Location Matters: Harnessing Spatial Information to Enhance the Segmentation of the Inferior Alveolar Canal in CBCTs

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Introduction – Segmentation of the Inferior Alveolar Canal (IAC)

A primary **challenge** in segmenting the IAC is the processing of **large 3D volumes**. To mitigate memory constraints, existing approaches employ **patch-based learning**, which involves **subsampling** small three-dimensional patches from the larger volume before inputting them into a deep learning model. However, this method **compromises neural network performance** by reducing access to global contextual information. To address this limitation, **we propose an innovative approach that leverages**

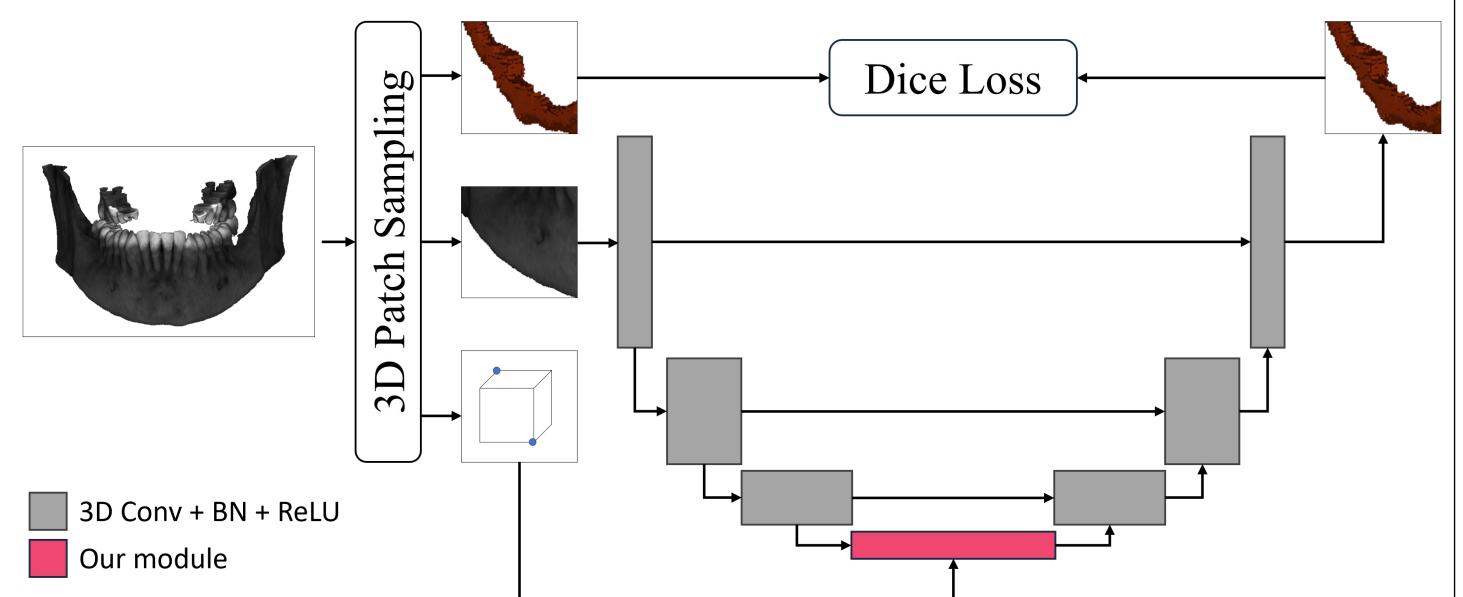


Figure 1. Segmentation pipeline Overview.

Method – Our Proposed Module and Post-processing

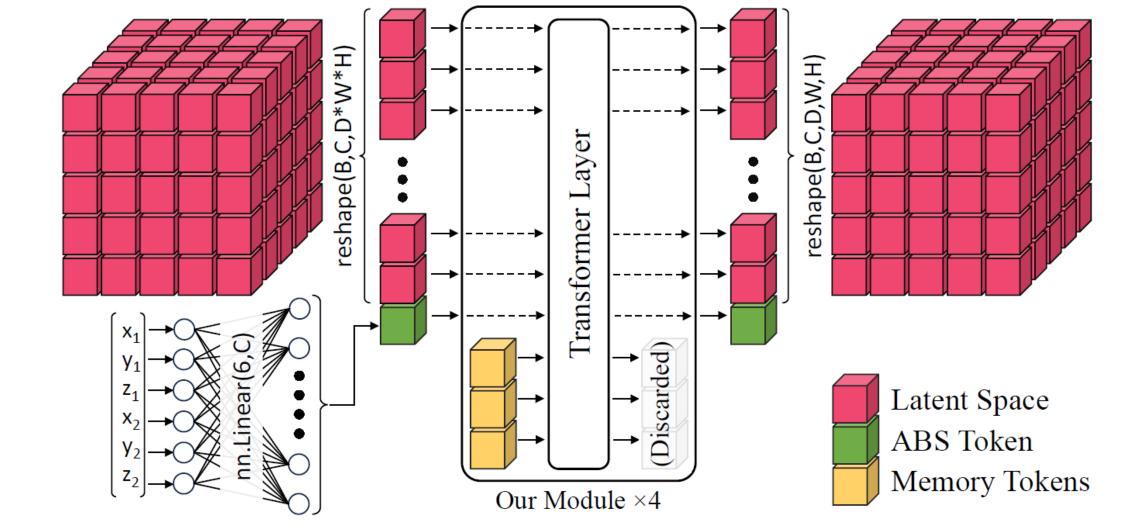


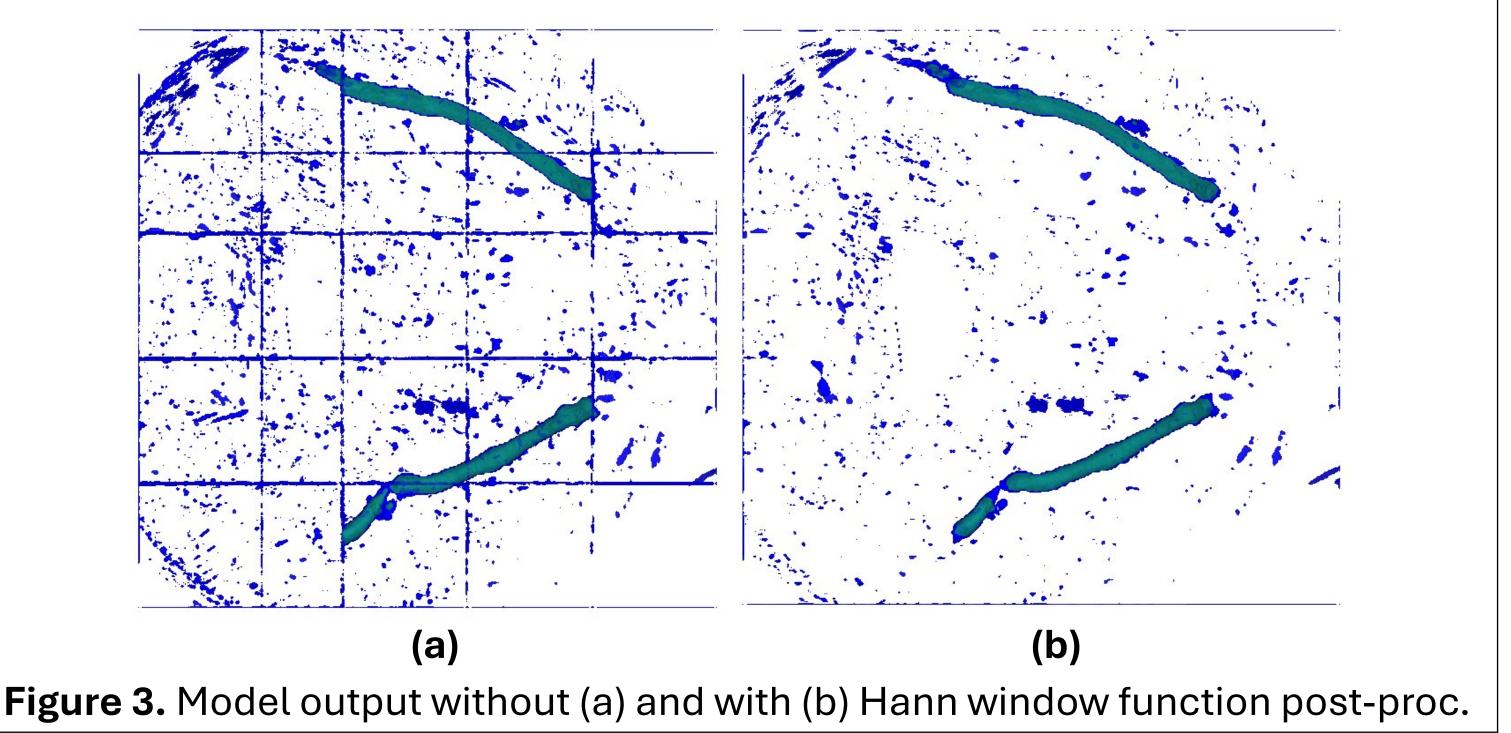
Figure 2. Our Proposed module.

To enhance overall segmentation performance, we employ a specialized **post-processing** technique inspired by audio encoding literature, specifically the **Hann window function**, which is defined as follows:

 $1 \left(2\pi i \right)$

To address the lack of global contextual information inherent in patchbased learning, **we propose a Transformer-based module** (Fig. 2) that leverages two key components:

- **ABS Token**: embeds the absolute position of each extracted patch, providing the Transformer with information about its location;
- **Memory Tokens:** assist the Transformer in retaining crucial prior concepts that are challenging to extract directly from image features but are essential for accurate interpretation.



$$W_{\text{Hann}}(i) = \frac{1}{2} \left(1 - \cos \frac{2\pi i}{I} \right)$$

where *i* represents an element within the interval *I*. To mitigate artifacts, we aggregate the contributions of Hann window functions shifted by I/2 (50% overlap). A graphical representation of this post-processing is illustrated in Fig. 3.

Results – Quantitative and Qualitative

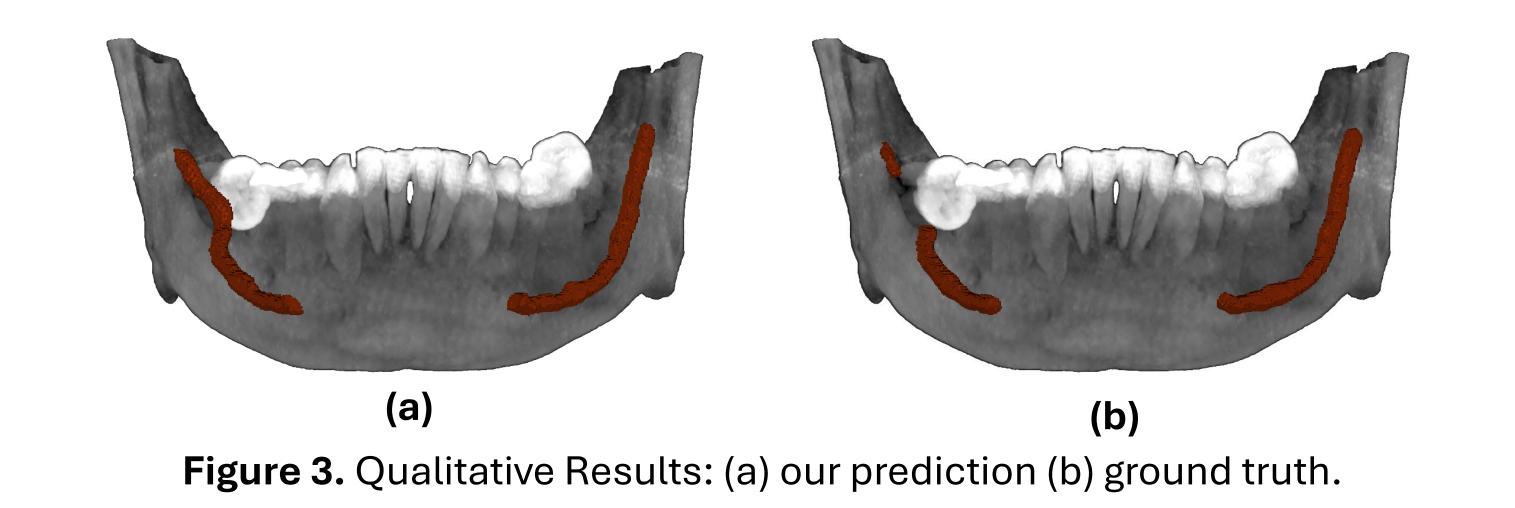
Table 1. Comparison with the state-of-the-art.

Dataset	Method	IoU	Dice
	Usman <i>et al.</i> [3]	—	0.770
Maxillo	Cripriano <i>et al.</i> [4]	0.650	0.790
	Zhao <i>et al.</i> [5]	—	0.810
	Ours	0.704	0.824
ToothFairy	Ours	0.710	0.831

Table 2. Ablation Study on the effect of ABS token, memory, and Hann window.

Method	Transf.	ABS Token	Memory	Hann Window	Dice
PosPadUNet3D	×	×	0	×	0.797 ± 0.006
TransPosPadUNet3D	✓	×	0	×	0.796 ± 0.009
TransPosPadUNet3D	✓	✓	0	×	0.801 ± 0.005
TransPosPadUNet3D	✓	×	128	×	0.800 ± 0.011
TransPosPadUNet3D	✓	1	128	×	0.802 ± 0.004
Ours (Complete)	✓	✓	128	✓	$\boldsymbol{0.809 \pm 0.004}$

We evaluate our proposal on two datasets, **Maxillo** [1] and **ToothFairy** [2], which are the biggest publicly available datasets for the segmentation of the IAC. The **comparison with the state-of-the-art** is shown in Tab. 1. Meanwhile, the **ablation study** concerning the effect of the ABS token, memory, and Hann window function are presented in Tab. 2. Qualitative results are shown in Fig. 3.



References

[1] Cipriano et al., Deep Segmentation of the Mandibular Canal: a New 3D Annotated Dataset of CBCT Volumes. IEEE Access, 2022
 [2] Bolelli et al., ToothFairy Dataset, https://toothfairy.grand-challenge.org/, MICCAI 2023
 [3] Usman et al., Dual-Stage Deeply Supervised Attention-Based Convolutional Neural Networks for Mandibular Canal Segmentation in CBCT Scans, Sensors, 2022

[4] Cipriano et al., Improving Segmentation of the Inferior Alveolar Nerve through Deep Label Propagation, CVPR 2022

[5] Zhao et al., Whole mandibular canal segmentation using transformed dental CBCT volume in Frenet frame, Heliyon 2023