Iowa Initiative for Artificial Intelligence

Final Report

Project title:	Automatic Segmentation and Volume Calculation of Intracranial Ventricular System on Computed Tomography	
Principal Investigator:	Fellow: Sedat Kandemirli	
Prepared by (IIAI):	Yanan Liu	
Other investigators:	Mentor Faculty: Girish Bathla	
Date:		
Were specific aims fulfilled:	Y	
Readiness for extramural proposal?	Y	
If yes … Planned submission date		N/A
Funding agency		N/A
Grant mechanism		N/A
If no … Why not? What went wrong?		

Brief summary of accomplished results:

We developed and validated a U-net model to automatically segment intracranial ventricular system. Averaged Dice Similarity Coefficient between AI predicted segmentation and manual segmentation was 0.841±0.271 for the validation group. The volume of intracranial ventricular system obtained from prediction image has strong correlation with volume obtained from manual segmentation.

Research report:

Aims (provided by PI):

· To develop a fully automated tool for brain ventricle parcellation (lateral, third and fourth ventricles) using deep neural network and automatic calculation of ventricular volume. The 'ground-truth' will be using manual segmentation performed by two radiologists in consensus in a training set of 80 patients. Volumetric analysis will also be carried out based on this manual segmentation.

· This segmentation model will be validated using an additional 20-30 manually segmented cases by two radiologists in consensus.

· To determine if changes in ventricular volumes, as determined by the model, correlate with changes in ventricular dimensions at specific locations (such as the third ventricle) and define the relationship between linear dimensions (at the third ventricle, atrium or temporal horns) and 3D-volumes.

· Finally, we aim to define the relationship between changes in ventricular volumes with changes in intracranial pressures in patients who had intracranial pressure monitoring.

As the project progressed, the team decided to focus on first three aims and the pilot project successfully completed all 3 aims as originally stated.

Data:

An internal UIHC data search yielded data from 99 subjects. Each subject has around 130-180 CT slices depicting human brain with 1mm thickness. Each slice is 512x512 size with 0.46875mmx0.46875mm resolution.

AI/ML Approach:

In this study, a U-net model was implemented for segmentation using Python. Patient-level training/validation split was 70/29. Each slice of each case was treated separately in 2D due to small data set. Total 10,886 and 4,537 slices were used as training and validation.

Experimental methods, validation approach:

Data Preparation

Data preparation or pre-processing is an essential step in any machine learning study. In this project, we converted all our CT datasets in compressed Nifti format (nii.gz). Due to a large HU value range in CT brain images, we extracted the brain using two fixed thresholds of 0 and 100 HU. [1] Any region between 0 and 100HU was considered brain tissue and the rest was labeled as background. Data normalization is an important step which ensures that each input parameter (pixel) has a similar data distribution. This makes convergence faster while training the model. After the extraction of the brain in each dataset, we normalized the image intensity to [0,1].

Ground truth obtained by semi-automated segmentation

Ventricular segmentation on CT was provided by expert radiologist who used a semi-automated approach using the 3D-Slicer tool. Using the semi-automated capabilities of 3D Slicer, an initial automated approach based on HU values was used. Brain ventricular system was interactively segmented based on HU threshold. After this step, the radiologist (SK) looked through the entire dataset and manually corrected all observed segmentation inaccuracies.

Unet

The Unet is convolutional network architecture for fast and precise segmentation of images. In this project, Unet was implemented with Keras functional API, which makes it extremely easy to experiment with different interesting architectures. (https://github.com/zhixuhao/unet)

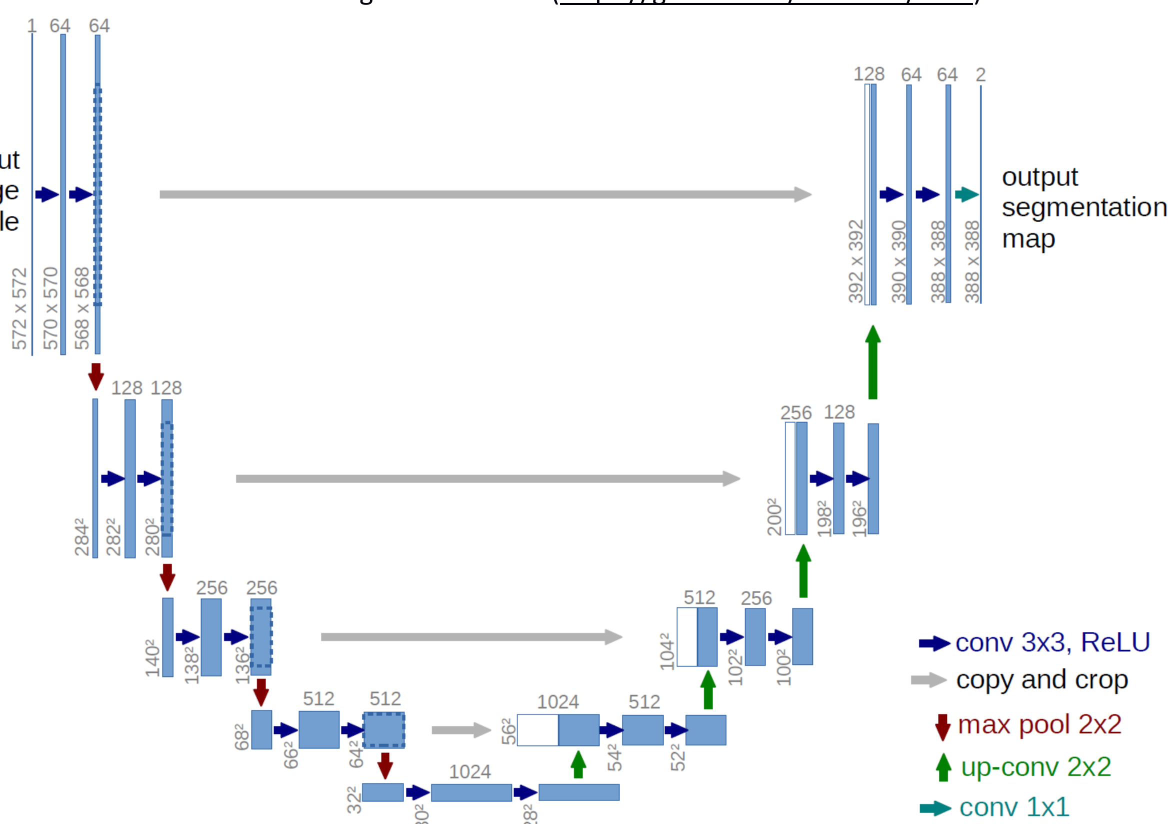

Figure 1. U-net architecture [2]

In the training phase, the input images and their corresponding masks are used to train the U-net, and in the test phase, we give an image as input to generate the corresponding mask as output. The training data is a set of 10,886 prepressed CT images (512x512 pixels). Each image comes with a corresponding ground truth segmentation mask. Output from the network is a 512x512 image which represents mask that should be learned. Sigmoid activation function makes sure that mask pixels are in [0, 1] range.

Results:

Due to the continuous character of ventricular segmentation labels in prediction results, we converted the prediction images into binary images using a fixed threshold of 0.05. Any prediction-image pixel intensity >0.05 was considered as 1 (= ventricle) and the rest was assigned 0 and considered non-ventricular brain tissue. Dice similarity coefficient (DSC) was used to measure the level of agreement between AI prediction and ground truth (manual segmentation). Averaged DSC was 0.841±0.271for the validation group (29 patients).
Figure 2 and 3 shows an example comparison of original CT image, extracted brain image, ground truth and prediction results for two typical sample subjects (one has DSC close to overall averaged DSC and the other has the highest DSC).

Number of non-zero pixels (volumes) per subjects was calculated from manually segmented masks and prediction masks in the validation group. Figure 4 shows the obtained relationship in a scatter plot chart.

In this project, we clearly showed that Unet can automatically segment intracranial ventricular system on Computed Tomography with a reasonable DSC. Due to data limitation for this pilot project, we only explored 2D Unet. With more data set, 3D Unet could be explored for segmentation.

Ideas/aims for future extramural project:

This ventricular segmentation tool can be tested on cases with sequential cranial CT available. The changes in ventricle size between two time points will be tested with the ventricular segmentation tool, and will be compared to the radiologist's report. For this purpose, a keyword search looking for reports with increase/decrease in ventricle size and stable ventricle size could be performed and available patient pool can be assessed with the deep learning tool.

Publications resulting from project:

N/A

References

1. X. Qian, Y. Lin, Y. Zhao, X. Yue, B. Lu, and J. Wang," Objective Ventricle Segmentation in Brain CT with IschemicStroke Based on Anatomical Knowledge", Hindawi Publishing CorporationBioMed Research International, Volume 2017, Article ID 8690892, 11pages. http://dx.doi.org/10.1155/2017/8690892
2. O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation," Med. Image Comput. Comput. Interv. -- MICCAI 2015, pp. 234–241, 2015.

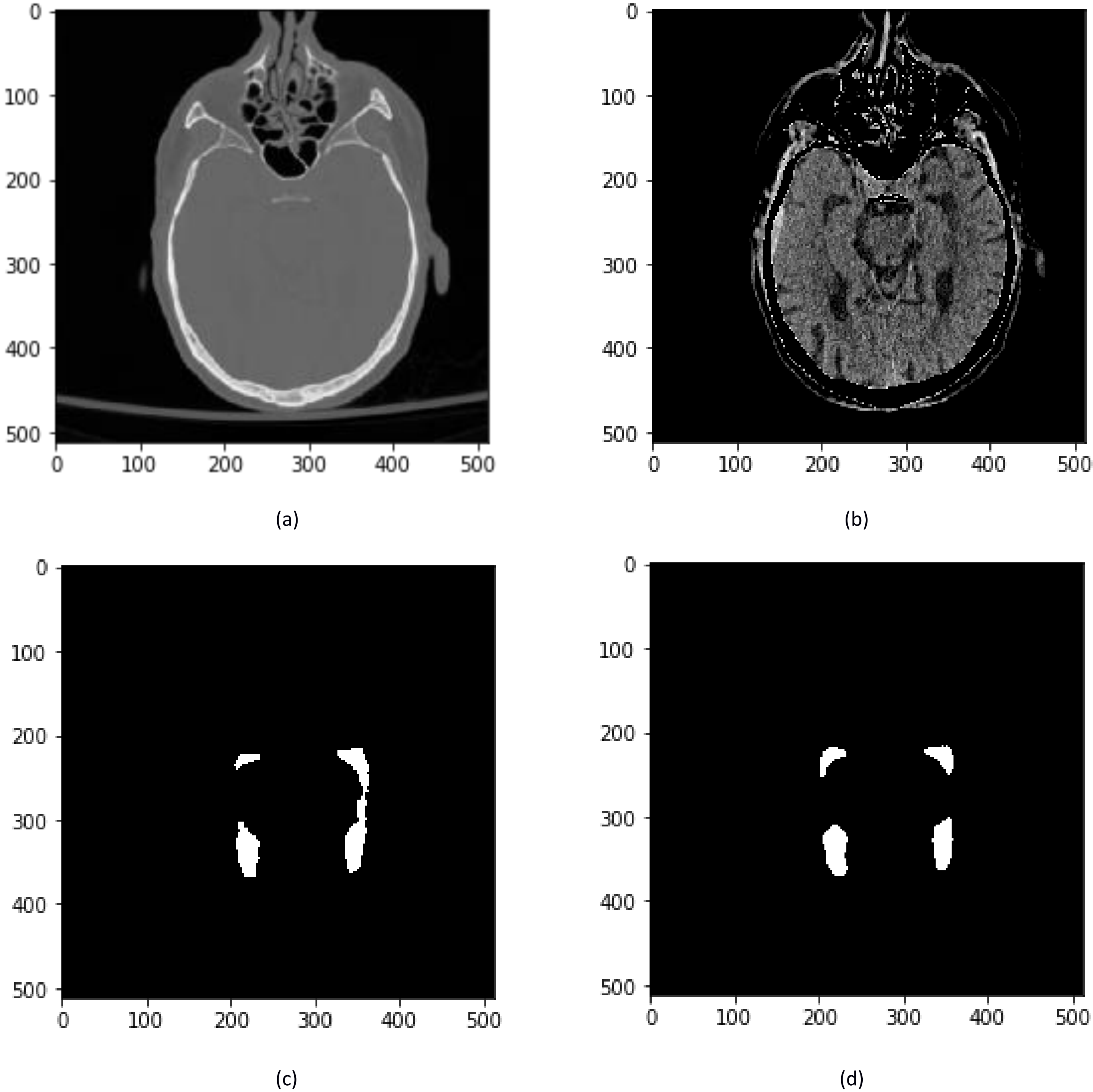

Figure 2. one typical CT image slice. (a) original CT image, (b) extracted brain image using HU [0,100], (c) ground-truth, (d) prediction. Dice=0.832

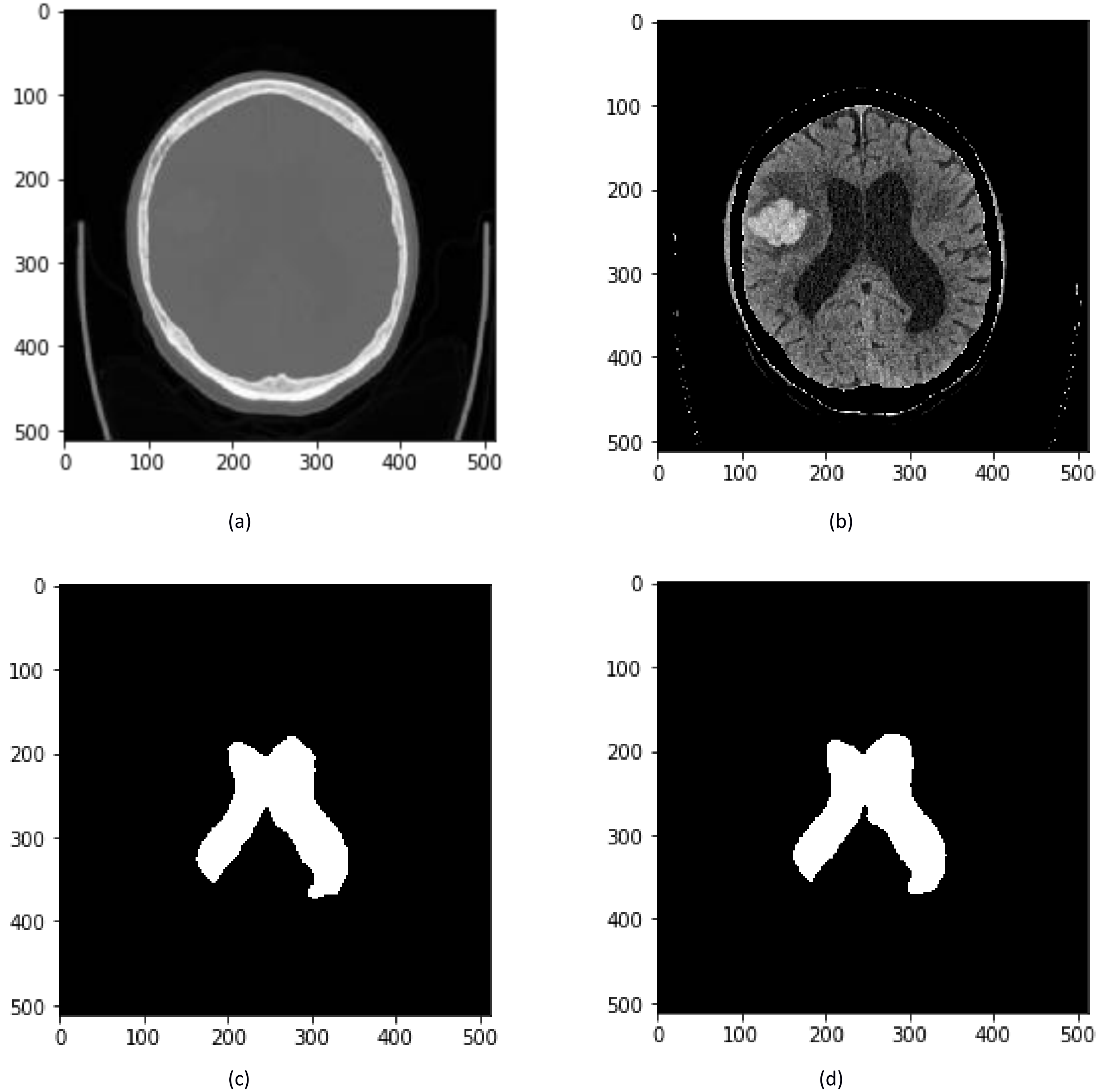

Figure 3. one typical CT image slice. (a) original CT image, (b) extracted brain image using HU [0,100], (c) ground-truth, (d) prediction. Dice=0.977

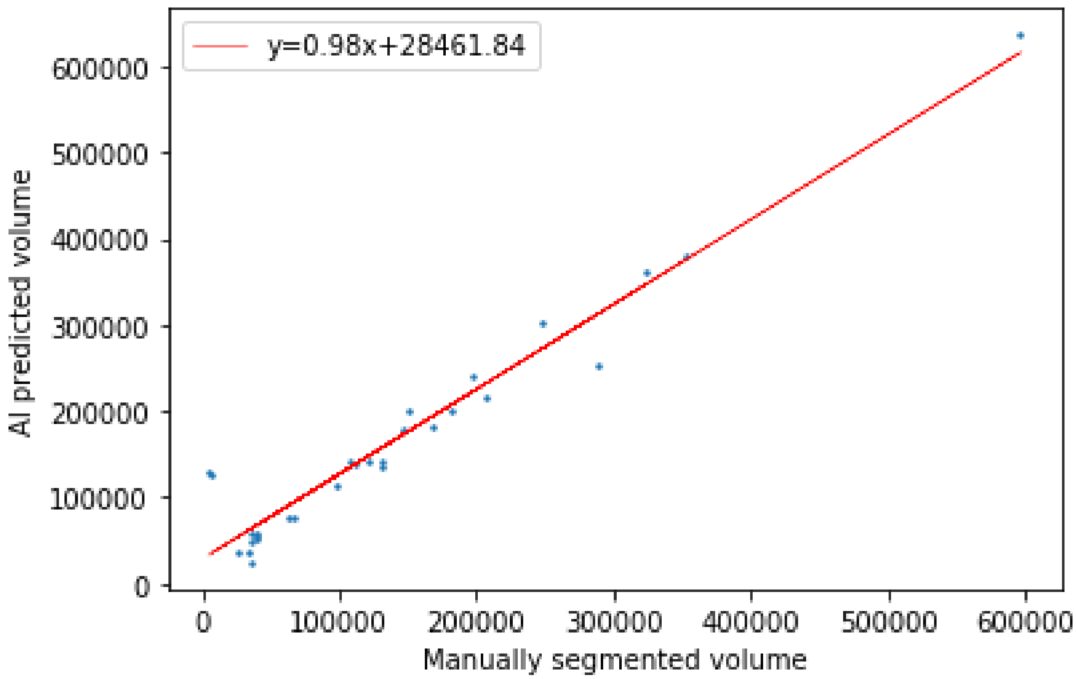

Figure 4. Manually segmented volume vs prediction volume scatter plot. X: Manually segmented volume; Y: predicted volume. Pearson's correlation coefficient=0.97.