Title:
A Cloud Collaborative Healthcare Platform Based on Deep Learning in The Segmentation of Maxillary Sinus

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Introduction:

According to market research statistics, the total global dental market in 2021 was 36.2 billion US dollars. In this market, the digital dental proportion is as high as 11.6% from 2012 to 2021. Additionally, the historical compound annual growth rate (CAGR) of the global digital dentistry market is 10.9%. Dental implants dominate the global digital dentistry market in 2021, accounting for 21.35% of the total revenue [1]. Clinically, the jawbone, the teeth root, the mandibular nerve canal and the maxillary sinus need to be considered before the dental treatment, especially for a dental implant procedure. In the dental implant procedure, dentists don't only need to clearly know the bone thickness and height, but also consider the distance between the implant placement and the adjacent teeth root, and the mandibular nerve canal, respectively for avoiding complications. Thus, a cloud collaborative healthcare platform based on deep learning in 3D maxillary sinus model reconstruction was proposed. Clinically, a perfect, accurate and efficient image recognition is a significant foundation to affect treatment and to evaluate the surgery performance. Therefore, it is necessary and important to use deep learning technology for robust oral image recognition, measurement, 3D model reconstruction and pathological diagnosis. The aim of this paper is using the deep learning method (nn-UNet) in an online collaborative platform for visualization and measurement. Firstly, the annotated data are used for an input in the nn-UNet method. The method is an automatic dental image segmentation by data normalization, three U-Net configurations and adaptive hyper-parameters adjustment. Secondly, a 3D model construction was done from the image segmentation. Thirdly, the pre-trained nnUNet model will be deployed on the backend of the cloud platform. When a dentist uploads a patient's cone beam computed tomography (CBCT) data, the deep learning model will efficiently perform the prediction computation on the web backend. Then, a 3D model of the patient's maxillary sinus is visualized on the platform and provided to the dentist for examination, assisting in diagnosis and treatment to achieve the goal of precise treatment. In addition, due to the characteristics of the cloud platform, remote diagnosis and collaborative treatment can also be achieved. Finally, the accurate 3D models are not only used for the visual rendering, but also physical practices by 3D printing preoperatively.

Traditionally, the dental image segmentation is to recognize accurately and objectively significant regions such as the jawbone, the teeth root, the pharyngeal airway, the maxillary sinus and so on. Thresholding [2], Region Growing [3] and Active Contour [4][5] are common methods for image segmentation. In practice, these methods are typically semi-automatic and based on the user's experience. Recently, some deep learning methods are proposed to improve the traditional methods. For instance, O. Ronneberger [6] proposed a deep learning architecture with contraction path and expansion path for learning and labeling from 2D medical images. After that, many researchers began to use U-Net in various fields, including bearing fault diagnosis in machines [7], building extraction and number statistics of image [8], and so on. However, it is difficult to implement in the medical image because of 3D dimension. Ö ÇİÇEK proposed 3D U-Net [9] based on U-Net [6] and improved the problem for establishing the z-axis order and orientation. After 3D U-Net was proposed, it has been widely used in the segmentation of medical images in various fields, including lung nodules [10], brain tumors [11], chest CT images [12], etc. This is a significant development for the medical field. F. Isensee [13] proposed nnU-Net based on a responsive framework of U-Net, 3D U-Net and U-Net Cascade, and ranked among the best in the 23 public datasets of the CHAOS (Combined (CT-MR) Healthy Abdominal Organ Segmentation) challenge, but there is no maxillary sinus segmentation in these datasets.

Main Idea:

A flowchart of the platform is shown in Fig. 1. Firstly, the studied dataset is collected by oral 3D CBCT from Kaohsiung Medical University School of Dentistry. Secondly, these studied datasets are annotated by an experienced dentist. Thirdly, the annotated data is used to build a model by training and validation in nnU-Net. Fourthly, the model is used for the segmentation of maxillary in the medical image. Finally, the 3D maxillary sinus is reconstructed and visualized in the cloud collaborative healthcare platform.

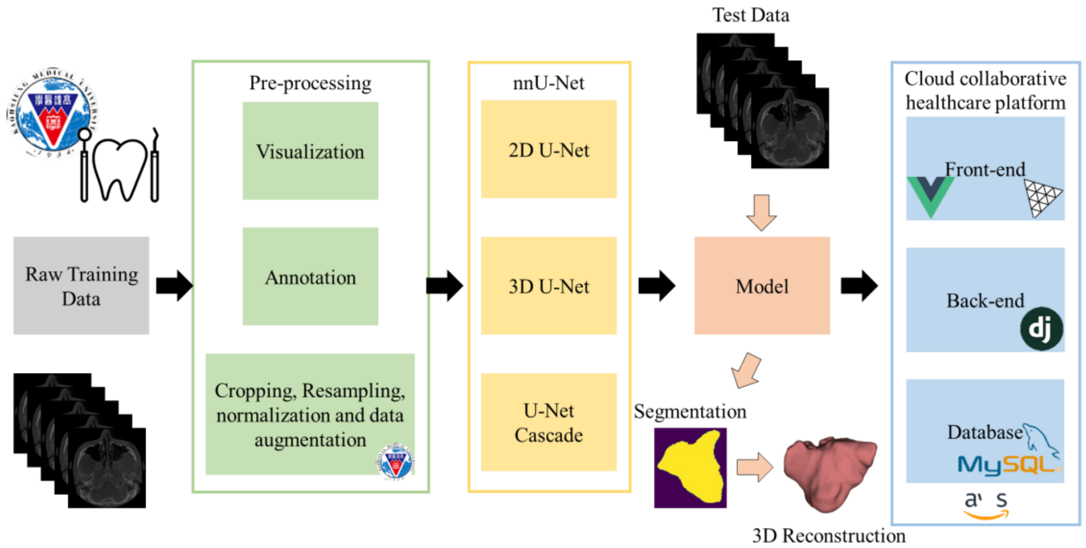

Fig. 1: The overall flowchart of the proposed platform.

A. Pre-processing

In this paper, 23 datasets were studied, and they were divided into three parts: 17 for training, 2 for validation, and the remaining for testing. To overcome hardware limitations during the training, we conducted image preprocessing by dividing the original patient images into left and right halves and resampling them to half of their original resolution. This reduced the data file size and solved the issue of insufficient Graphics Processing Unit (GPU) memory. The regions of the maxillary sinus in the training dataset were annotated by 3D Slicer (National Institutes of Health, USA), and then cropping, resampling, normalization, and data augmentation were performed. Data augmentation techniques included rotations, scaling, Gaussian noise, Gaussian blur, brightness and contrast adjustments, simulation of low resolution, gamma correction, and mirroring.

B. nnU-Net (Deep learning network)

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The nnU-Net is used for medical image segmentation in this study. The first step is to capture the data fingerprint from the training dataset. The data fingerprint includes image size, voxel spacing, number of classes for all images and other relevant parameters and properties.

According to data fingerprints and hardware limitations, some significant data fingerprints are used for the image segmentation of the specific region, because they are essential and able to be formulated explicit dependencies. Additionally, they could also be inferred to adapt by a set of heuristic rules because these rules condense domain knowledge. And the pipeline fingerprint is formed by supplementing the fixed parameters.

These heuristic rules are used to allow for almost-instant adaption on the specific application and called inferred parameters. These parameters include intensity normalization, image resampling strategy, patch size, batch size, adaption on GPU memory. On the other hands, some parameters called fixed parameters don't require adaption between datasets. These parameters consist of architecture template, optimizer, training procedure, learning rate, data augmentation, and loss function. In practice, the data fingerprint, pipeline fingerprint, inferred parameters and fixed parameters are brought into the network training. In the network, three different U-Net networks (2D U-net, 3D U-Net, U-Net Cascade) are established respectively. During the training, a 5-fold cross-validation method is adopted to determine postprocessing and run the ensemble selection for the region of maxillary sinus. In the end the best model will be set as the prediction model.

In Network training, 2D U-net, 3D U-Net, and U-Net Cascade are adapted by user. 2D U-Net is mainly used for anisotropic datasets. A 3D U-Net performs at full image resolution and a 3D U-Net cascade includes two 3D U-Net. The first 3D U-Net is used to downsample images. Then, the second 3D U-Net is adapted to refine the segmentation maps created by the first 3D U-Net at full resolution, as shown in Fig. 2. Besides, Relu was replaced by leaky ReLU (negative slope, 0.01) in nnU-Net.

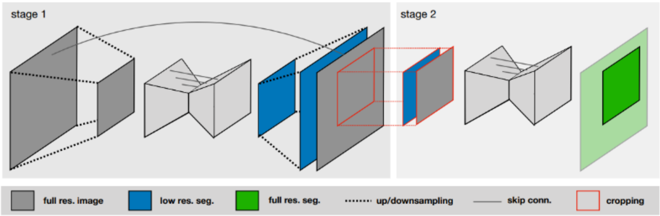


Fig. 2: Architecture diagram of cascaded 3D U-Net [8].

C. Cloud collaborative healthcare platform

In this paper, a cloud platform was developed with Django as the backend, and Vue.js with three.js as the frontend. Additionally, MySQL was adopted to provide a relational database management system for each patient's maxillary sinus and models. Furthermore, the cloud platform is based on Amazon Web Services (AWS), as shown in Fig. 3.

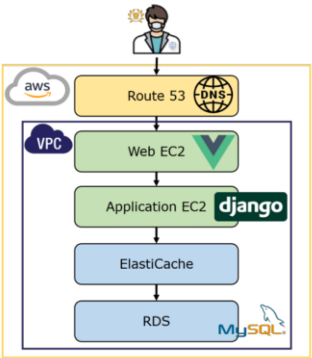
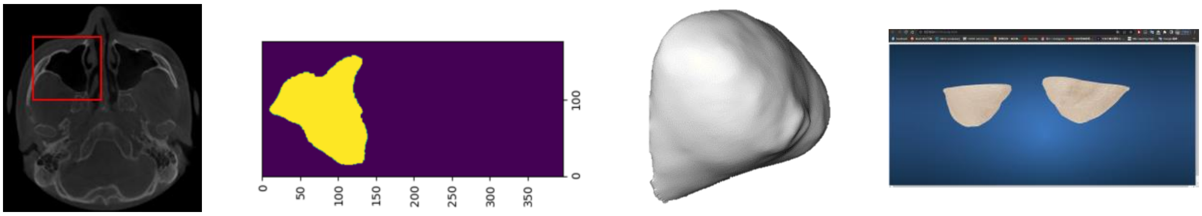


Fig. 3: A cloud collaborative healthcare platform.

In this paper, Route53 was utilized to acquire a hospital-related domain name and manage a private domain name system (DNS) with Amazon virtual private cloud (VPC). Within the VPC, we employ Vue.js 2 in the Web elastic compute cloud (EC2) to render an efficient and responsive user interface. On the other hand, the application EC2 employs Django as the primary framework for handling logical operations and utilizing models. Furthermore, we implement caching strategies using ElastiCache to enhance the efficiency between the application and the relational database service (RDS).
The CBCT is uploaded to the platform, and the maxillary sinus were extracted automatically by the trained model. Then, the extracted 3D models were rendered directly in the web by three.js. Hence, the platform could be used for remote diagnosis and collaborative treatment in different regions.

D. Implementation

In this paper, the experiment for training and test was conducted on Windows 11 with Python 3.8.5, and PyTorch 1.12.0 as deep learning framework. The model was trained on Intel Core i9 13900K with 32GB of RAM, and NVIDIA RTX 4090 GAMING X TRIO (24G). PyTorch is used to modify the original nnU-Net. In the training, loss function includes cross-entropy loss and Dice loss, and Adam is the optimizer. All networks are trained for 1,000 epochs, each one epoch being defined as iteration over 250 mini-batches. Finally, the patient’s CBCT can be automatically segmented and then 3D maxillary sinus model can be visualized via the proposed cloud collaborative healthcare platform, as shown in Fig. 4.



(a) (b) (c) (d)

Fig. 4: Visualization of extraction results: (a)CBCT raw image (b)CBCT annotation image (c) 3D model (d) Cloud Collaborative Healthcare Platform.

<u>Conclusions:</u>

This research aims to develop a deep learning network for automatic segmentation of the maxillary sinus and integrate it into a cloud medical collaboration platform using AWS. The platform allows dentists to upload patient medical images and obtain a comprehensive 3D maxillary sinus model. Once the 3D maxillary sinus model is obtained, the volume, surface area, and specific location of the patient's maxillary sinus could be calculated for preoperative simulation. This method enhances the precision of diagnosis and surgical planning while reducing reliance on experience. In summary, the advantages of the proposed platform presented in this paper are as follows:

- Compared to the traditional medical image segmentation with a lot of manual boundary selection, the proposed platform developed a deep learning network with adaptive hyper-parameters adjustment for automatic segmentation of maxillary sinus.
- With a cloud collaborative healthcare platform, multiple collaborators, remote collaboration, and interaction with each other synchronously and asynchronously could be done.
- In the future, we may use active learning and DCGAN to train deep learning models with limited datasets. Active learning reduces manual annotation efforts, while DCGAN generates more diverse and universal data than traditional data augmentation methods. This synthesized data augmentation is expected to have a more significant impact.

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