Stroke Lesion Segmentation Final Report

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A. Introduction

Ischemic lesions in the brain arise as a result of stroke. As patients are admitted, doctors work against the clock to mitigate tissue damage from hypoxia. The motivation behind this experiment is to reduce the time taken to diagnose a stroke through automatic segmentation of affected areas.

As MRI scans are 3D images, this problem lends itself well to 3D convolution and segmentation. In this paper, we describe our methods and experiments for training a 3D CNN capable of classifying abnormalities in these brain scans. The goal evolved to become centered around modifications made to the model, loss, optimization or data that yielded improvement. Ultimately, the network was successfully trained to find certain sized lesions to a relatively accurate degree, but segmentation and shape were inaccurate. This meant that the end result did not resemble anything close to a clinical reliable product. We don't doubt however, that with more data and clever engineering, it is possible to increase the accuracy further. The applications for an accurate model capable of aiding in the diagnoses of such conditions are significant. By providing further confidence to Neurologists in a brief period of time, it's possible that strokes become easier and faster to treat. This applies in general to all conditions that are visibly identifiable through 2D or 3D scans. [4]

B. Related Work

Here we summarize some of the work related to stroke segmentation, including 2D-based CNN, 3D-based CNN, and the traditional loss function used in segmentation.

Before deep learning became popular in recent years, hand-crafted feature based methods were being used. Proposals based on those methods were based on linear regressions and relied on precise design of features. They had good performance on small data sets, but the performance could not be generalized to large data sets. [7]

Then, proposals were made based on 2D-based CNN, which worked by converting the MRI data to 2D slices and applying 2D segmentation CNN for each slice. Then, the 2D segmentation results were connected to generate the 3D results. Because of the limitation of the 2D slices characteristics, the crucial 3D context information in the data was ignored, which caused the lack of continuity in predictions. [7]

3D-based CNN had proven to be much more effective. Two typical frameworks were fully convolutional network (FCN) and U-Net. [6] Though FCN achieved end-to-end segmentation, the details of segmentation results were not ideal. U-Net, a variant of FCN, was made up of an encoder and a decoder, where the encoder encoded images into abstract feature representations and the decoder provided effective target information from the representations. U-Net was a powerful model because of its strong representational learning abilities, multi-layer abstracting and a massive number of parameters. U-net was what we used in our attempt.

Binary cross-entropy, a loss function widely used in segmentation tasks, calculated the gradient from the difference in probability distribution of each pixel in the predicted and the real sample. Dice loss, also a common loss function, calculated the gradient through the dice overlap coefficient of the predicted and the real sample. Different proposals tended to use different loss functions (usually a combination of CE loss and dice loss) that worked best according to their experiments. The loss function that we used was a combination of generalized dice loss and CE loss.

C. Method

C.1. Data Preprocessing

Data was split 80/20 into train and test segments. The train bias was largely due to the lack of large amounts of training data. Therefore, it was worth it to train on a larger set even if testing became less accurate due to this.

Using 3D convolutional models resulted in numerous issues. One of which was that it took too long to train due to the size of the tensors. We solved this problem in two different methods.

The first method that we used was simply downsizing the tensors. This resulted in some success, but its largest issue was that it meant the model was training on data that was different from what it would need to be tested on in the end.

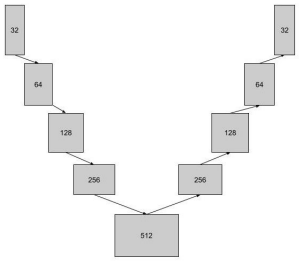
The second method that was utilized was rejection sampling. This entailed creating a method that grabbed random NxN blocks within a datum. This method then tested how much of the target was contained within this chunk, and threw out blocks which contained a percentage less than the thresholded percentage. Given the large size of the initial samples and our strict limitations, we ended up using a threshold of 40 percent.

The data that was used was very similar in format, so we elected not to normalize the data.

C.2. Model

As this is a segmentation task, one form of model was considered. This was U-Net. In each block, we considered using either 3D convolution or 2+1D convolution. Very quickly, it was found that 2+1D convolution often capped out its loss at a very unsatisfactory level. As such, 3D con-

volution was what was used. Each block was 3D double convolution. A diagram of our model is presented below. The numbers on each level are annotating the width of each level. Each level contains a convolution, a batch normalization, and a ReLu. All three of those processes occur twice in each level. [2]



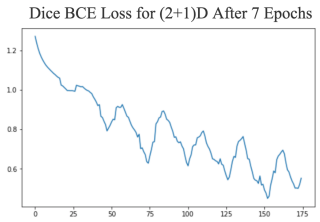
C.3. Loss

Cross entropy is the pixel-wise classification loss and generalized dice is the multi-class extension of Dice loss.

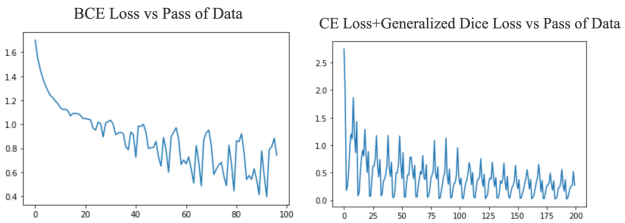
Generalized dice can balance the loss of the foreground and background according to the pixel number. However, it does nothing when the prediction does not overlap with the foreground ground truth. Thus, the cross entropy loss is introduced. The combination of generalized dice and cross entropy complement each other to produce a better result. In our code, we take the sum of two loss functions, which gave us a good loss, while in Song's paper, log was used. [3]

D. Experiments

The hypothesis for this experiment was that by splitting 3D convolution into two distinct processes, memory usage and performance would be improved. This has been used in practice and research to classify video data by letting the third dimension represent temporal changes. (2+1)D convolutional blocks achieve this by using a 3 x 3 x 1 filter to convolve along the height and width axis, followed by a 1 x 1 x 3 to include depth. In the context of this assignment, the memory limitation of Google Colab meant that scans needed to be downsized to 64 x 64 x 64 before training. However, (2+1)D allowed for data to be passed through the network at twice the resolution as before, 128 x 128 x 128. Thus the hypothesis was correct, although it is unclear if this improved accuracy. More voxels means that the shape of the target is more detailed and this might have affected accuracy measurements by the Dice coefficient. Additionally, whilst the higher resolution images were now viable, the batch size had to be smaller. [5]

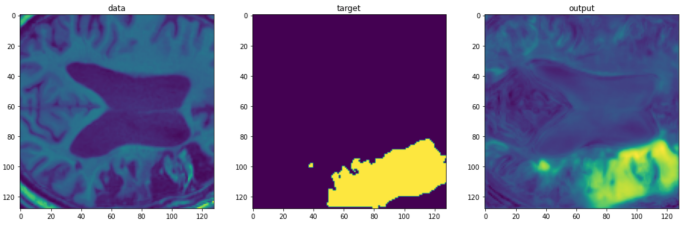


In the base code, the loss function that we used was the DiceBCE function, which gave us an average loss of .69 on the test set. [1] To optimize the losses, we implemented a new loss function by combining CE loss with generalized dice loss, which gave us an average loss of 0.0093 on the test set. The performances of both functions on the training data can be found in the graphs below. However, the predicted images of this combined loss function are less accurate than the DiceBCE function. One reason could be that our training set is pretty small considering that our data set is not big and that we have split it into 80/20 for training and testing.



E. Conclusions

This model is effective at finding the general area of where the lesion is. However, it is extremely poor in finding exact edges, and is often very inaccurate. Below is shown a model trained in 3D with DiceBCE loss and 64x64 sections' performance on an image in the test set compared to the target area where the lesion should be. At a visual glance, this image is consistent accuracy-wise with the rest of the images in the 3D test tensor.



Our model does find the lesions to some degree. However, the flaws of not using a pretrained model become clear. The model, despite hours of training, is very poor at removing noise and showing clear results. Overfitting was a relatively insignificant issue. While this model after 20 epochs

recorded an average in-sample loss of .66, it recorded an out of sample DiceBCE loss of .69. What was, however, significant was outliers. The difference in loss on certain datums compared to others reached as high as .72 in the training dataset here. Some form of further data processing would probably have benefitted this model significantly. As such, this would be a strong emphasis of future work along with using a pretrained model from other brain work.

F. Contribution

- Introduction - Oscar
- Related Work - Jian
- Methods - Oscar, Joey, Jian
- Experiments - Oscar and Jian
- Conclusions - Joey

https://github.com/Oscar-Mo/big_brain_BC

References

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[6] Yue Zhang. Application of deep learning method on ischemic stroke lesion segmentation. 2022. 1

[7] Yongjin Zhou. D-unet: A dimension-fusion u shape network for chronic stroke lesion segmentation. 1