GPU Acceleration of Convolutional Neural Network for Brain Carcinoma MRI Image Segmentation by cuDNN

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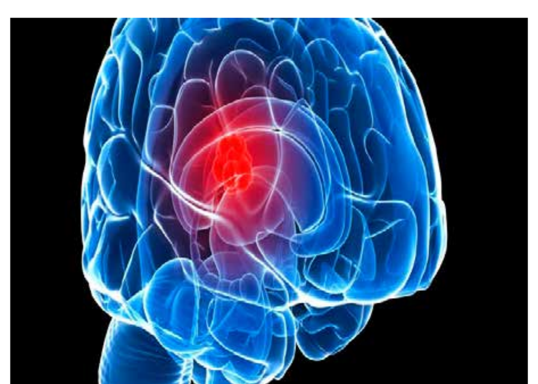
Abstract

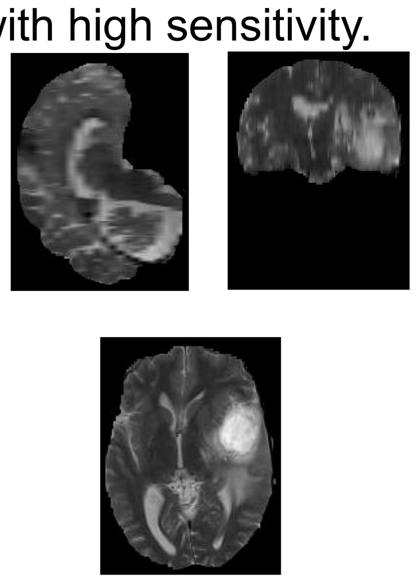
Brain carcinoma is one of high-risk diseases in the modern society, and MRI is an important approach for diagnostic screening. Traditionally, recognizing and segmenting brain tumor from patient MRI images are time-consuming assignments by radiologists, and machine learning approaches such as Convolutional Neural Network (CNN) can be developed to increase the efficiency of brain carcinoma diagnosis. However, since the number of MRI image slices is large, the computational time cost of CNN based brain tumor segmentation is too high to satisfy the clinical needs. In this poster, we developed a fast CNN by Nvidia's new Deep Learning library cuDNN (cuDNN-CNN) to accelerate brain tumor segmentation. Computational results show that, cuDNN-CNN significantly accelerates brain tumor segmentation than the conventional CNN (CNN): for a 160×216×176 clinical brain carcinoma imaging dataset, cuDNN-CNN segments brain tumors in minutes while the conventional CNN costs hours. Computational results also show that, cuDNN-CNN is as accurate as the conventional CNN.

Introduction



← Cerebral malignancy is one of high-risk diseases in the modern society, and cerebral malignancy has four subtypes: Gliomas, Meningiomas, Pituitary adenomas and Nerve sheath tumors. Cerebral malignancy always leads to a rapid progress and poor prognosis, the survival rate of patients with Cerebral malignancy is less than one year.

→ Brain MRI scan is a powerful approach to detect the brain internal structure for abnormalities such as tumor, stroke and blooding. Brain MRI takes advantages of magnetic field and radio pulses to take inner photos of the brain. The patients usually receive T2 scan with 5mm resolution and 20 images. Also, function MRI is the other approach to detect the brain abnormalities such as stroke with high sensitivity.



← Recent technology of 3D MRI imaging produces multi-channel 3D brain dataset with different contrasts. 3D MRI excites the whole brain in every time step. 3D MRI imaging includes two phase encoding and one frequency encoding, and the images are reconstructed by 3D FFT. The acquisition time of 3D MRI is usually longer than 2D MRI, which is decided by TR, excitations and encoding in *y* and *z* directions. The signal amount of 3D MRI is larger than 2D MRI, and 3D artifacts such as truncation artifact exist while 2D MRI does not.

Currently, radiologists read brain MRI images for possible crebral malignancy: they compare the texture and intensities of different channels to detect possible tumors. To increase the efficiency of reading MRI images, machine learning approaches such as Convolutional Neural Network (CNN) can be developed. However, since the number of MRI image slices is large, the computational time cost of the conventional CNN based brain tumor segmentation is too high to satisfy the clinical needs. In this poster, we developed a fast CNN by Nvidia's new Deep Learning library cuDNN (cuDNN-CNN) to accelerate brain tumor segmentation.

Methods

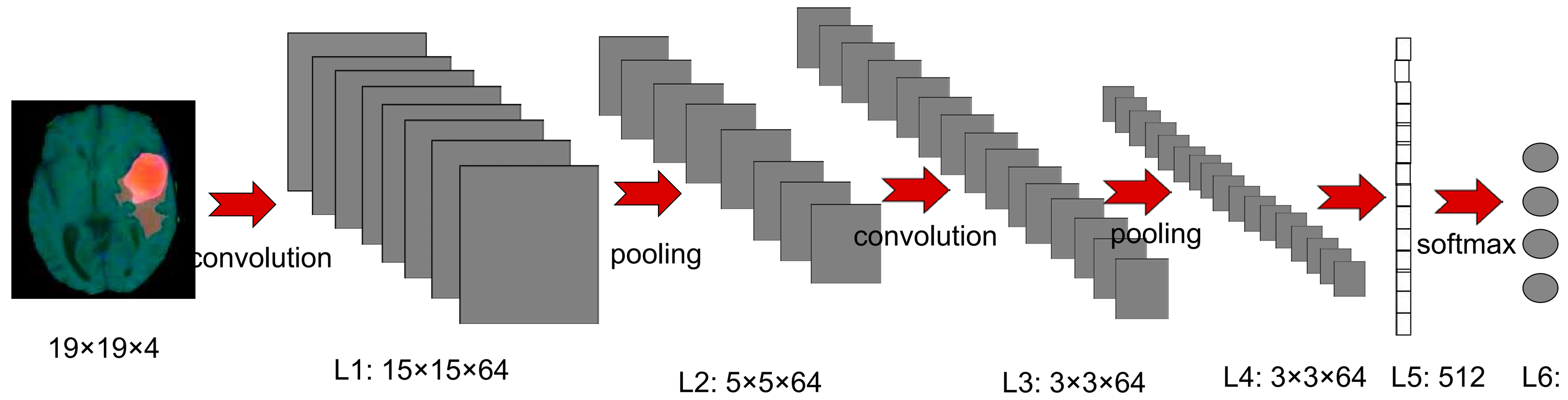


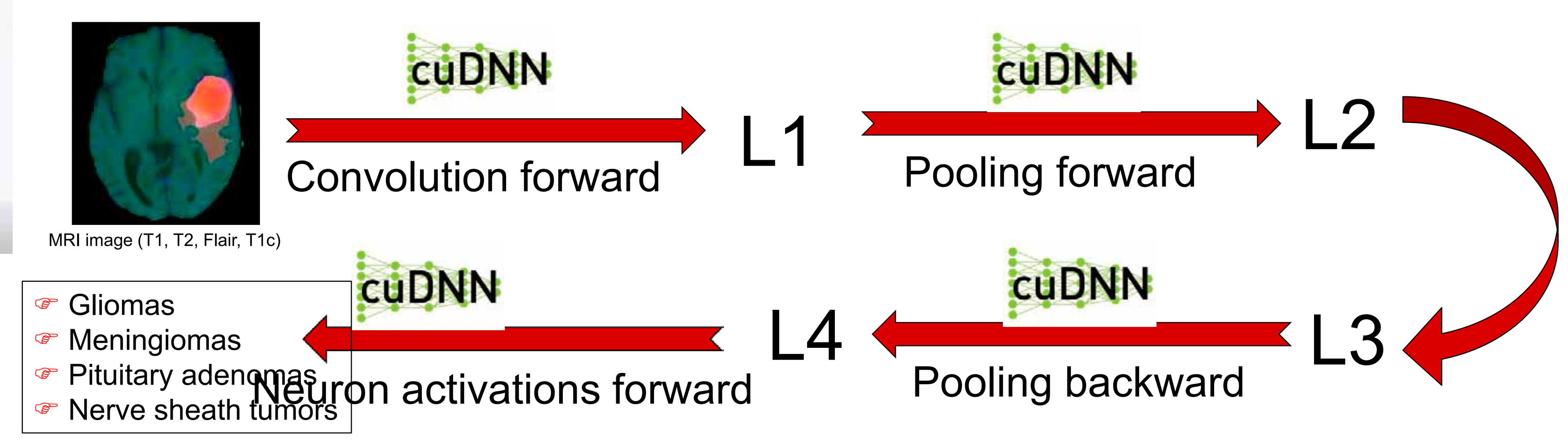
Figure 1. CNN Architecture for Brain Tumor Segmentation

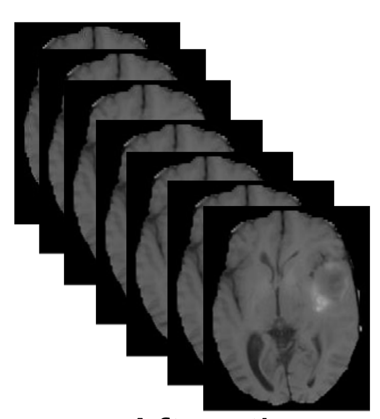
↑ The CNN architecture for brain tumor segmentation is shown in **Figure 1**. From **Figure 1** we can see, similar to the famous Le-Net 5, the CNN architecture for brain tumor segmentation consists of five layers: the first convolutional layer, the first pooling layer, the second convolutional layer, the second pooling layer and the softmax layer.

A 19×19×4 slice is extracted from the whole brain image dataset, which is the input of CNN architecture for brain tumor segmentation. The slice passes to the first convolutional layer, which leads to 15×15×64 feature maps. The feature maps are under-sampled by the first pooling layer, and the sizes of feature maps decrease to 5×5×64 feature maps. These feature maps are subject to the second convolutional layer, which leads to 3×3×64 feature maps. The second pooling layer is followed to reach 3×3×64 feature maps. The feature maps are reshaped into a 512×1 vector for the softmax layer, and finally the 512×1 classification results are obtained.

cuDNN

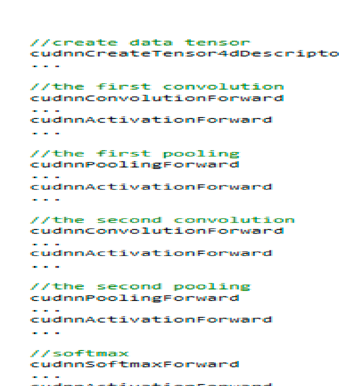
Convolution forward	Softmax forward
Convolution backward	Softmax backward
Pooling forward	Neuron activations forward
Pooling backward	Neuron activations backward





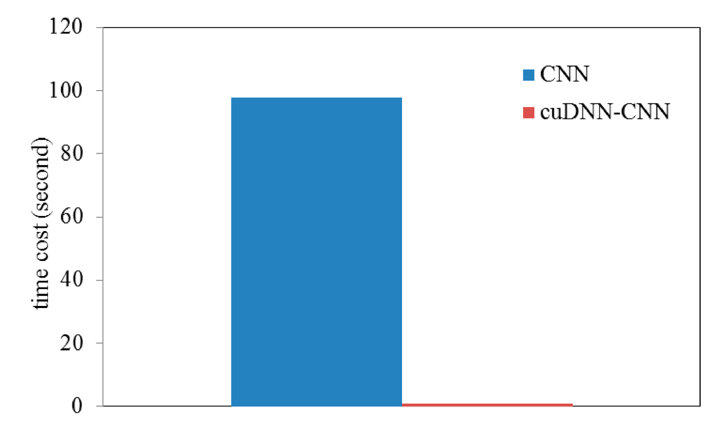
← The problem of 3D brain tumor segmentation is solved by segmenting the 2D slice in the axial direction one by one, and the input of cuDNN-DNN is 2D image. The 3D CNN problem is calculated by 2D convolution in cuDNN. Each pixel in 2D images is classified into four brain tumors subtypes, and the classification of 2D images into the results of 3D brain tumor segmentation problem.

→ After the network architecture is decided, programming CNN by cuDNN is straightforward and convinient, no details of convolution and pooling are needed, and maximum efficiency is automatically provided by cuDNN. In our cuDNN-CNN implementation, the convolutional layer is implemented by cudnnConvolutionForward, the softmax layer is implemented by cudnnSoftmaxForward, the pooling layer is implemented by cudnnPoolingForward, the activation layer is implemented by cudnnActivationForward.



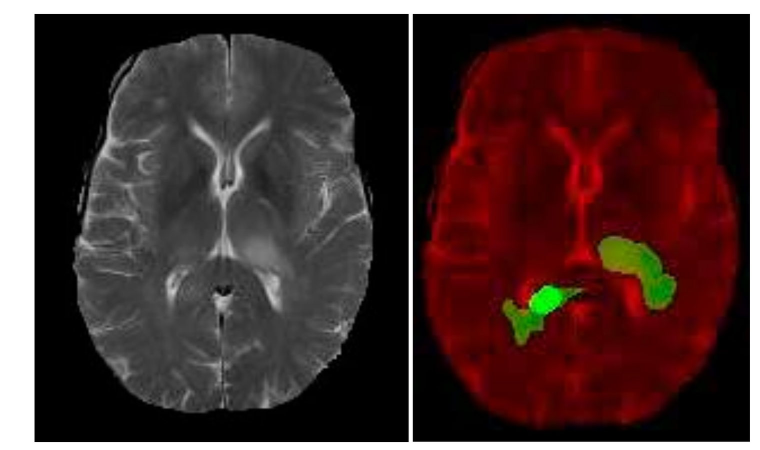
Computational Results

We program the conventional CNN by MATLAB (CNN) and the fast CNN by CUDA/cuDNN (cuDNN-DNN), and we test the codes on a GPU node with two Intel E5-2680 V2, 128G memory and Nvidia K20 GPU. We use BRATS2012 dataset, which consists of 27 high grade (HG) and 15 low grade (LG) of 160×216×176 3D MRI brain images, and these images are the multi-channel 3D data with 4 different 3D MR contrast images: contrast enhanced T1, T1, T2 and FLAIR.

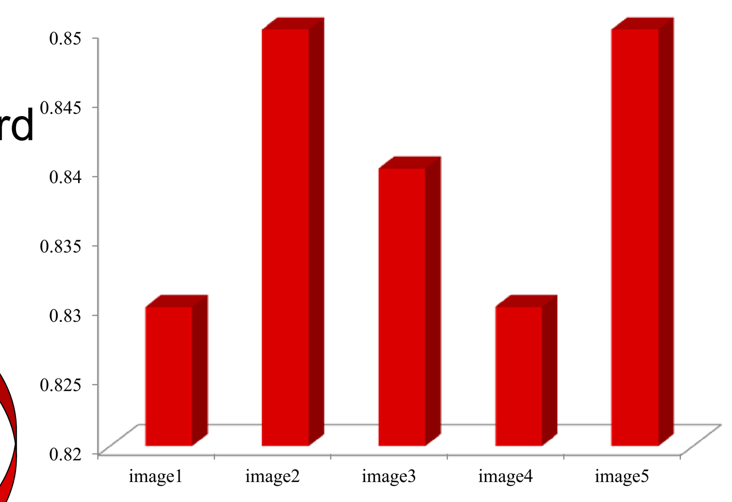


← The time cost of DNN and cuDNN is shown in the left figure. From the left figure we can see, cuDNN-DNN is much faster than the conventional DNN. The reason is: while DNN handles the 3D MRI brain dataset slice by slice, cuDNN-DNN handles the 3D MRI brain dataset in batch mode.

→ Example of recognized brain carcinoma by cuDNN-DNN is shown in the right figure: (a) the original image and (b) the recognized tumor. As shown in the right figure, cuDNN-DNN successfully recognizes the tumor in (b) from the original MRI image (a).



(a) (b)



← The performance of cuDNN-DNN for brain carcinoma recognition is evaluated by Kitware/MIDAS (http://challenge.kitware.com/midas/), and the calculated dice score is plotted in the left figure. As shown in the left figure, cuDNN-DNN produces high dice scores.

Conclusion

- ➢ Convolutional Neural Network is an promising approach for tumor segmentation from brain MRI image.
- ➢ cuDNN significantly accelerate the conventional Convolutional Neural Network for the brain tumor segmentation.
- ➢ GPU computing is the ideal platform for the brain cancer image analysis.

References

[1] Wenlu Zhang, Rongjian Li, Houtao Deng, Li Wang, Weili Lin, Shuiwang Ji, Dinggang Shen, Deep convolutional neural networks for multi-modality isointense infant brain image segmentation, 2015.
[2] Rongjian Li, Wenlu Zhang, Heung-Il Suk, Li Wang, Jiang Li, Dinggang Shen, Shuiwang Ji, Deep Learning Based Imaging Data Completion for Improved Brain Disease Diagnosis, Medical Image Computing and Computer-Assisted Intervention – MICCAI 2014, Lecture Notes in Computer Science, 2014,8675:305-312.
[3] Di Zhao, High-accuracy Optimization by Parallel Iterative Discrete Approximation and GPU Cluster Computing, Journal of Software, 2014,9(9):2366-2377.