International Journal of Aquatic Science
ISSN: 2008-8019
Vol 13, Issue 01, 2022

Application of mi based prediction of the deep learning cnn model to enhancement and Scheduling the gpu utilization of the ds

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ABSTRACT: ***A segmentation process involves labeling an image or images to obtain more meaningful information. On biomedical images, this activity plays an important role in helping the pathologist to carry out in-depth analyses. After the introduction of Graphics Processing Unit (GPU) not only for necessary graphics but also for goal calculation, the segmentation process which is computationally expensive can potentially be improved. The good accuracy of the detection and segmentation result provides morphological information to the pathologist. As a result, more approaches have been developed to ensure good detection and segmentation performance such as deep learning approach. Convolutional Neural Network (CNN) is one of the deep learning architectures with complex computation. This article presents an overview of the use of CNN as an important deep learning architecture under the GPU platform and provides an approach for using GPUs as potential additional parallel techniques in CNN. Keywords: Image segmentation; deep learning; convolutional neural network; medical image, GPU speed***

1. INTRODUCTION

Image segmentation is an important and difficult part of image processing. It has become a reference in the field of image understanding. It is also a bottleneck that limits the application of 3D reconstruction and other technologies. Image segmentation divides the entire image into different regions, which have similar properties. Simply put, it's about separating the objective from the background of an image. Currently, image segmentation methods are developing in a faster and more accurate direction. By combining various new theories and technologies, we find a general segmentation algorithm that can be applied to image types [1]. With the advancement of medical care, all kinds of new medical imaging equipment are becoming more and more popular. Types of medical imaging widely used in clinic are mainly CT, MRI, PET, X-ray and UI. Besides, it also includes some common RGB images, such as microscopy and retinal fundus images.There is very useful information in medical images. Doctors use CT scan and other medical images to judge the patient's condition, which has gradually become the main basis for doctors' clinical diagnosis [2]. Therefore, research in medical image processing has become the focus of attention in the field of computer vision with the rapid development of artificial intelligence, especially deep learning [3], methods of deep learning-based image segmentation have achieved good results in the field of image segmentation. . Compared to traditional methods of machine learning and computer vision, deep learning has certain advantages in terms of segmentation accuracy and speed. Therefore, the use of deep learning to segment medical images can effectively help doctors to confirm the size of diseased tumors, quantitatively assess the effect before and after treatment, greatly reducing the workload of doctors. To best summarize the different methods, we searched the keywords “medical image processing” or “deep learning” from Google Scholar and ArXiv to get the most recent literature. Also, top medical imaging conferences are also good places to get papers, such as MICCAI, ISBI, and IPMI. The articles we have selected rely primarily on deep learning methods. We ensure that all article findings are verified. Unlike existing reviews [4–6], this survey examines recent advances, benefits and disadvantages in the field of medical image segmentation from a deep learning perspective.Compare and summarize related methods and identify challenges for successful deep learning methods for medical imaging segmentation activities in future work. In this article, we provide a comprehensive review of DL medical imaging technology over the past few years, focusing primarily on the newest methods released within the last three years and the classic methods from the past. He mainly focuses on the application of deep learning technology in medical image segmentation in the past three years. A more in-depth study is being conducted on the structure and modalities of its network. at the same time, its strengths and weaknesses are analysed. Second, some advanced segmentation methods are summarized based on the characteristics of different organs and tissues. Third, we have shared many evaluation metrics and medical image segmentation datasets for readers to evaluate and train the network. The structure of the article is as follows: Section 2 examines what is the segmentation of medical imaging. In Section 3, we explained the concept of deep learning and the application of deep learning. Sections 4 and 5 constitute the main body of literature reviewed.Section 4 introduces the three network structures, FCN, UNet, and GAN, based on deep learning medical image segmentation. Section 5 presents the methods of segmentation of the different organs and tissues. Section 6 is about sharing assessment metrics and datasets, which are derived from the influential challenges of medical image analysis.

LITERATURE SURVEY

Deep learning is a research trend in the rise of machine learning and artificial intelligence. It uses deep neural networks to simulate the learning process of the human brain and extract features from large-scale data (sound, text, images, etc.) in an unsupervised way [19]. A neural network is made up of several neurons. Each neuron can be considered as a small information processing unit. Neurons are connected to each other in a certain way to form the whole deep neural network. The emergence of neural networks makes end-to-end image processing possible. When the hidden layers of the network unfold at multiple levels, it is called deep learning. In the field of computer vision, deep learning is mainly used in data dimensionality reduction, handwritten number recognition, pattern recognition and other fields. such as image recognition, image repair, image segmentation, object tracking, scene analysis, etc., showing a very high efficiency [20].

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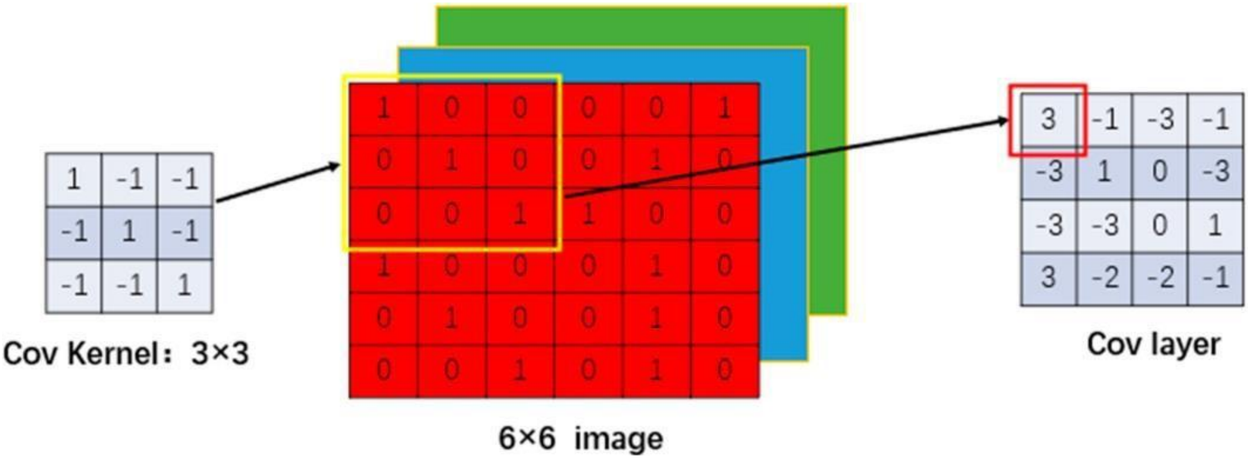
CONVOLUTIONAL NEURAL NETWORK

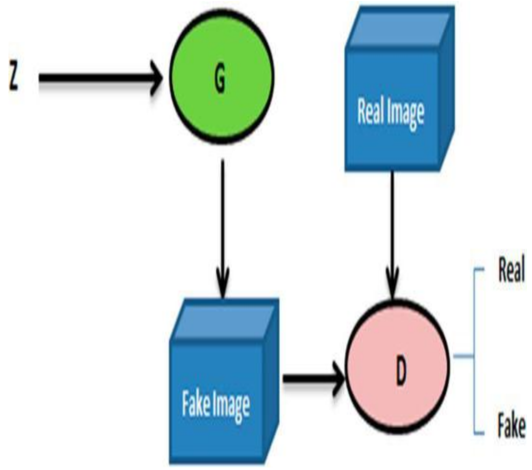
The convolutional neural network (CNN) [21] is a classical model produced by the combination of deep learning and image processing technology. As one of the most representative neural networks in the field of deep learning technology, it has made many advancements in the field of image analysis and processing, including image extraction and image feature classification, pattern recognition, etc. The convolutional neural network is a deep model with supervised learning.reduce the number of parameters by using relative spatial relationships to improve training performance. The proposal of receptive fields and neurocognitive machines in human visual information is an important theory at the embryonic stage of the theory. In 1962, Hubel et al [22] showed by biological research that the transmission of visual information to the brain from the retina occurs by the excitation of the receptive field at several levels. This is the first proposal of the concept of receptive field. In 1980, Fukushima [23] proposed a neurocognitive machine based on the concept of receptive fields. It is considered to be the first network implementation of convolutional neural networks.In 1998, Lecun et al [24] proposed LeNet5 using gradient based backpropagation algorithm for supervised network learning, CNN is composed of input layer, output layer and multiple layers hidden. Each layer in the hidden layer performs a specific operation, such as convolution, pooling, and activation. The input layer is connected to the input image and the number of neurons in this layer is the pixel of the input image. The central convolutional layer.performs feature extraction on the input data through a convolution operation to obtain a feature map. The result of the convolution operation depends on the configuration of the parameters in the convolution kernel. The clustering layer behind the convolutional layer filters and selects feature maps, simplifying the computational complexity of the whole network, the general convolutional neural network is 2D CNN.



Structure like VGG and ResNetand the structure of the encodercoder.letnet and Alexnet are the first network models.Inception uses multiple convolution kernels of different sizes and adds pooling. Thus, the result of the convolution and the pool are together in series. The depth of the entire network has reached 22 layers. The CNN network grew from the seven layers of AlexNet to the 19 layers of VGG, followed by the 22 layers of GoogleNet. When the depth reaches a certain number of layers, the further increase may not improve classification performance, but will slowly converge the network. To train a deeper network with good results, He et al [26] proposed a new 152-layer network structure: ResNet.ResNet solves this problem by using a shortcut consisting of several.

SYSTEM ARCHITECTURE

A new method has recently been introduced to train generative models to generate adversarial networks. Goodfellow et al [51] proposed a contradictory method in 2014 to learn a deep generative model, GAN. Its structure is shown in Figure 7 and consists of two parts. The first part is the generation network, which receives a random noise z (random number) and generates an image through this noise. The second part is the fight against the net, which is used to judge whether an image is "real". Its input parameter is x (an image) and the output D(x) represents the probability that x is a real image. Simply put, it is through training that two networks compete. The generator network generates fake data and the adversarial network uses a discriminator to determine authenticity. Finally, it is hoped that the data generated by the generator can be imposters.

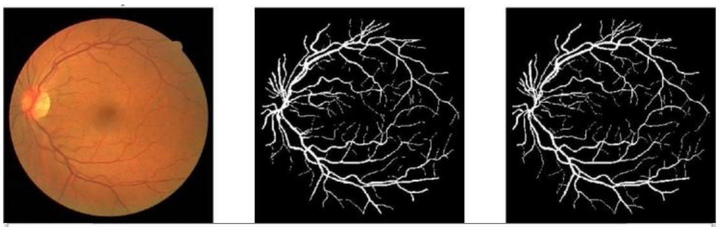


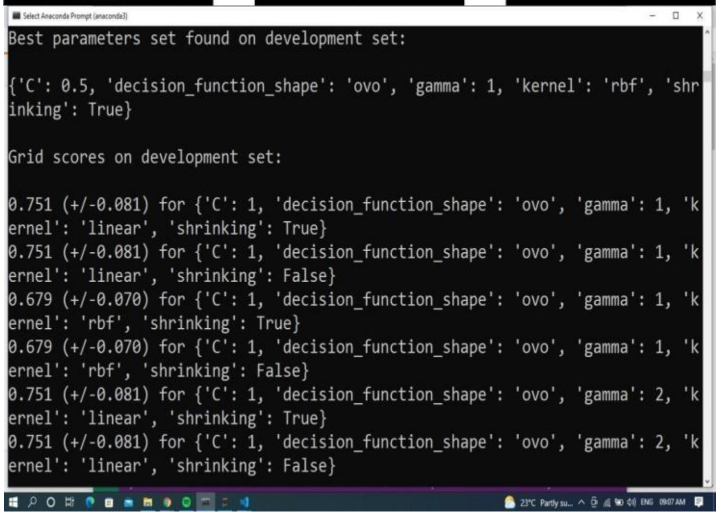
SEGMENTATION METHOD FOR VARIOUS HUMAN ORGAN AREA

The human body has several organs and tissues. The different parts have their own specificities. For example, the segmentation area for the diagnosis of brain tumors and lung nodules is relatively large, while retinal blood images require segmentation of blood vessels. The latter requires greater segmentation precision. Researchers extract insights from these messages and design segmentation algorithms for different organs to improve segmentation accuracy. The best way to segment different organs will be presented below. Reading the literature, we summarized the methods of segmentation of the brain, eyes, chest, abdomen, heart and other parts.

2. RESULTS

The quality assessment of an algorithm requires a correct objective indicator.Nuts (A, B) = 2 | A ∩ B | |A | + | B | (3) Jaccard's Index: The Jaccard's Index is similar to the die coefficient. Given two sets A and B, the metrics are defined as follows: Jaccard (A, B) = |A ∩ B | | AUB | (4) Segmentation Accuracy (SA): Accurate segmentation area represents the percentage of the actual area in the GT image. Of these, - | R represents the reference area of the segment drawn annually by the expert. Tsrepresents the real area of the image obtained by the segmentation of the algorithm. RsTs indicates the number of pixels that are badlysegmented.Digital retinal images for the extraction of the sample diagram of the vessel (drive) and the manual labeling sample.(b) manual annotation 1 of sample; (c) manual annotation 2 of sample.





Although research on medical image segmentation has made great progress, the segmentation effect is still unable to meet the needs of practical applications. The main reason is that current research on medical image segmentation still presents the following difficulties and challenges: Medical image segmentation is an interdisciplinary field between these two disciplines. The conditions of clinical medical pathology are complex and diverse. However, artificial intelligence scientists do not understand clinical needs. Doctors do not understand the specific technology of artificial intelligence. Therefore, AI cannot respond well to specific clinical needs. In order to promote the application of artificial intelligence in the medical field, broad cooperation between doctors and machine learning scientists should be strengthened. This cooperation will solve the problem that machine learning researchers cannot obtain medical data. It can also help machine learning researchers develop deep learning algorithms more in line with clinical needs and apply them to computer-aided diagnostic equipment, thereby improving diagnostic efficiency and accuracy.Medical images are different from natural images.The deep learning model has its flaws. It mainly focuses on three aspects: network working structure design, 3D data segmentation model design, and loss function design. The design of the network structure is worth exploring. 3D medical data can more accurately capture target geometry information, which may be lost when the

3. REFERENCES

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[13] 3D data is sliced slice by slice. Therefore, a researchable direction is the design of 3D convolution models to process 3D medical image data.

[14] 5. The design of loss function has always been a difficult point in deep learning research.