Performance of Artificial Intelligence in Detecting Dental Features in Pediatric Bitewing Radiographs

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Introduction

Background Artificial intelligence (AI) deep learning shows promise in dental imaging, but current systems fail to address pediatric dentistry's unique challenges. Primary teeth differ significantly from permanent teeth (thinner enamel, larger pulps, distinct pathology) yet most AI models train on adult dentition. Mixed dentition creates overlapping structures that complicate automated analysis.[1-9]

Gap No AI systems adequately detect comprehensive dental features in primary teeth: caries, restorations, pulp pathology, appliances, and stainless steel crowns (SSCs).[5-9]

Purpose Develop and evaluate a You Only Look Once version 8(YOLO v8)-nano model for automated detection of dental features in pediatric bitewing radiographs.

Hypothesis A specialized deep learning model can accurately identify multiple dental features in primary dentition with performance comparable to expert pediatric dentists.

Methods and Materials

Study Design Retrospective detection study (IRB #5250319). 441 bitewing radiographs from pediatric patients <9 years with primary teeth (January 2018-June 2025).

Annotation Three-tier validation system achieving Cohen's κ=0.85 (inter-rater) and ICC=0.90 (intra-rater). 18 classes including tooth numbering (A-T), caries (ICDAS 1-6), restorations, SSCs, furcation involvement, and space maintainers.

Model Development We developed a YOLOv8-nano object detection model with CSPDarknet53 backbone and PANet neck. Dataset split: 70% training (n=309), 15% validation (n=66), 15% test (n=66). NVIDIA RTX 4090, batch size 16, AdamW optimizer, cosine annealing. Early stopping at epoch 150 of 2000 maximum epochs.

Statistical Analysis Fisher's exact test and χ^2 test for class performance. Wilson score method for 95% CIs. Independent t-tests for gender comparisons, one-way ANOVA for age groups (α=0.05). Python SciPy 1.16.2 (Figure 1).

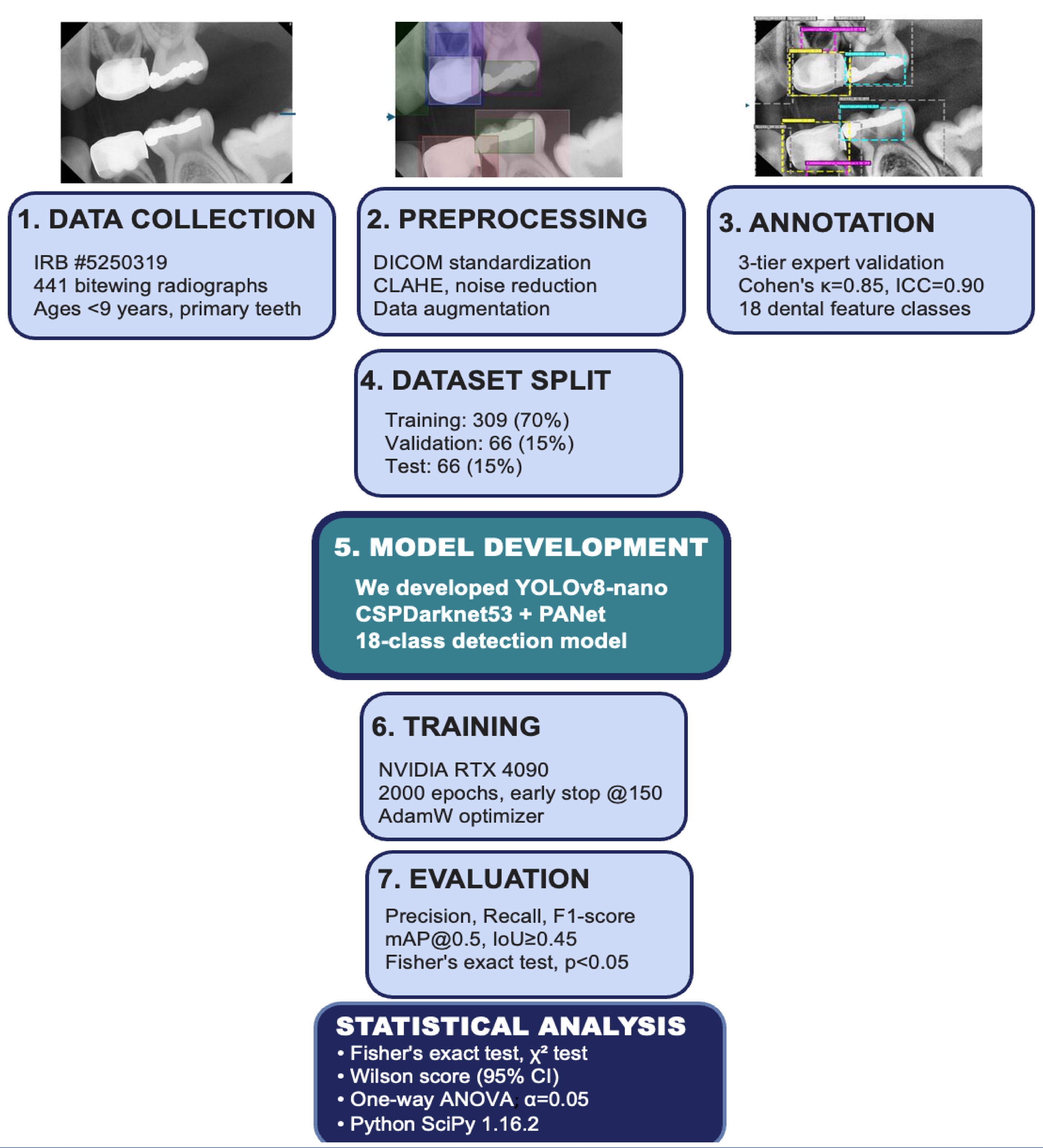

Figure 1- Flowchart of the deep learning pipeline for dental feature detection in pediatric bitewing radiographs, illustrating YOLOv8-nano architecture for multi-class object detection. The image was produced using custom implementation of the source code developed for this study.

Results

- 441 radiographs analyzed (43% male, 57% female, Figures 2,3,4)). Overall test performance (n=66): mAP@0.5=97.4%, precision=95.5%, recall=95.5%, F1=95.0%.
- Optimal performance: SSC (mAP@0.5=100.0%), restorations (mAP@0.5=100.0%), tooth identification (mAP@0.5=98.8%, F1=97.8%), all *P*<0.001. Dentin caries (mAP@0.5=91.0, *P*<0.001) (Table 1,2).
- Primary limitation: Enamel caries detection (mAP@0.5=53.9%, *P*=0.042). Errors predominantly false negatives, not misclassifications.
- No significant differences by gender (*P*=0.512) or age group (*P*=0.678).

Subgroup	n (%)	Precision	Recall	F1-Score	p-value
Gender					
Male	26 (40%)	95.2±3.1	95.1±2.8	94.8±2.9	0.512
Female	40 (60%)	95.7±2.9	95.8±3.2	95.2±3.0	—
Age Group					
6-9 years	36 (55%)	95.6±2.8	95.7±3.0	95.1±2.8	0.678
3-6 years	26 (40%)	95.3±3.2	95.2±3.1	94.9±3.1	—
<3 years	4 (5%)	95.8±2.5	96.0±2.6	95.3±2.4	—

Table 1. Performance comparison by gender and age group in test sample size (N=66).

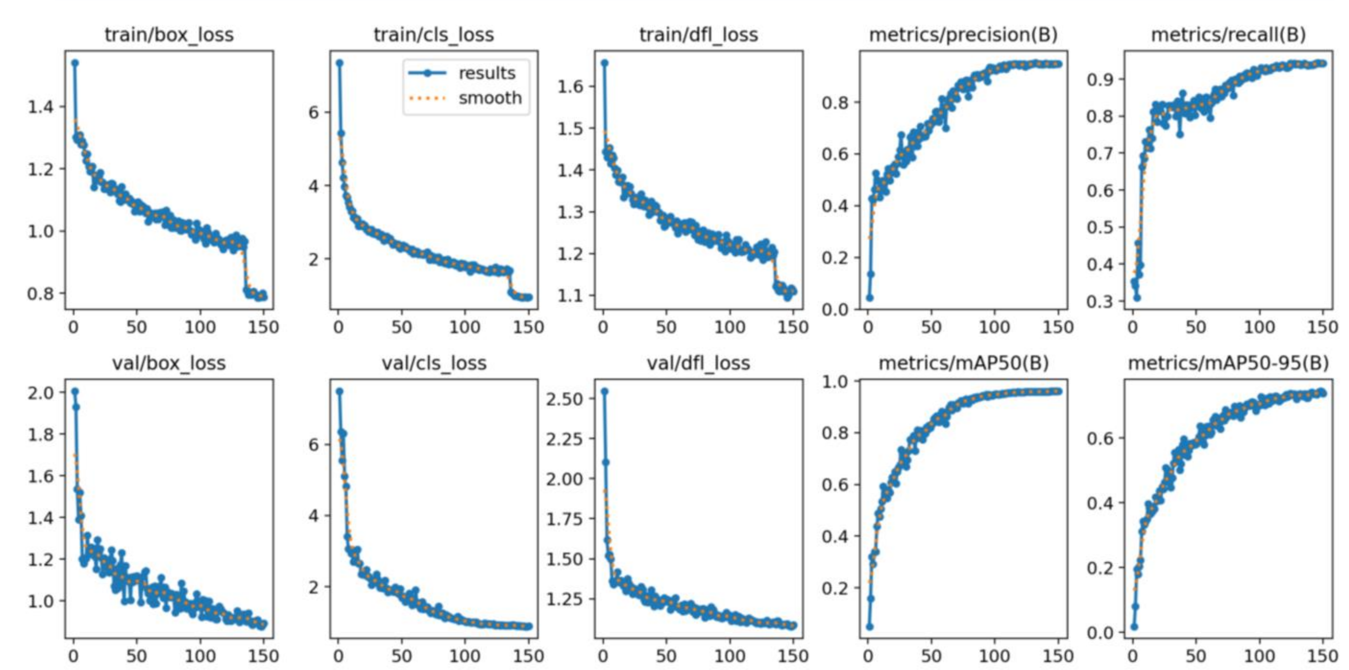

Figure 2. Training and validation loss curves for YOLOv8-nano (box, classification, DFL losses). Parallel decline without divergence demonstrates convergence without overfitting (150 epochs).

Class	Precision	Recall	mAP@0.5	F1 Score
All	95.5%	95.5%	97.4%	95.0%
Dentin Caries	87.9%	90.6%	91.0%	89.2%
Enamel Caries	66.7%	43.8%	53.9%	52.8%
Not intact lamina dura	92.0%	92.0%	93.8%	92.0%
Restorations	97.8%	100.0%	100.0%	98.9%
Stainless Steel Crowns	96.4%	100.0%	100.0%	98.2%
Space Maintainers	83.3%	100.0%	92.7%	90.9%
Teeth A	100.0%	100.0%	100.0%	100.0%
Teeth B	96.3%	100.0%	100.0%	98.1%
Teeth C	100.0%	100.0%	100.0%	100.0%
Teeth H	100.0%	100.0%	100.0%	100.0%
Teeth I	100.0%	100.0%	100.0%	100.0%
Teeth J	97.3%	100.0%	100.0%	98.6%
Teeth K	100.0%	100.0%	100.0%	100.0%
Teeth L	100.0%	100.0%	100.0%	100.0%
Teeth M	91.7%	97.1%	96.2%	94.3%
Teeth R	96.4%	96.4%	98.4%	96.4%
Teeth S	100.0%	100.0%	100.0%	100.0%
Teeth T	100.0%	100.0%	100.0%	100.0%

Table 2. Performance of AI model for labeling each class (ground truth: annotation by clinicians.

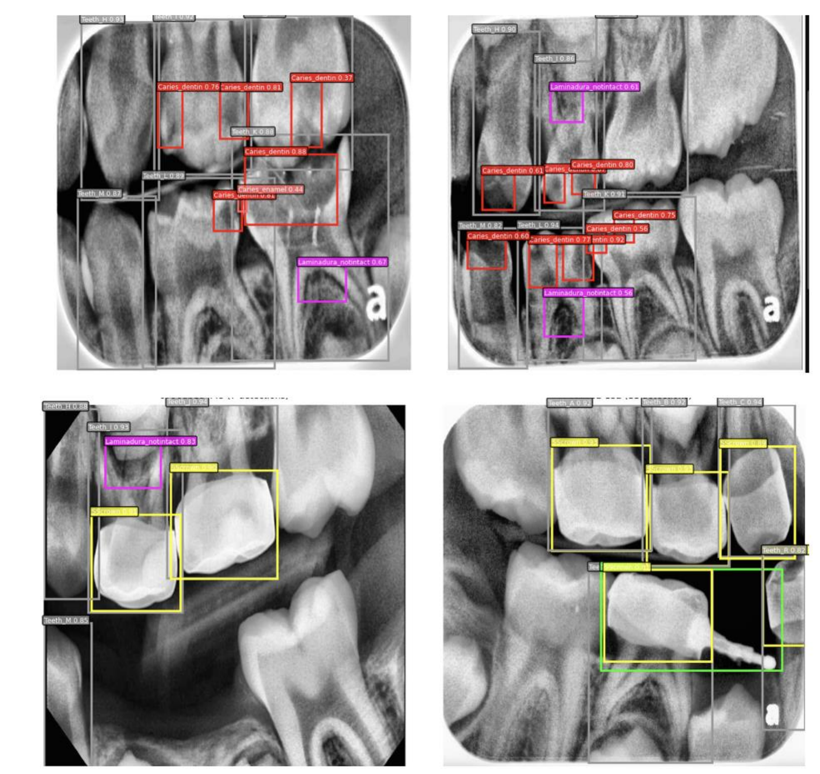

Figure 3. This example shows the model performing tooth numbering and classifying different dental conditions. The detected classes are color-coded: tooth numbers (grey), stainless steel crowns (yellow), caries lesions (red), space maintainer (green), and non-intact lamina dura (purple).

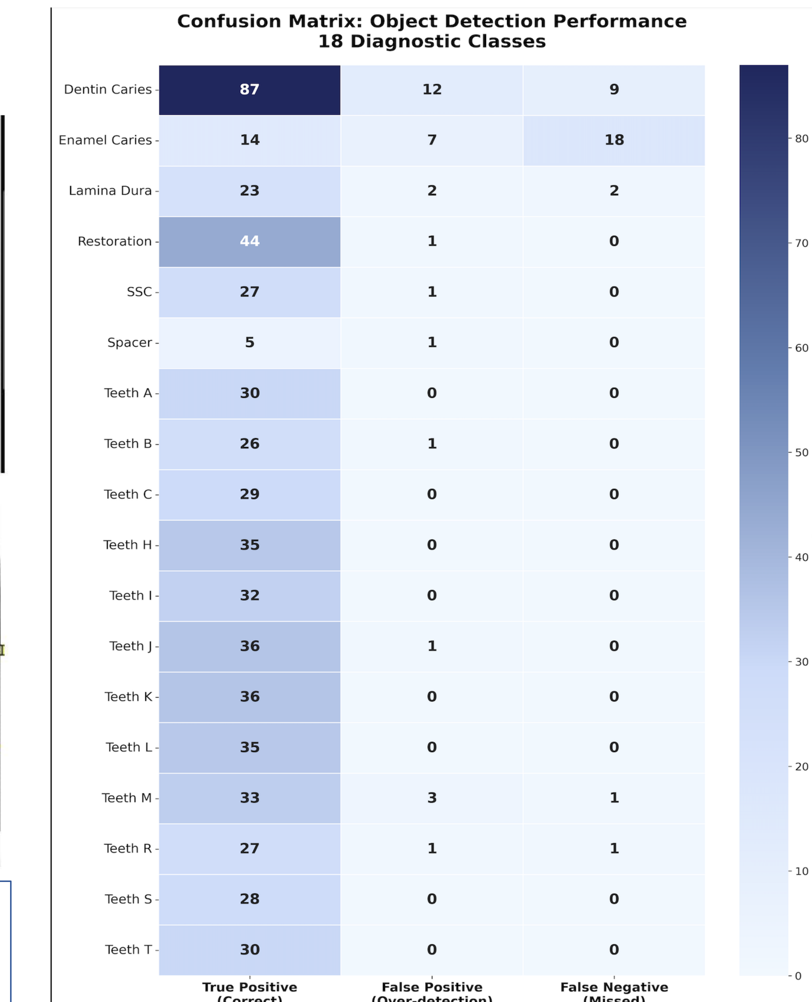

Figure 4. Confusion matrix showing True Positives (correct detections), False Positives (over-detections), and False Negatives (missed detections) across 18 classes.

Discussion

- ***Null Hypothesis*: REJECTED** - Model achieved 95.5% precision/recall, significantly exceeding ≥85% threshold (p<0.001).
- ***Literature Comparison*** Outperformed existing pediatric systems: dentin caries F1=89.2% vs Lee et al. F1=64.14%; SSC/restoration mAP@0.5=100% vs Celik et al. 97.3%. Enamel caries challenges (F1=52.8%) consistent with literature, reflecting subtle radiographic presentation.
- ***Strengths*** First comprehensive 18-class primary dentition system. Large dataset (n=441). Real-time inference. Demographic robustness.
- ***Limitations*** Single-site data. Low enamel caries sensitivity (43.8%). Excludes developmental anomalies.
- ***Future Directions*** Multi-site validation. Human-AI collaborative frameworks. Clinical metadata integration. Expanded pathology detection.

Conclusions

The following conclusions are drawn from this study:

YOLOv8-nano demonstrated high detection performance (97.4% mAP@0.5) for multi-class detection in pediatric bitewing radiographs, effectively identifying teeth, restorations, stainless steel crowns, space maintainers, and dentin caries.

Early-stage enamel caries detection remains challenging (43.8% recall), requiring further optimization and potentially human-AI collaborative approaches.

These findings support deep learning as a detection aid in pediatric dentistry, with future priorities including multi-center validation, clinical integration studies, and expansion of detectable feature classes.

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