision based on the density of each cluster calculated. HNNs have been used to segment color and gray-level images [8], [5]. In the history of neural networks, HNN is an important algorithm since it is considered the modest and most applicable feedback network [4], [7].

This work is based on [5], in which the authors presented an automatic segmentation system to detect lung cancer in its early stages using HNN based on sputum color images. the system successfully classifies sputum cells into nuclei, cytoplasm, or background classes.

The neural network structure consists of a grid of *N x M* neurons, where each column represents a cluster and each row represents a pixel. The network is designed to categorize the image of *N* pixels of *P* features among *M* classes such that the assignment of the pixels minimizes the criterion function:

$$E = \frac{1}{2}\sum_{k-1}^{N}\sum_{l-1}^{M} R_{kl}^{2}\, V_{kl}^{2} \qquad (1)$$

where $R_{kl}$ is the Euclidean distance measure between the $k^{th}$ pixel and the centroid of class $l, V_{kl}$ is the output of the $k^{th}$ neurons. The minimization is achieved using HNN and by solving the motion equations satisfying:

$$\frac{\partial u_i}{\partial t} = \mu(t)\frac{\partial E}{\partial V_i} \tag{2}$$

where $\mu(t)$ is, as defined in [5], a scalar positive function of time used to increase the convergence speed of the HNN. By applying the relation to equation (1), we yield a set of neural dynamics given by:

$$\frac{dU_{kl}}{dt} = -\mu(t)[R_{kl}^2 V_{kl}] \tag{3}$$

where $U_{kl}$ and $V_{kl}$ are the input and output of the $k^{th}$ neuron, respectively. To assign a label *m* to the $k^{th}$ pixel, we use the input-output function given by:

$$V_{km}(t+1) = 1, if\ U_{km} = Max[U_{kl}(t), \forall 1]$$
$$V_{km}(t) = 0, \text{otherwise} \tag{4}$$

The HNN segmentation algorithm can be summarized in the next steps:

1. Initialize the neurons' inputs to random values.

2. Apply the input-output relation given in (4) to obtain the new output value for each neuron, establishing the assignment of pixel to classes.

3. Calculate the centroid for each class as next:

$$\overline{X_L} = \frac{[\sum_{k=1}^{n} x_K v_{kl}]}{n_l} \tag{5}$$

where $n_l$ is the number of pixels in class *l*.

4. Solve the set of differential equations in (3) to update each neuron's input:

$$U_{kl}(t+1) = U_{kl}(t) + \frac{dU_{kl}}{dt} \tag{6}$$

5. Repeat the steps from step 2 onward until convergence, and then terminate.

We performed a comprehensive set of experiments using the Liver Tumor Segmentation Benchmark (LiTS) [10]. It is used for the development and evaluation of the system. To analyze the efficiency of the proposed algorithm in segmenting chest CT images into liver area and background area, we converted 130 volume images to a total of 58,638 2D images. In turn, we cleaned the data and removed the images for a better result. The images with mask mean=0 were removed, leaving 19,163 images remaining. Then, we converted the pixels into gray-level to reduce the computing complexity.

We used 90% of the images for training and 10% for validation. The ground truth data consisted of a binary image where 1 and 0 corresponded to the ROI pixels and to the background pixels, respectively. Then, the proposed method was applied on the test images. Every image outcome was compared to the ground truth data.

Performance evaluation was measured in terms of sensitivity, specificity, and accuracy. For performance measurement, first, the true positives were calculated (i.e., pixels that were correctly classified as liver cells' pixels TP's), false positives (i.e., pixels that were incorrectly classified as liver cells' pixels FP's), true negatives (i.e., pixels that were correctly classified as non-liver cells' pixels TN's), and false negatives (i.e., pixels that were incorrectly classified as non-liver cells' pixels FN's).

Accuracy is formally defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}; \tag{7}$$

Additional measurements are based on these values [9]:

$$Sensitivity = \frac{TP}{TP+FN}; \tag{8}$$

$$Specificity = \frac{TN}{TN+FP}; \tag{9}$$

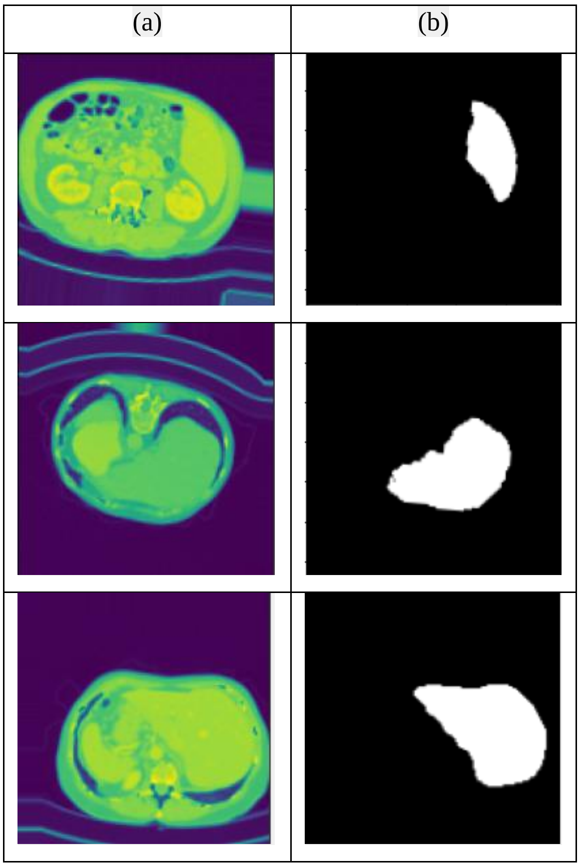
$$Precision = \frac{TP}{TP+FP}; \tag{10}$$

Also, the Dice score is an F1 score that measures the harmonic mean of precision and recall.

$$Dice = \frac{2TP}{(2\,TP + FP + FN)}. \tag{11}$$

## IV. Segmentation Result

We applied the HNN with the description mentioned above to 19,163 CT images. The algorithm segmented the CT images successfully into liver and background, as shown in Figure 1.



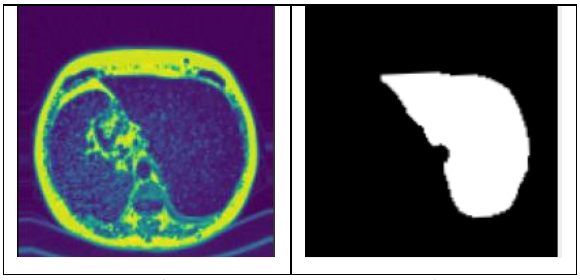


Fig. 1: Examples of HNN segmentation algorithm for abdominal CT images: original raw images in (a) and their segmentation results using HNN in (b).

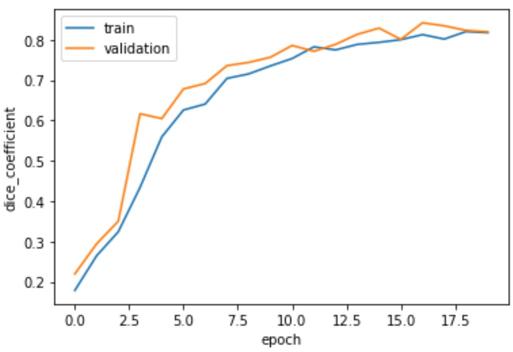



Fig. 2: Dice coefficient of HNN segmentation algorithm.

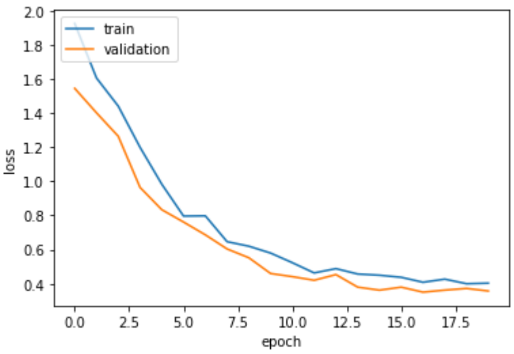



Fig. 3: Learning error waveforms of HNN segmentation algorithm during the segmentation process.

The HNN performed well in segmenting the liver organ in CT images. Therefore, the HNN has the capability to extract the liver region successfully, where the Dice coefficient of the liver segmentation results reached 81.7%, and the accuracy reached 98.25% (see Figures 2 and 3).

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