3D CNN Deep Learning On Brain Lesion Segmentation

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Background

- To evaluate the how accurately and efficiently that 3D CNN model works on the segmenting the brain lesion, we used the brain lesion dataset to train two different 3D CNN model, DeepMedic and 3DUnet and make the test.
- In MRI scans, brain lesions was recognized as dark or light spots that don't look like normal brain tissue which is generally lighter and more transparent. Traditionally, neurologists need lots of studying and certifications to locate those abnormal areas in those MRI images. However, even the best neurology experts might still make mistakes. For years, Researchers have been seeking a way to use artificial intelligence to help human accurately and efficiently detect brain lesions from medical imaging, and one day probably replace human diagnostics

Methods

First of all, the image from the dataset is required to be preprocessed to fit the both of the 3D CNN models.

The first 3D CNN model we choose is referencing from the 3D unet. The model is build from the keras library from python, which provides many useful class to construct the 3D unet model. The model is first applied with two types of levels of convolution blocks, the max pooling and up-convolution which both are the classes provided the keras library. Each levels is based on the depth and number of the base filter.

The second 3D CNN model we choose is referencing from the 3D CRF model with application of the residue connection, specifically the DeepMedic model. The DeepMedic model is mainly constructed through the Theano library provided from the Python. According to the paper, DeepMedic is a double pathway architecture for multi-scale processing. To implement, the feature map per layer is set to be [30,40,40,50] and dimension of kernel per layer is set to be [[5,5,5],[5,5,5],[5,5,5]].

The complete model is then trained by applying our specific training algorithm with the manually segmented, ground truth annotations. We set the learning rates to be 0.00001 and drops it with a factor of 0.5 for each iteration of learning process. Then we set the epoch to be 4 for the DeepMedic model and 10 for the 3DUnet. We train our model on a machine that has the AMD with 8 CPU core and 32 gb ram so that it allows us to run on a machine with enough memory which could potentially prevent exceeding memory allocation problem.

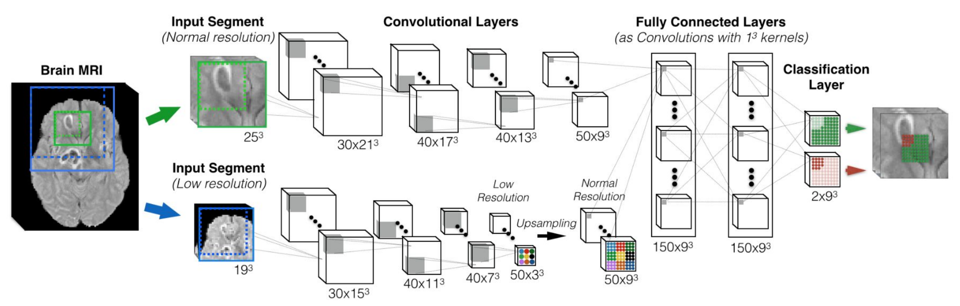

Figure.1

Figure 1. An example of double pathway architecture for multiscale processing

Figure 2. This plot represents the 3D u-net architecture, where blue boxes are feature maps.

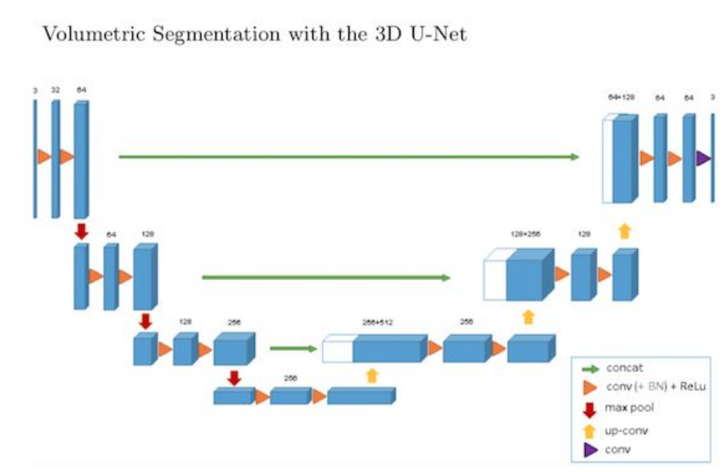

Figure.2

Results

3DUnet. The prediction result mostly accurately segments the brain lesion portion. However, there is some error by speculating the prediction image and compare it with the ground truth image. From Fig. 2 we could clearly see the different that the 3D uNet model does make a lot of prediction error by including sparsing portion of the brain that is not actually being damaged. However, it is reasonable because we assume that the image pixel at those are slightly different from the normal tissue of the brain since their color are slightly lighter compared to the dark tissue by speculation.

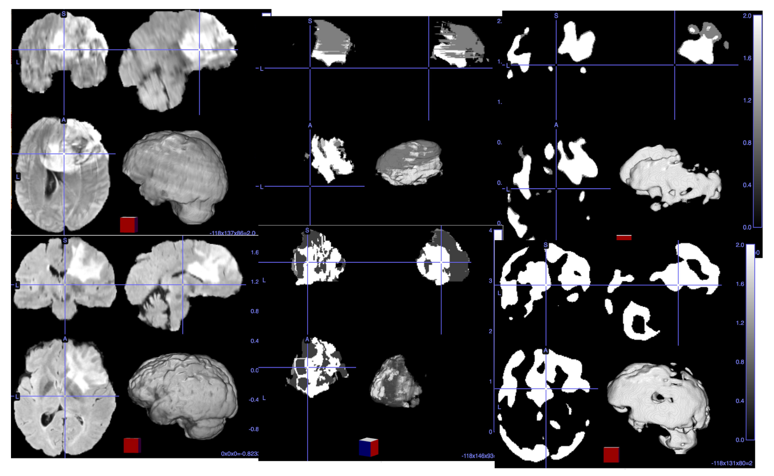

Figure.2

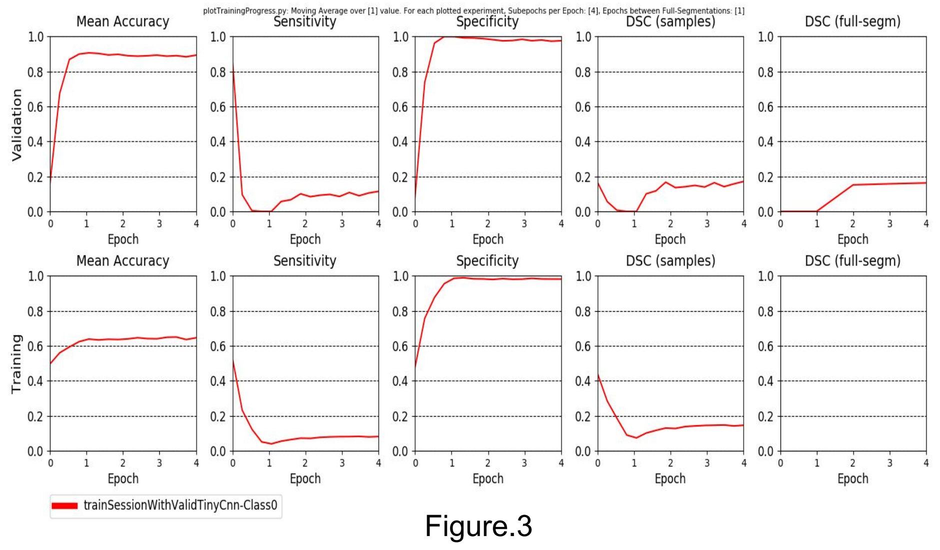

Figure.3

Figure 2. two of the Result of the 3D Unet model on brain lesion segmentation. The model is trained with approximately 400 NIFTI files and trained in 10 epoch. From left to right: (1)The original flair of the brain. (2) The ground truth image (3) the prediction

Figure 3. Result of the training progress of DeepMedic Model

DeepMedic. The accuracy rate is approximately 0.8. We also have found that DeepMedic model training is relatively fast compared to the 3DUnet. We trained a about 40 dataset which is smaller but finish training them only about 20 minutes.

However, the sensitivity and specificity is not really high so that the actual positive or negative could be potentially overlooked by our model, but throughout the training we could see that they are indeed increasing steadily so that we could conclude if we train the model in a longer epoch and more data, we could achieve an accurate model.

Conclusion

- By looking at the result of both post-trained 3DUnet model and DeepMedic model, we made a conclusion that 3D CNN could make accurate predictions on the brain lesion segmentation and it could be trained efficiently at a relatively fast rate if chosen the correct algorithm. However, it is important to choose the appropriate python library to utilize the GPU fully to make the training process efficient. Because of the exceptional performance of DeepMedic, we believe that DeepMedic could be the most correct way to implement such deep learning model. We also believe that Theano is the key part mostly suitable for this kind of deep learning application which could make the training to be fast.

References

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Source Code:

https://github.com/LawrenceXu13467/UCLA_CS168_W18