CNN-based Brain Tumour Segmentation Network

Shao Yinghui[1], He Xinling[1], Liu Haoyang[1], Liu Beini[1], Chen Yiting[1], Yan Zikai[1]

[1] Imperial College London

[2] Data Science Summer School Team 5

Abstract: Tumors are known to pose a major threat to health, especially in the brain .Brain tumor is one of the leading causes of cancer death. Accurate segmentation and quantitative analysis of brain tumor are critical for diagnosis and treatment planning. Our project focuses on the design of deep neural network to complete brain tumor image segmentation in MR brain images. To complete the final task segmentation of brain tumors, we completed the following work. The experimental data of this project is more than 7000 MR images, we need to divide the data set into a training set and a validation set.At the same time, image enhancement was performed on the training set. The second step is to design the U-NET network and construct the segmentation model of brain tumor. The third step is to define the project's loss function and evaluation function. Fourth, train and evaluate the model. At the same time, we designed an algorithm for image display.

Keywords: Deep learning; Brain Tumour; Image Segmentation; U-net

1 Introduction

As a major part of medical data, medical imaging data is widely used in clinical medicine, among which the common medical data analysis: classification and segmentation in medical images are often applied in several clinical fields. Before the extensive usage of Deep Learning, or to say before the extensive usage of CNN or DNN which significantly promote the application of deep learning in the field of image analysis, traditional machine learning techniques, such as model-based and Atlas-based methods, had been widely used in the field of medical image analysis. However, these methods usually require significant artificial feature engineering to achieve satisfactory accuracy. In contrast. Deep learning refers to the neural network combines multiple nonlinear processing layers, abstracts the original data layer by layer and thus obtains different levels of abstract features from the data. This allows deep learning to replace manual feature acquisition with unsupervised learning and efficient algorithms for layered feature extraction.

Looking back to the history of CNN network, in 1998, Lecun et al.[1] applied CNN into the field of image recognition for the first time. This network can directly input the original image, which can avoid the complex pre-processing steps. In recent years, CNN has been widely used in brain tumor segmentation. Due to variety of brain tumor types, Malathi M et al.[2] make use of convolution neural network segment brain tumor into four classes like edema, non-enhancing tumor, enhancing tumor and necrotic tumor to improve the likelihood of successful treatment. But because the traditional 2D CNN can't extract the difference information among different modes with satisfaction, Qiwei Cao et al.[3] proposed a solution based on 3D multi-pooling CNN by implementing mlti-scale input and multi-scale down-sampling. Some researchers had also made some progress in data processing to improve the accuracy and robustness of brain tumor segmentation. For example, Dongli Shuai et al.[4] proposed an automatic segmentation algorithm based on CNN and fuzzy inference network.

In the evolution of CNN models, as the result of significantly enhanced computing power, there are some innovations that are combinations of CNN and other new methods. Ragupathy et al.[5] research is an example. Classification of brain tumor is achieved by CNN, and then segmentation is completed by multiple kernel K means clustering (MKKNC). SIFT is a common algorithm for image feature extraction. Qian Wei et al.[6] applied multi-scale CNN to the segmentation of brains tumor images, and fused with SIFT features to obtain feature description as the feature of CNN. These methods not only improve efficiency but also accuracy. In the future, the brain tumor processing method based on CNN will continue to develop in the direction of the combination of multiple methods, and the auxiliary diagnosis function will be more accurate and effective.

Except for CNN-based methods, nowadays there are some improved methods. To overcome the difficulties on brain tumor image segmentation, Lei X et al. [7] proposed the Sparse-based Shape image segmentation algorithm, the most important is to establish base Prior constraint model by the image of brain tumor. Additionally, HU Chu-yan et al. [8]proposed a method based on superpixel and improve U-net mean shift. The first part is segmentation of the contour region of brain tumor, and the second part , the improved U-NET algorithm is used to segmentation the contour region of brain tumor image.

However, currently without a systematic theory to explain neural networks, the medical experts who use those models cannot know exactly why they make those judgments. This led to the crisis of trust from medical experts when using models. Mercifully, at present, more and more research focus on the "explanability" and interpretability of DL models, which will help to increase the transparency of DL models, and thus could lay the foundation for the applications of deep learning in the field of medical images on a deeper level in the future.

To conclude, the current medical image analysis (medical image segmentation etc.) based on deep learning model cannot be used as a solution to supplant medical experts, but it can help them make decisions. In the future, with the continued pursuit of high precision, the pursuit of interpretability will be paid more and more attention.

2 Methodology

This project focuses on the design of deep neural network to complete brain tumor image segmentation in MR brain images. Accurate detection of brain tumors has been a difficult and real-world challenge with important clinical implications. Specifically, we need to divide the data set into a training set and a validation set. Among them, the training set participates in model training, and the verification set does not participate in model training. Another point to note is that generalization is critical for deep learning models. For the image segmentation project, we need to define the appropriate project loss function and evaluation function. The most important point is that we need to design a deep learning network, and u-NET is more suitable for this experiment.

2.1 General design

First, the data set is processed, such as data segmentation and data enhancement. The second step is to design the U-NET network and construct the segmentation model of brain tumor. The third step is to define the project's loss function and evaluation function. Fourth, train and evaluate the model. At the same time, we designed an algorithm for image display.

2.2 Defined function/class

2.2.1 SplitData

The original images and their segmentation map are randomly shuffled and divided into train set and validation set and then copied to /Train/Yes and Val/Yes paths, while the corresponding IDs' list are generated for the DataGenerator class defined below.

2.2.2 DataGenerator

We defined the DataGenerator class. The initialization of a DataGenerator instance requires ID list, batch size, data shape(image shape and channels), shuffle(as a boolean type) as arguments. Its method __getitem__(along with __data_generation) reads and delivers one batch of the data(shape = [batch_size, 240, 240, 3]). The data augmentation is also done within the __getitem__method. We use ImageDataGenerator from keras.preprocessing.image to add noises and modify the brightness of the images.

2.2.3 Evaluate Function

Next, we defined a metric(iou_coef) to evaluate the similarity between the predicted and true segmentation map. It is defined as:

$$\text{iou\_coef(y\_true,y\_pred)} = \frac{\text{intersection area} + \text{smooth}}{\text{union area} + \text{smooth}}$$

where smooth is a given constant, and in our experiment smooth is set to 1, y_true and y_pred are the segmentation maps of one batch's data.We also define the loss function based on iou_coef as:

$$Loss(y_true, y_pred) = -log(iou_coef(y_true, y_pred))$$

In this way, the loss function will be 0 as iou_coef reaches 1, and will be $+\infty$ if iou_coef approaches 0. Then we use the classic unet to build our own model.

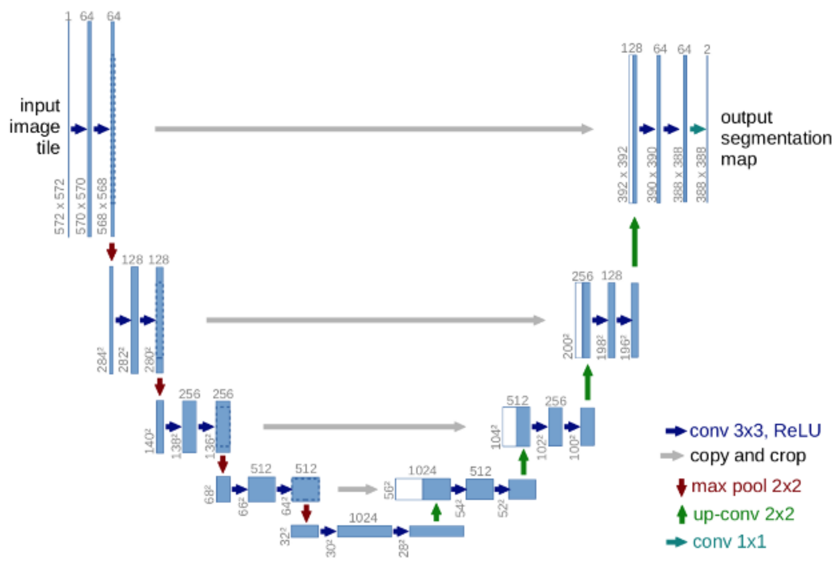

Figure 1: U-net

2.2.4 Predicted

After that, the predicted and true segmentation maps are printed using matplolib.pyplot, so that we can visualize the results and verify our outcomes. The accuracy of the training is also shown at this step.

Since the segmentation needs to be a 0-1 map, we use a threshold function to convert the output(possibility) to the desired form.

3 Result

In this section, we are trying to find out how batch size and number of epochs effect the performance of trained model. Batch size refers to the number of samples that will be propagated in an iteration(training step), while number of epochs refers the number of complete passes through the training dataset.

To investigate the influence of batch size, other parameters are kept the same: number of epochs is fixed to 2, Adam optimizer with 1e-3 learning rate. Since the usage of GPU, the batch size exceeding 20 will cause OOM(out of memory) problem in the computers used, finally 3 different batch sized were chosen to run the experiment, which are 4, 6, 12.

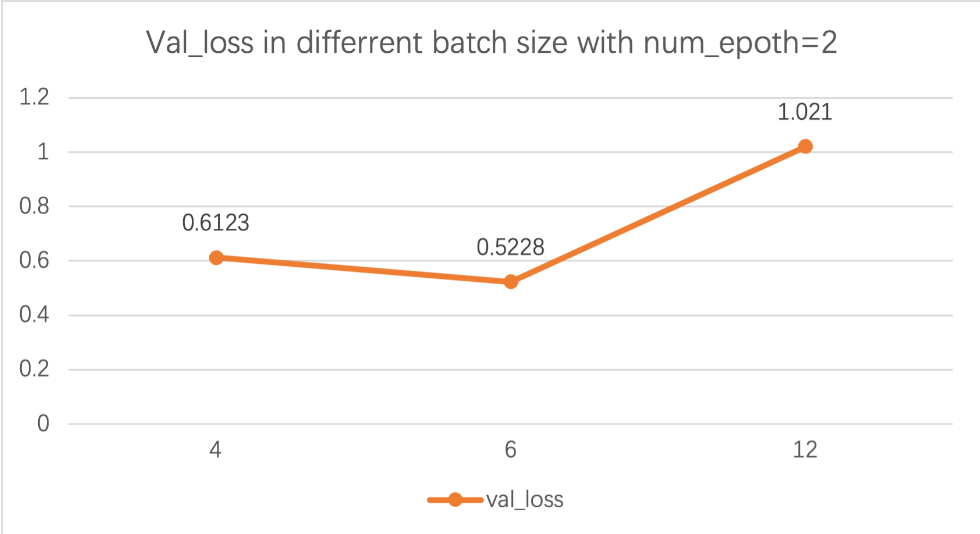

Figure 2: Figure2

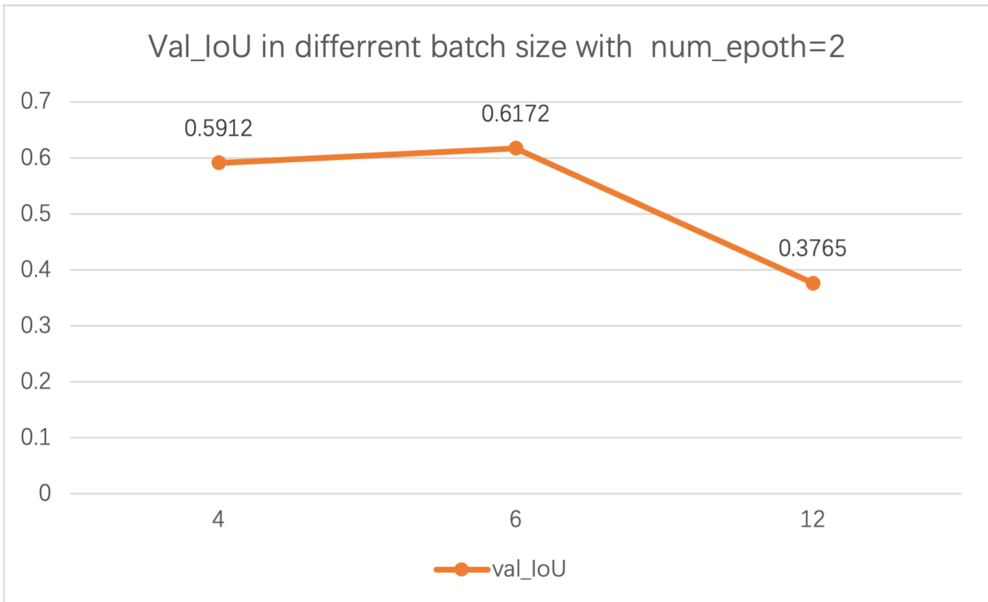

Figure 3: Figure3

Fig.2 shows that the loss value of producing the validation database, when batch size is 12, the loss is significantly higher than the rest of two loss value, which means that it when batch size is 12, we might get a worse prediction model after training. This may because large batch size means the model makes very large gradient updates and very small gradient updates, and at the same time it is widely accepted that too large of a batch size will lead to poor generalization (but definitely in this experience batch size 12 is far from too large). Additionally, the loss value of the loss when patch size = 6 is a little bit better than when batch size = 4. Although because of GPU limit, 4 and 6 are both very small batch size compared to what normally used in DL, but we could try to explain when 6 is better because with smaller batch size, it is more likely that it is too late to converge while training.

After seeing the loss, it is no surprise to see the accuracy (as Fig.2 shows). One thing should be mentioned here is that since currently the test dataset hasn't been released, thus we could only see the performance of our model while dealing with validation dataset, and this is the reason why all values is called "Val_xxx". When batch size = 12, accuracy is much lower, and best accuracy is when batch size = 6.

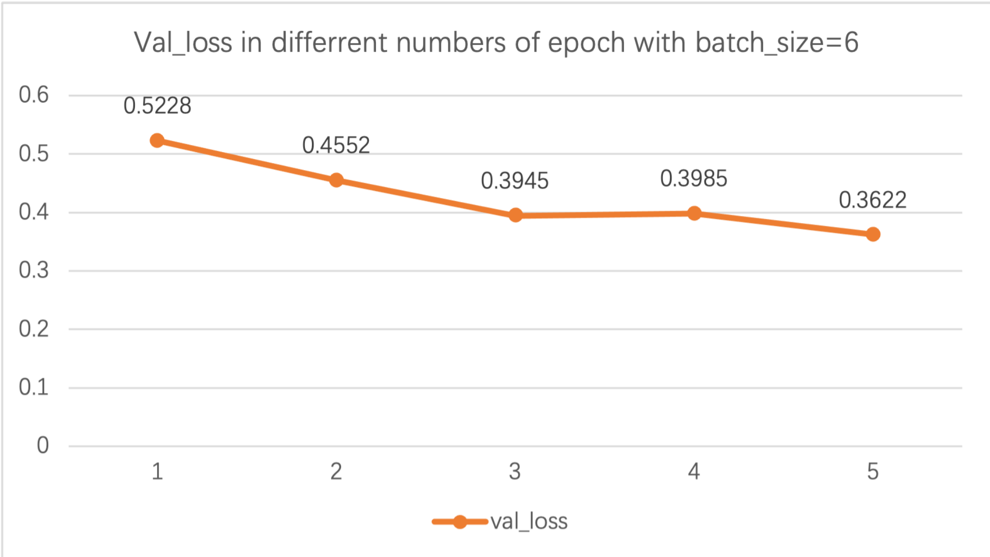

Figure 4: Figure4

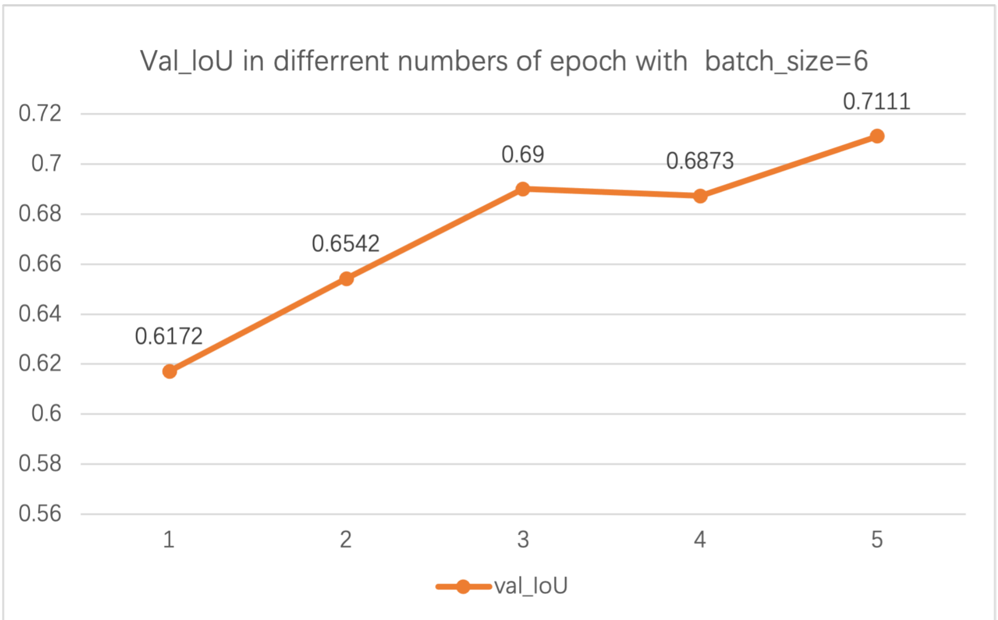

Figure 5: Figure5

Next we are focusing on the training process. Batch_size = 6 is chosen as they have best performance in last section, and we try to see the val_loss and val_IoU in each epoch. According to Fig.4 and Fig.5, it seems that convergence begins by the third epoch. Before the third epoch, the loss value is decreasing much more rapidly, but after the third epoch, the loss value begins to fluctuate.

4 Discussion

The model we trained indicate a fairish accuracy. But there are still many further improvements we could be. For instance, currently because we are limited by the GPU power, larger number for both batch size and number of epochs were not given a try, but doing those may find us a much better model. Furthermore, since a problem occurs after we are training model for different patch sizes and number of epochs, and also because the time limit, we could not find a solution to solve that problem. So there are other parameters we could adjust. For instance, learning rate and also different optimizer could be given a try.

5 Conclusion

Our project focuses on by writing the code based on the usage of U-net neural network to train a model to complete brain tumor image segmentation in MR brain images. In conclusion, because some limits, our result may not be precise enough, but there should definitely some part of our self-written code could be improved further.

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