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LETTER

The Innovation Medicine

Artificial intelligence- and pediatric CBCT-aided developmental recognition and personalized treatment of periapical diseases

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Received: October 18, 2024; Accepted: February 19, 2025; Published Online: February 20, 2025; https://doi.org/10.59717/j.xinn-med.2025.100118

Citation: Zhang S., Liu Y., Li D., et al. (2025). Artificial intelligence- and pediatric CBCT-aided developmental recognition and personalized treatment of periapical diseases. *The Innovation Medicine* **3**:100118.

Dear Editor,

The automatic analysis of children's Cone-Beam Computed Tomography (CBCT) image data for tooth segmentation during the mixed dentition stage, the determination of the developmental stages of young permanent teeth, and the formulation of individualized treatment strategies pose a considerable challenge. To improve treatment success rates and personalize care, we have devised the first multi-stage deep learning (DL) framework specifically tailored for the analysis of children's CBCT image data. This framework enables the simultaneous segmentation, classification, and prediction of the developmental stages of all tooth types, integrating diverse information sources to generate customized treatment plan recommendations for young premolars with chronic periodontitis. Given the substantial influence of the developmental stages of permanent teeth on treatment decision-making and the existing limitations in specialized pediatric dentistry, this research constitutes a pioneering advancement in enhancing the precision of dental and jaw disease treatments through artificial intelligence (AI)-driven, personalized care strategies.

DATA SOURCES FOR THIS STUDY

A retrospective examination of CBCT imaging data from the study's host institution, was carried out from 2020 to 2022. The study encompassed 115 children aged 5-12 years, with 80 cases (3,114 teeth) serving as the training group, 20 cases (749 teeth) as the internal validation group, and 15 cases (422 teeth) as the external validation group. All participants were imaged using various CBCT machines. Additionally, an independent sample of 123 children, aged 8-12 years, who underwent treatment for periapical diseases of the premolars and achieved a cure, was included, with radiographic data available from before treatment and at the six-month follow-up.

Exclusion criteria encompassed poor-quality CBCT images, metal artifacts, severe craniofacial deformities, jaw lesions, and children with mental or intellectual disabilities. The age distribution of the participants was relatively homogeneous. All CBCT data were acquired with the principle of keeping radiation doses as low as reasonably achievable (ALARA) in mind. The data were anonymized, and all CBCT scans were clinically indicated, with none obtained exclusively for this study.

Sample acquisition and annotation

The pediatric dentist-radiologist team manually delineated the marginal edges in 100 complete dental arch CBCT images (training and internal validation sets) by utilizing ITK-SNAP software (version 3.6.0), which served as the gold standard. Furthermore, the tooth developmental stages were evaluated according to Nolla's staging system,[1] thereby establishing the fundamental data for the development of an automatic segmentation and staging framework.

Multi-stage deep learning model

In the previous study, the emphasis was on the multi-class segmentation of the mixed dentition in children.[2] In the present research, an instance segmentation technique within a multi-stage framework is adopted to precisely segment, classify, and predict the developmental stages of various tooth types. The procedure commences with the identification of tooth germ centers in high-resolution CBCT images, followed by the cropping of these images into 128 × 128 × 128 patches for efficient training. The region of interest (ROI) for each tooth is demarcated using bounding boxes to facilitate accurate segmentation. Teeth are categorized into five classes based on root morphology, with the integration of lower-resolution data to decrease resource requirements while enhancing the classification network's capacity to capture contextual information. The permanent tooth germ staging module utilizes a hierarchical ROI-based classification network, consisting of three ResNet-50 networks, processing dual-channel data that combines CBCT images and segmentation results for multiclass staging ranging from 1 to 10. The AI segmentation system has shown high accuracy in localizing, segmenting, classifying, and staging both deciduous and permanent teeth (Figure 1A).

Training details

The AI framework was implemented using PyTorch (v1.12.1) and trained on an NVIDIA GeForce RTX 3090 GPU (24 GB). Tooth germ localization, segmentation, and classification were accomplished through a series of networks that combined cross-entropy and Dice loss functions, as detailed in equations (1) and (2). Training was optimized with a stochastic gradient descent optimizer, employing a batch size of 2, an initial learning rate of 0.01, and running for 1,000 epochs. For the tooth germ staging network, L2 loss and the Adam optimizer were utilized, with a batch size of 8, an initial learning rate of 0.001, and trained for 300 epochs.

$$L_{CE} = -\frac{1}{N}\sum_{n=1}^{N} y_n log\widehat{y_n} \tag{1}$$

$$L_{Dice} = -\frac{1}{N}\sum_{n=1}^{N} \frac{2y_n\widehat{y_n}}{y_n{}^2\widehat{y_n}^2} \tag{2}$$

where y_n is the ground truth of the n^{th} pixel, and $\widehat{y_n}$ is the predicted value.

STATISTICAL ANALYSIS

Several evaluation metrics were employed to quantify the disparities between the tooth results generated by the proposed AI framework and the ground truth. For segmentation accuracy, the Dice Similarity Coefficient (DSC) and Average Symmetric Surface Distance (ASSD) were utilized. The DSC and ASSD are defined as follows:

$$\mathrm{DSC}(X,Y) = \frac{2|X \cap Y|}{|X| + |Y|} \tag{3}$$

$$ASSD(X,Y) = \frac{\sum_{x\in S_X} \min_{y\in S_Y} d(x,y) + \sum_{y\in S_Y} \min_{x\in S_X} d(y,x)}{|S_X| + |S_Y|} \tag{4}$$

where X represents the ground truth, and Y represents the model-generated segmentation.

Detection Accuracy (DA) and Identification Accuracy (FA) were employed to assess the identification and classification performance.[3] These metrics are defined as:

$$DA = \frac{|D|}{|D \cup G|} \tag{5}$$

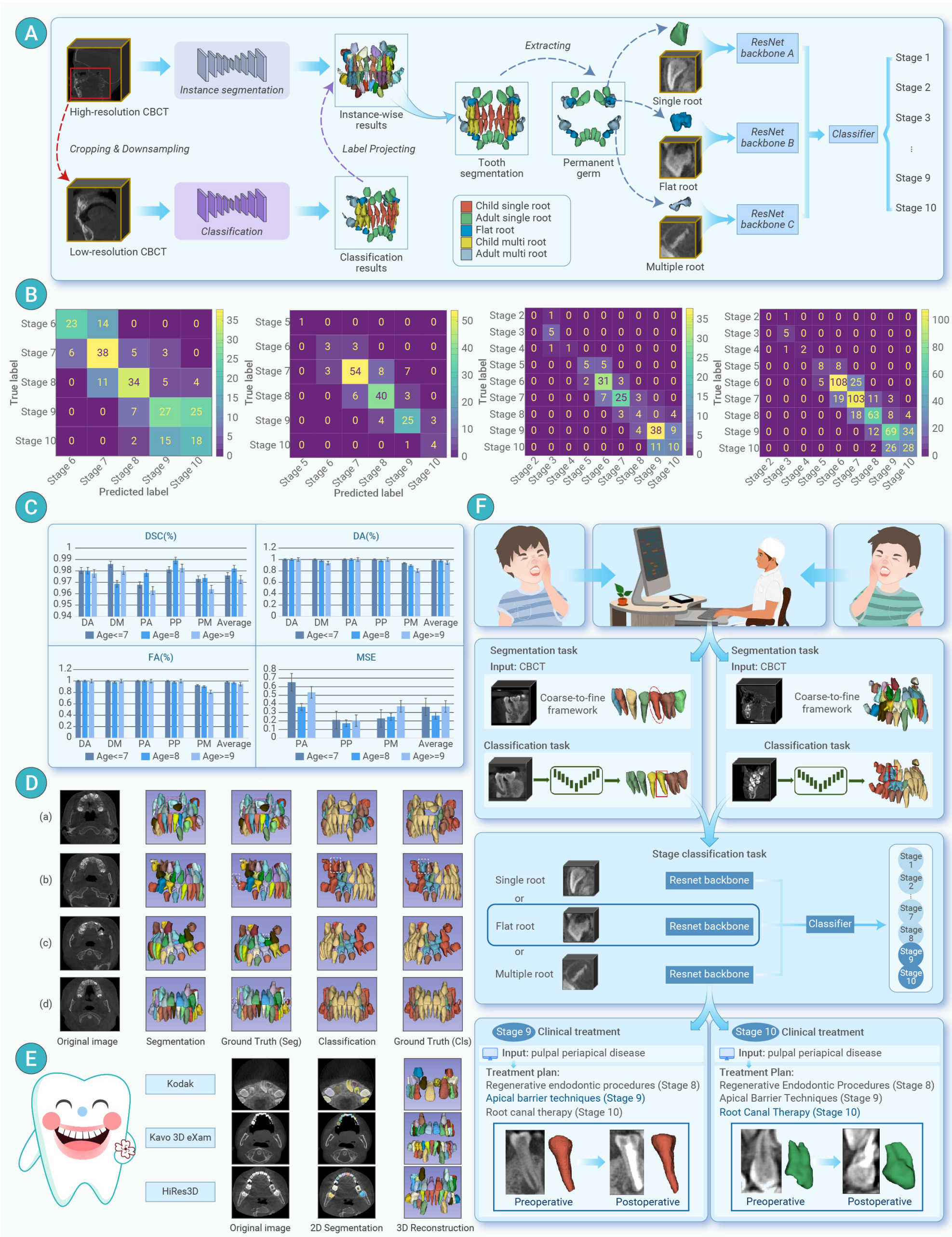

Figure 1. (A) This illustration presents the architecture of the proposed multi-stage deep learning model. It incorporates a multi-task network specifically engineered for simultaneous tooth segmentation and classification, supplemented by a hierarchical region of interest-based classification network assigned with the task of predicting the staging of tooth germs. (B) Confusion matrices depicting the model's performance for permanent anterior, permanent premolar, permanent molar teeth, and the overall sample set. (C) Performance comparison among different age groups regarding the mean Dice Similarity Coefficient, average symmetric surface distance, detection and identification accuracy for tooth identification, and mean square error for tooth germ staging. (D) Visual representation of the model's segmentation and classification performance in four representative cases. The red box indicates a tooth with an abnormal orientation, the green box indicates a misclassification, and the yellow box indicates a missed detection. (E) Visual demonstration of the model's segmentation and classification performance across various CBCT imaging sources. (F) A flow chart outlining the end-to-end treatment planning process for premolars using the deep learning model. The input comprises of a CBCT image and a periapical disease prompt, with the output encompassing tooth segmentation, classification, and staging results, culminating in a personalized treatment plan.

$$FA = \frac{L}{|D \cup G|} \quad (6)$$

where G is the set of all teeth in the ground truth, D is the set of teeth detected as correct by the model, and L is the number of teeth with correct labels within D.

Staging accuracy was evaluated using Mean Squared Error (MSE), calculated as:

$$MSE = \frac{\sum_{i=1}^{n}(x-y)^2}{n} \quad (7)$$

where x is the set of actual tooth stages in the ground truth, and y is the set of stages predicted by the model.

The consistency between the model-recommended treatment and the actual treatment carried out in the clinic was evaluated using the Kappa test. All statistical analyses were conducted using the IBM SPSS Statistics program (version 26).

The AI segmentation system attained a high level of accuracy in localizing, segmenting, classifying, and staging both deciduous and permanent teeth

The initial analysis of CBCT scan results using the proposed model indicated that permanent premolars displayed the highest DSC of 98.41% and the lowest ASSD of 0.16 mm. Deciduous and permanent anterior teeth achieved a perfect DA of 100%, while deciduous and permanent molars obtained a perfect FA score of 100%. However, the FA score for permanent molars was slightly higher due to some incomplete detections. The tooth germ staging performance, evaluated using MSE, presented an average MSE of 0.36, with specific values of 0.52 for anterior teeth, 0.19 for premolars, and 0.29 for molars.

The proposed AI framework performed stably, with the majority of errors occurring in a single element adjacent to the main diagonal of the confusion matrix, which is considered clinically acceptable (Figure 1B). Errors in positioning, segmentation, and classification could affect the accuracy of tooth germ staging. The staging results for anterior teeth were less satisfactory compared to those for premolars and molars. Further analysis disclosed disparities in the staging of permanent anterior teeth within the 8-10 stage range, potentially due to the small apical foramen areas of maxillary incisors and canines.[4] The voxel spacing for CBCT was set at 0.25 mm, and the slice thickness was 0.25 mm, which could lead to errors when examining the apical areas of permanent anterior teeth.

When the validation set was divided into three age intervals (≤ 7, 8, and ≥ 9 years), the 8-year-old group achieved the best average segmentation results, outperforming the ≤ 7 and ≥ 9 years old groups. However, segmentation accuracy tended to decline in the older age groups, particularly evident in the DA values for permanent molars in the ≥ 9 years age group, which were the lowest. This might be attributed to the difficulty in identifying third molar germs before Stage 2 in the older age groups, influencing the overall segmentation and detection accuracy (Figure 1C).

Strong performance and generalizability of an AI framework for CBCT-based tooth segmentation and classification

In our endeavors to ensure the robustness and accuracy of our model, we closely examined its performance on the validation set. The model demonstrated a strong performance on the validation set. The red box in Figure 1D

(a) illustrates an anterior tooth with an abnormal orientation, presenting a challenge for the model, yet it was precisely segmented and classified. Figure 1D (b-d) highlight instances where early staging tooth germs were missed during validation. Figure 1D (b-c) show the third permanent molar germ that was falsely filtered due to intersection over union with neighboring teeth, influenced by the spatial orientation of the dental arch. The green box in Figure 1D (b) indicates a misclassification where a deciduous molar was wrongly identified as a permanent molar.

To evaluate the model's generalizability across different CBCT sources, we applied the framework to 15 CBCT images from three additional CBCT machines: HiRes3D, Kavo 3D eXam (0.4mm voxel), and Kodak 9000 Extraoral Imaging System (small field of view). The framework exhibited excellent performance in CBCT tooth segmentation, laying a solid foundation for subsequent tasks (Figure 1E).

The personalized treatment of periapical diseases based on AI intelligent design

The novel model, encompassing segmentation, classification, staging, and end-to-end output, was incorporated into clinical practice. This integration is in line with the recent progress in AI-driven dental applications,[5] which emphasizes the potential of AI to improve the accuracy of diagnosis and treatment planning. In our study, the model was employed to predict and offer personalized treatment plans for periapical diseases in 123 cases involving young premolars. The Kappa values comparing the model-recommended treatment with the actual clinical treatment were 0.849 for the first premolar and 0.929 for the second premolar, indicating a high degree of consistency between the model's predictions and clinical treatments. Our designed framework is capable of providing an end-to-end output from patient consultation to the provision of personalized treatment plans (Figure 1G).

Superior accuracy and efficiency of AI-driven tooth segmentation and staging in pediatric dental imaging

AI technology has been extensively applied in dental imaging, including panoramic radiographs[6] and CBCT[7], for tasks such as tooth identification, lesion detection, and bone loss assessment. In this study, we evaluated the performance of our proposed DL-based method in comparison with state-of-the-art multi-stage instance-based segmentation methods (ToothNet,[3] BA-Net,[8] HMG-Net,[9] SGA-Net[10]) for CBCT tooth segmentation. Our method achieved superior accuracy, with a DSC approximately 7% higher than tooth-wise instance methods and 2.46% higher than quadrant-wise methods, while requiring fewer model parameters. The results were clinically validated and considered suitable for personalized dental treatment. Additionally, for tooth staging, ResNet-50 outperformed ResNet-18, attaining an average staging MSE of 0.36, with the lowest MSE (0.19) observed for premolars. These findings emphasize the efficiency and accuracy of our framework for clinical applications.

PERSPECTIVE

This study pioneers a multi-stage DL model for pediatric tooth segmentation, classification, and treatment planning, with a focus on predicting tooth germ staging. The nnUnet framework we constructed enables the automatic and personalized treatment of periapical diseases by precisely segmenting pediatric teeth and predicting their developmental stages from CBCT images. This innovation holds profound clinical significance, providing valuable decision support and treatment guidance to non-specialized pediatric dentists, particularly those who may not yet possess extensive professional training or clinical experience. The framework offers actionable treatment plans and guidance, which can help prevent treatment errors or delays, ensuring that patients receive appropriate care. Through the application of our framework, the efficiency and accuracy of the diagnosis and management of diseases related to the dental field have been significantly enhanced, and the development of more efficient and precise diagnosis and treatment methods has been facilitated.

REFERENCES

1. Nolla C. M. (1952). The development of permanent teeth. (University of Michigan Ann Arbor)
2. Liu Y., Zhang S., Wu X., et al. (2024). Individual graph representation learning for pediatric tooth segmentation from dental CBCT. *IEEE Transactions on Medical Imaging*. DOI:10.1109/TMI.2024.3501365
3. Cui Z., Li C. and Wang W. (2019). ToothNet: Automatic tooth instance segmentation and identification from cone beam CT images. *IEEE/CVF Conference on Computer Vision and Pattern Recognition* 6361-6370. DOI:10.1109/CVPR.2019.00653
4. Mizutani T., Ohno N. and Nakamura H. (1992). Anatomical study of the root apex in the maxillary anterior teeth. *J. Endod.* **18**:344–347 DOI:10.1016/S0099-2399(06)80486-3
5. Turosz N., Chęcińska K., Chęciński M., et al. (2024). Artificial intelligence (AI) assessment of pediatric dental panoramic radiographs (DPRs): A clinical study. *Pediatr. Rep.* **16**:794–805 DOI:10.3390/pediatric16030067
6. Turosz N., Chęcińska K., Chęciński M., et al. (2023). Applications of artificial intelligence in the analysis of dental panoramic radiographs: An overview of systematic reviews. *Dentomaxillofac. Radiol.* **52**:20230284 DOI:10.1259/dmfr.20230284
7. Mureșanu S., Almășan O., Hedeșiu M., et al. (2023). Artificial intelligence models for clinical usage in dentistry with a focus on dentomaxillofacial CBCT: A systematic review. *Oral Radiol.* **39**:18–40 DOI:10.1007/s11282-022-00660-9
8. Wu X., Chen H., Huang Y., et al. (2020). Center-sensitive and boundary-aware tooth instance segmentation and classification from cone-beam CT. *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)* 939-942. DOI:10.1109/ISBI45749.2020.9098542
9. Cui Z., Fang Y., Mei L., et al. (2022). A fully automatic AI system for tooth and alveolar bone segmentation from cone-beam CT images. *Nat. Commun.* **13**:2096 DOI:10.1038/s41467-022-29637-2
10. Li P., Liu Y., Cui Z., et al. (2022). Semantic graph attention with explicit anatomical association modeling for tooth segmentation from CBCT images. *IEEE Transactions on Medical Imaging* **41**:3116–3127 DOI:10.1109/TMI.2022.3179128

FUNDING AND ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (82072984), Beijing Natural Science Foundation (7252058), Beijing Municipal Science and Technology Commission Project (Z221100007422046), Innovation Foundation of Beijing Stomatological Hospital, Capital Medical University (23-09-23), and Beijing Nova programme (20230484404). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

S.Z and Y.L managed data curation, formal analysis, and drafted the initial manuscript. They, along with L.W, also validated the findings and co-developed the software. D.L and J.L participated in the investigation, and S.Z and D.L devised the methodology. S.Z and Z.F obtained funding and acquired the data. Z.F and L.W oversaw the conceptualization, administration, resources, and provided supervision. All authors contributed to the manuscript's revision.

DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

The study protocol and procedures adhered to the ethical guidelines outlined in the Declaration of Helsinki, and the Ethics Committee of Beijing Stomatological Hospital, Capital Medical University, approved this study (CMUSH-IRB-KJ-PJ-2023-17) and written informed consent was obtained.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.