

CEPHALOMETRIC LANDMARK DETECTION USING DEEP LEARNING



CONTROL SYSTEMS AND INSTRUMENTATION ENGINEERING PROGRAM

Nutchanon Hemapattama, Atiwit Saelim,

Advisor : Dr. Teema Leangarn, Co-Advisor : Assoc. Prof. Dr. Patcharapit Promoppatum

ABSTRACT

Orthognathic surgery is a surgical procedure aim at correcting facial abnormalities by adjusting the structure of the jaw. This procedure is particularly suitable for patients with conditions such as cleft palate, facial deformities, and malocclusions (misalignment of the teeth), which can impact everyday activities such as eating and speaking. During orthognathic surgery, careful analysis of cephalometric landmark is essential to determine the appropriate direction for repositioning the jaw. The surgical plan includes identifying the specific points for incisions on the jaw. In modern practices, deep learning techniques have been introduced to analyze these landmarks in both two-dimensional and three-dimensional formats. This project focuses on using deep learning techniques for the three-dimensional analysis of cephalometric landmark and predicting jaw movements. The objective is to enhance the efficiency of the surgical planning process for orthognathic surgery and reduce the time for planning. We are currently working on improving the performance of the model, as the results show mean radial errors and successful detection rates below 2 mm between ground truth and prediction. Specifically, for the training dataset, these values are 2.41 and 47%, respectively, while for the testing dataset, they are 9.91 and 16.67%, in sequence. Currently, it is in the process of refining the model to enhance performance for acceptable criteria by doctor.

INTRODUCTION

- **Orthognathic Surgery** also known as **jaw surgery**, is a surgical process aimed at improving the structure of the jaw and enhancing facial aesthetics.

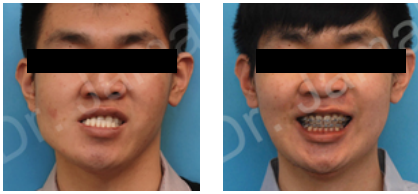


Fig 1 Before and after orthognathic surgery [6]

Benefits of Orthognathic surgery

- Improved Facial Symmetry
- Correction of Bite Irregularities
- Enhanced Speech
- Boosted Self-Esteem
- Long-Term Stability
- Enhanced Bite Function
- Improved Quality of Life

- **Cephalometric landmarks** are specific points on the human skull used in orthodontics, orthognathic surgery, and other fields of dentistry for diagnostic and surgical planning such as point of jaw relocation, facial bone shape analysis, etc.

- **Manual process for cephalometric landmark Software :** Some doctors lack proficiency in certain skills.
Paper : Time-consuming (30 min/case)

- **This project** focuses on using deep learning techniques for the two-dimensional analysis of cephalometric landmark and predicting jaw movements. The objective is to enhance the efficiency of the surgical planning process for orthognathic surgery and reduce the time for planning.

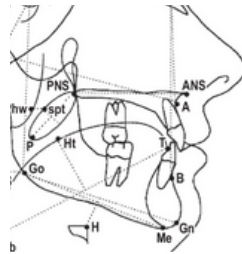
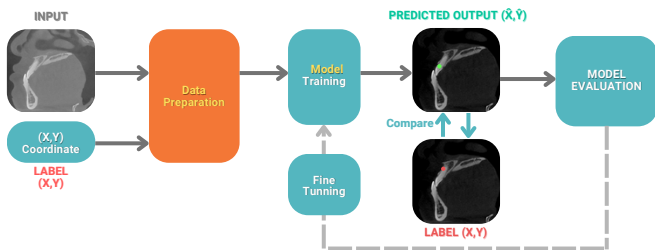


Fig 2 Cephalometric landmark [8]

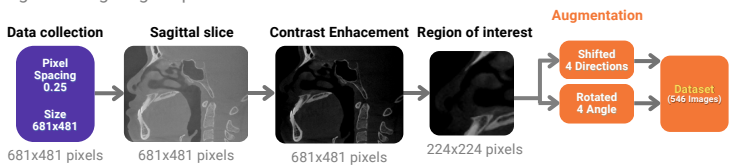
METHODS

System overview



Data preparation

- We obtained real data from 712 patients with difference facial bone shape in DICOM format. Most of the raw data have an image size of 681x481 pixels and a pixel spacing 0.25, data. And we focus Anterior nasal spine (ANS) point because ans is an important landmark for anatomical reference, It helps in determining the location of other structures in the midface region during surgical process.

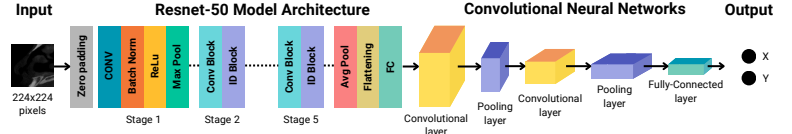


- **Data preprocessing** task, we selected sagittal slice images capturing the skull's side view to located cephalometric landmarks. Brightness and contrast are adjusted within a specified Hounsfield unit range (minimum 226, maximum 3071) to enhance bone quality. Subsequently, we cropped around average landmark points into square shapes to focus on relevant skull regions for analysis.

- **Data augmentation** was performed on the training dataset to increase the accuracy of our model. The data augmentation was shifting 1 and 3 pixels in 4 different directions (right, left, down, up) and rotating 2, -2, 4 and -4 degree [4].

MODEL

We used the ResNet-50 architecture as our backbone to extract features. Then, we add Convolutional Neural Networks, which directly outputs the coordinate of the landmark



- Resnet50 model architecture for pre-trained
- Add CNN layer for predict coordinates X and Y (Output)

RESULTS

We used two indicators to evaluate the performance of the model.

- **Mean Radial Error (MRE)** is average distance (mm) error from the center of the target.

$$MRE = \frac{1}{n} \sqrt{[(X - \hat{X}) \times \text{pixel spacing}]^2 + [(Y - \hat{Y}) \times \text{pixel spacing}]^2}$$

X, Y = ground truth, \hat{X}, \hat{Y} = predicted output, n = number of sample

- **Success detection rate (SDR)** is success detection rate in any criteria range.

$$SDR = \frac{Na}{N} \times 100$$

Na = Indicates the number of accurate detections, N = Total number of detections

The results of the ResNet-50 model indicate that mean radial error and successful detection rate below 2 mm between ground truth and prediction, are 2.47 and 47%, as shown respectively, for the training dataset. For the testing dataset, these values are 9.91 and 16.67%, respectively, as show in table 1 and table 2.

- **MRE in Acceptable range :** < 2 mm.

Table 1 Mean error (mm) and SD (mm) for each ANS coordinates.

Landmark	Training set		Test set	
	Mean Error (mm)	SD (mm)	Mean Error (mm)	SD (mm)
ANS (X1)	1.82	1.46	8.5	9.22
ANS (Y1)	1.20	1.22	3.76	3.71
Mean Radial Error (mm)	2.41		9.91	

- **Expected SDR :** in 2mm range > 80 %

Table 2 Success detection rate (SDR) for ANS in 4 error range (mm).

Landmark	1 mm (%)	2 mm (%)	3 mm (%)	4 mm (%)
ANS (Training set)	17.02	47.91	68	81.68
ANS (Test set)	0	16.67	16.67	22.22

CONCLUSION

This project aims to create an automatic cephalometric landmark localization using deep learning technique to reduce time-consuming task. In the preprocessing and augmentation task, we already enhanced bone quality in images by changing Hounsfield unit range, while employing shifting and rotation techniques to augment the training dataset, aiming to narrow the gap between predicted and ground truth standard deviations. Nevertheless, it is worth highlighting that the performance of the model does not currently meet the clinically acceptable standards for surgical planning, primarily due to significant disparities between the training and test datasets. Addressing these challenges necessitates refinement of the model's hyperparameters.

REFERENCES

1. Lee, S. M. (2019). Automatic 3D cephalometric annotation system using shadowed 2D image-based machine learning.
2. Giloi, M., Miranda, F., Bazzani, B., Ruffalo, A., Sargel, M., Al Turkastani, N., Anichini, L., Hahn, N., Fillon robin, J. C., Allamand, D., Bianchi, J., Cavallone, L., & Carlos Prieto, J. (2023). Automatic landmark identification in cone-beam computed tomography.
3. Liu, G., Zhang, Y., Kong, Y., Member IEEE, Zhang, C., Coatrieux, J.-L., Fellow, L., & Shu, H. (2022). Landmark Localization for Cephalometric Analysis Using Multiscale Image Patch-Based Graph Convolutional Networks.
4. E. A. D. L., Vasamsetti, S., Kishore, P. V. V., & Sanketi, H. K. (2019). AUTOMATIC LOCALIZATION OF LANDMARKS IN CEPHALOMETRIC IMAGES VIA MODIFIED U-NET.
5. Mohamed Nouridine, M. N., & Uztag, B. (2021). Automatic Localization of Cephalometric Landmarks using Convolutional Neural Networks.
6. Dr. Jamal, M. (u.i.u.). Patient 4, Orthognathic Surgery Photo Gallery. Omsify. https://www.omsify.com/project/patient-4-orthognathic-surgery-photo-gallery/
7. Tabata, L. C., & Nyirenda, C. N. (2021). Faster R-CNN Based Cephalometric Landmarks Detection.
8. Vasubhavan, S., Wang, L., R. W., Pivan, T., & Petocz, P. (2010). Differences in Craniofacial Structures and Obesity in Caucasian and Chinese Patients with Obstructive Sleep Apnea.
9. Phongthit, N. (2018, September 19). Convolutional Neural Network (CNN) Rso.5s. Phongthit, N. (2018, September 19). Convolutional Neural Network (CNN) Rso.5s. https://medium.com/@nathawaphongthit/convolutional-neural-network-cnn-rso-5s-72e55772e557
10. Tarnath, M., & B. (2018). การวิเคราะห์การเปลี่ยนแปลงรูปร่างของกระดูกขากรรไกรบนและขากรรไกรล่างในผู้ป่วยที่มีภาวะผิดปกติของกระดูกขากรรไกรบนและขากรรไกรล่าง.
11. Kang, S. H., Jeon, K., Hak-Jin, K., Seo, J. K., & Lee, S. H. (2019). Automatic three-dimensional cephalometric annotation system using three-dimensional convolutional neural networks: A developmental trial. https://doi.org/10.1002/ajb.1461