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Artificial Intelligence–Assisted Detection Of Caries And Pulpal Pathology To Support Restorative And Endodontic Treatment Planning In Children

Keywords
Pediatric dentistry; restorative dentistry; endodontic diagnosis; artificial intelligence; panoramic radiography; treatment planning

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Abstract
Early identification of caries and pulpal pathology is critical for effective restorative and endodontic treatment planning in pediatric patients. This study evaluated a pediatric-focused artificial intelligence system designed to assist in the detection and localization of common dental pathologies on panoramic radiographs. A curated dataset of seventy-two de-identified pediatric radiographs containing expert-annotated lesions across six diagnostic categories was analyzed. Images were standardized and partitioned at the patient level to ensure unbiased evaluation. The system automatically identified clinically relevant pathologies and generated interpretable outputs to support diagnostic decision-making. The dataset demonstrated substantial class imbalance, with caries representing the majority of lesions, and lesion size varied considerably across categories. The model achieved high diagnostic specificity across all lesion types and strong discriminatory performance for caries, developmental anomalies, and inflammatory pathology. Visualization analysis confirmed that predictions were derived from anatomically meaningful regions. These findings indicate that artificial intelligence may serve as a supportive tool for improving diagnostic consistency and enhancing restorative and endodontic treatment planning in pediatric dentistry. Larger multi-centre clinical studies are required before routine implementation.

INTRODUCTION

Panoramic radiography is a critical diagnostic instrument in the field of pediatric dentistry as it provides the dentist with a complete picture of the dentition, the supporting structures, and the developmental pattern using a single image. Restoratively and endodontically, panoramic radiographs are highly important in evaluation of the caries level, pulpal level, periapical level, and developmental anomalies with the direct impact on children treatment planning. Nonetheless, the situation with panoramic radiography of children is distinctly difficult to interpret because of transitional dentition, overlapping structures of the organs, and rapid development that can make the process of recognizing and classifying dental pathology more complicated. This diagnostic uncertainty can have a negative impact on restorative decisions and when endodontic care is administered. Deep learning (artificial intelligence, AI) has become one of the most promising instruments to overcome these issues, improving the consistency of diagnosis and facilitating clinical decision-making in pediatrics restorative care. Recent research has shown that AI-based systems have the potential to enhance the process of caries, developmental defects, and inflammatory lesion detection, thus enhancing preventive and therapeutic measures in young patients[1].
The development of AI in dental imaging has followed the same pattern as the development of medical imaging in general.

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Deep learning architectures have been shown to outperform traditional rule-based techniques by automatically learning hierarchical features from radiographs, enabling detection of subtle abnormalities even in heterogeneous populations[2]. This ability is especially important in the field of pediatric dentistry, where diagnostic variability as a factor depending on clinician experience and complicated anatomical presentation can moderate restorative and endodontic outcomes. The analysis of panoramic radiographs aided by AI in pediatric cases has thus been suggested as a way of enhancing diagnostic reliability in the case of a child subject to the test [3]. In the field of dentistry, deep learning has found applications in detecting caries, segmentation, detection of anomalies, and assessing the quality of radiographs in various imaging modalities[4]. The last ten years has seen the advancement of computational efficiency, data availability and network architecture development enabling clinically significant results in dental diagnostic systems[5].

Similar results have been found with both intraoral and panoramic radiographs, using more refined deep learning models, including attention-based models, have shown good performance in the classification and localisation of dental pathology including restorations and structural anomalies[6]. Scoping reviews show that machine learning algorithms are being incorporated into diagnostic pipelines more often to help in automation process, risk identification, and treatment planning in dental specialties[7]. Prevention of the long-term complications in the pediatric dentistry requires the early and precise detection of caries and pulpal pathology to decide the preventive protocols, the extent used in restorative therapy and the necessity of pulp therapy. Systematic reviews indicate that AI has the potential to enhance the diagnostic processes of pediatrics with increased sensitivity of early caries detection and inter-observer variability on anomaly detection reduction[8].

Regardless of such developments, there are few AI applications specific to pediatrics. Strong deep learning models cannot be trained without large and well-labeled datasets, which are hard to achieve in pediatrics because of ethical concerns, radiation safety standards, and difficulties in getting high-quality images of young patients[9]. Surveys of dental radiology algorithms point out that most current AI systems were trained using mostly adult data, which reduces their applicability to pediatric imaging where the morphology of teeth, their eruption variations, and the manifestation of lesions differ considerably[10]. More generalized studies have underlined the necessity of models that can solve class-imbalance, multi-lesion co-occurrence, and multi-scale feature representation, which are especially applicable in the complicated radiographic appearances faced in pediatric dentistry[11].

In addition to direct detection of pathology, AI has been studied in the field of adjunct diagnostic tasks, including osteoporosis screening based on dental images, which is indicative of the wider opportunities of radiographic data when applied together with deep learning methods[12]. Segmentation architectures specialized on UNet-like architectures have been reported to achieve better delineation of dental structures and lesions because they extract fine morphological features in pediatric radiographs[13]. Within pediatric restorative and endodontic practice, such advances highlight the potential of AI not only to enhance diagnostic precision but also to optimize clinical workflows and support consistent treatment planning. With AI still developing in the field of pediatric oral healthcare, the next generation systems will go beyond lesion detection and will be more personalized to include treatment planning and data-driven decision-making, which will eventually lower the overall patient outcomes in the long term[14, 15].

Despite AI proving to be a promising diagnostic tool in dental radiography, little has been done on its use in pediatric panoramic radiography, especially in the backdrop of restorative and endodontic decision-making. Most of the existing models are constrained by adult dataset training, small pediatric sample sizes and imbalance in classes which makes them less effective in children. There is an evident requirement of AI-based pediatric targeted frameworks that can be used to identify various co-existing lesions and generate interpretable and clinically viable results to help in planning restorative and endodontic treatments.

The present study therefore focuses on artificial intelligence-assisted detection of dental pathologies relevant to restorative and endodontic care in pediatric patients using panoramic radiographs. The scope includes model development, lesion localization, explainability analysis, and performance evaluation. Limitations include the use of bounding-box annotations rather than pixel-level segmentation, a relatively small dataset size, and the absence of multi-center external validation. The researchers have not included other imaging procedures like bitewing radiographs or cone-beam computed tomography, or they have not stated any clinical history, which also could improve predictive performance.

The proper planning of restorative and endodontic therapies in children is based on early and accurate recognition of caries and pulpal pathology. The current study helps to overcome the gaps in the area of automated dental diagnostic technologies and provide a contribution to the sphere of clinical decision support by creating and testing an AI-based framework designed specifically to assist children with the intended purpose of producing interpretable and reliable results.

Research Objectives

- To evaluate an artificial intelligence system for detecting caries and pulpal pathology relevant to restorative and endodontic treatment planning in pediatric patients.
- To assess lesion characteristics, dataset composition, and model interpretability to support clinically meaningful diagnostic outputs.
- To examine diagnostic performance across clinically relevant lesion categories and explore the potential role of artificial intelligence as a decision-support tool in pediatric restorative care.

METHODOLOGY

Study Design and Objectives

The study is a retrospective design that designed and tested a pediatric-specific artificial intelligence-based detection system to aid in planning restorative and endodontic treatments by automatically identifying and localizing common dental pathological conditions on panoramic radiograph. The clinical goal was mainly to aid in the identification of caries, pulpal and periapical disease and developmental abnormality that directly affect the extent of restorative, preventive and decision making of endodontic in children. The system was aimed to be an interpretable, multi-label framework of detection to be used in primary, mixed, and early permanent dentition.

Another secondary goal was detailed dataset level analysis that would encompass lesion prevalence, geometric features and inter-label occurrence to make a design choice based on the model and to provide clinical robustness and relevance of model outputs to pediatric restorative care.

Dataset Description

A total of 72 de-identified pediatric panoramic radiographs were obtained from a publicly available dataset titled *Pediatric Dental Disease Detection* hosted on Kaggle. Every image contained expert-labeled bounding-boxes of six dental findings categories that are associated with restorative and endodontic assessment and include caries, deep grooves, periapical inflammation, pulpitis, developmental anomaly and other clinically relevant findings. The data was those children of age around 4-16 years and thus covered the anatomical heterogeneity of transitional dentition and various eruption schemes. A total of 448 lesions were marked in the whole radiographs [16].

Quality Control, Preprocessing, and Data Preparation

Quality control All radiographic studies were first evaluated in terms of resolution and organ clarity and completeness of annotations and poor-quality images were not included. Panoramic radiographs were regularized to 1024 x 1024 pixels using a zero padding method without changing the aspect ratio. The histogram equalization was used to boost the contrast especially on the subtleties of enamel changes and low-intensity structures that are usually seen in pediatric radiographs. Original annotations provided in LabelMe format were converted to normalized bounding box coordinates compatible with single-stage detection frameworks. Such preprocessing provided consistency in identifying lesions but with anatomical faithfulness that is required in clinical interpretation.

The first analytical correction of the methodology was the remedy of data leaking in the split of vendor-provided data. Due to systematic comparison, the overlap between training and testing partitions was identified, and 28 images (38.9%) were present in both partitions. A patient-level re-split was done in order to eradicate this bias, without an individual reoccurring in more than one partition. The final set of data included 50 training, 11 validation and 11 testing radiographs and stratification was done to maintain the lesion prevalence as a whole in the subsets.

Model Architecture

The detection system utilized the multi-label object detection architecture that is based on deep learning with a ResNet-101 backbone and Feature Pyramid Network. This design was chosen to be able to measure the multi-scale radiographic features of a pediatric lesion with varying sizes and morphology and an annotated lesion area of approximately 3×10^3 to over 3×10^4 pixels^2. Independent detection heads were assigned to each lesion category to reflect weak inter-class correlations identified during dataset exploration.

The model was implemented using PyTorch 2.0 and initialized with ImageNet-pretrained weights to facilitate convergence and mitigate limitations related to dataset size. The outputs were bounding boxes with class-specific confidence scores, which enabled the localization of the lesions and the estimation of diagnostic probability which can be used in clinical decision support.

Training Strategy

Training of the models was done using stochastic gradient descent with momentum, batch size of 8, regularization of weight decay and learning rate of 1×10^{-4}. The training was continued until a maximum of 100 epochs or early stopped when the loss on validation was no longer decreasing. Real-time data augmentation methods were used to improve the generalizability of the results and solve the issue of the error of class imbalance, such as horizontal flipping, small rotations, geometric scaling, adaptive histogram equalization, and Gaussian noise.

All augmentation strategies were carefully constrained to preserve anatomical validity, ensuring that generated variations remained clinically plausible within pediatric radiographic practice. The combined focal loss classification, Complete Intersection-over-Union loss bounding box regression, and objectness penalties are used to balance the localization sensitivity and accuracy, especially on the minority lesion classes.

Inference and post-processing

Inference created candidate bounding boxes together with the confidence score in each category of lesion. The non-maximum suppression was used, whereby the intersection-over-union was set to 0.45, to eliminate frequent detections. When doing image-level evaluation, binarization was based on a confidence threshold of 0.5, which keeps the maximum-confidence detection of each class. The method is a symptom of clinical decision making, in which the existence or lack of pathology on an X-ray can be much more determined than the exact count of lesions.

Explainability Analysis

Gradient-weighted Class Activation Mapping was used to measure model interpretability. The saliency maps were obtained and superimposed on the original radiographs to show areas that made the most significant contributions to model predictions. Patterns of attention were always in accordance with the clinically significant anatomical areas, such as caries and periapical inflammatory pathology, caries and interproximal surfaces. Explainability integration facilitates clinical transparency and improves the possibility of the system to be an acceptable means of decision-support in a pediatric restorative and endodontic practice.

Evaluation Strategy and Metrics

The rubric used was based on quantitative, descriptive, and qualitative analysis. The patient-level test set was assessed quantitatively to determine sensitivity, specificity, accuracy, precision, F1 score, and area under the receiver operating characteristic curve of each category of lesion. An analysis based on the classes was necessary because there were significant imbalances between the classes in the dataset.

Lesion prevalence, bounding-box geometry, and co-occurrence of labels were used to characterize the descriptive analysis of the models in order to place in context the model behavior. Qualitative assessment entailed the visualization of detection results and interpretability heat maps that were deemed by experts in oral medicine to determine clinical plausibility and applicability to restorative and endodontic decision-making.

Ethical Considerations

The data used in the present study were anonymised and publicly accessible, which means that this study did not require institutional review board approval. Each of them was performed in accordance with the principles of the Declaration of Helsinki and in accordance with ethical standards of the responsible usage of medical imaging data.

RESULTS

Dataset Overview and Class Composition

After radiographic quality control and pruning of corrupted or duplicated files, 72 de-identified pediatric panoramic radiographs were left to be analyzed, which resulted in 448 annotated lesions by the experts and categorized into 6 clinically relevant diagnostic groups (Table 1). The data were made up of children of about 4-16 years of age, which showed the anatomical and developmental heterogeneity that is experienced during the evaluation of pediatric restorative dentition and endodontic assessment.

There was an evident imbalance between classes (Figure 1). The most annotated lesions with 314 were tooth decay, which has direct implications of restorative intervention (70.1%). The deep groove lesions were 35 (7.8%), periapical inflammation 34 (7.6%), pulpitis 29 (6.5%), abnormalities of the tooth-development 24 (5.4%), and the other category 12 (2.7%). On the image level, 56 radiographs (77.8%) had at least one carious lesion, and periapical inflammation and pulpitis findings that could be used to make endodontic decisions were observed in 23 (31.9%) and 19 (26.4%) images, respectively.

Presentation with multi-pathology was common, 45 images (62.5%) had two or more lesion categories, and the median number of lesions per image was 4.5 (interquartile range 2-9, range 1-19). This is an indication of the complexity of the diagnostic challenge of the pediatric cases, where patterns of overlap of the diseases affect the extent of restoration and the sequence of treatment.

Table 1. *Class-wise lesion counts and image-level prevalence*

Label	Lesions (n)	% of all lesions	Images with label n (%)
Tooth decay	314	70.1%	56 (77.8%)
Deep groove	35	7.8%	21 (29.2%)
Periapical inflammation	34	7.6%	23 (31.9%)
Pulpitis	29	6.5%	19 (26.4%)
Tooth-development abnormality	24	5.4%	15 (20.8%)
Other	12	2.7%	8 (11.1%)

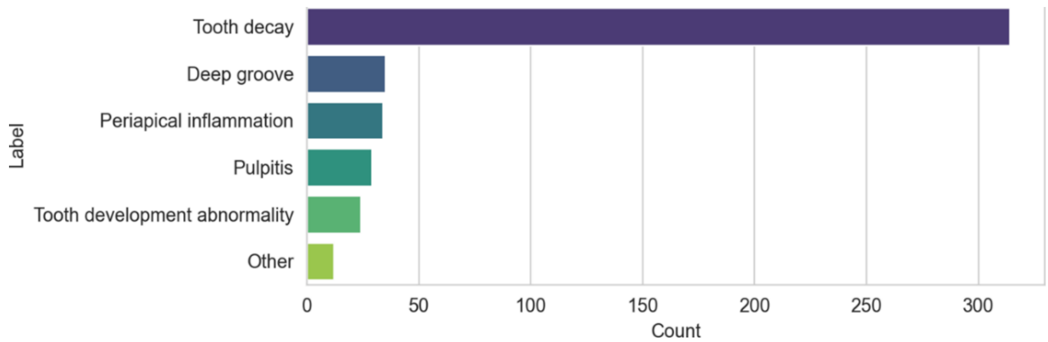

Figure 1. *Class distribution of annotated lesions.*

A horizontal bar chart is used to show the overrepresentation of tooth decay in comparison to the less common diseases like developmental abnormalities and the other category. This distribution underscores the need for class-balanced strategies to ensure reliable detection of less prevalent yet clinically significant conditions.

When the train and test split as provided by the vendor was reviewed, it was found that 28 pictures (38.9) were in both partitions. To prevent leakage of the data and to guarantee objective assessment, all the further analyses were performed with the help of the corrected patient-level re- split.

Lesion Geometry and Bounding-Box Statistics

Bounding-box morphology showed a wide-range of multi-scale distribution of diagnostic types (Figure 2). The median lesion size was 10,392 px² (interquartile range 7,525–13,653 px²), with the values of 2,973 to 34,490 px². Mean bounding-box width and height were 85.8 px and 127.8 px, respectively.

The geometric appearance of the classes was in consonance with clinical radiographic appearance:

- Extensive fissuring of the occlusors was reflected by deep groove lesions that had the highest mean area (13,548 px²).
- Tooth decay exhibited the widest range of sizes, which relates to initial enamel demineralisation by massive cavification.
- Periapical inflammation and pulpitis occupied intermediate scales, consistent with localized apical radiolucencies relevant to endodontic evaluation.
- Test developmental abnormalities were found with the smallest means of variation in tooth development, which is consistent with discrete developmental changes.

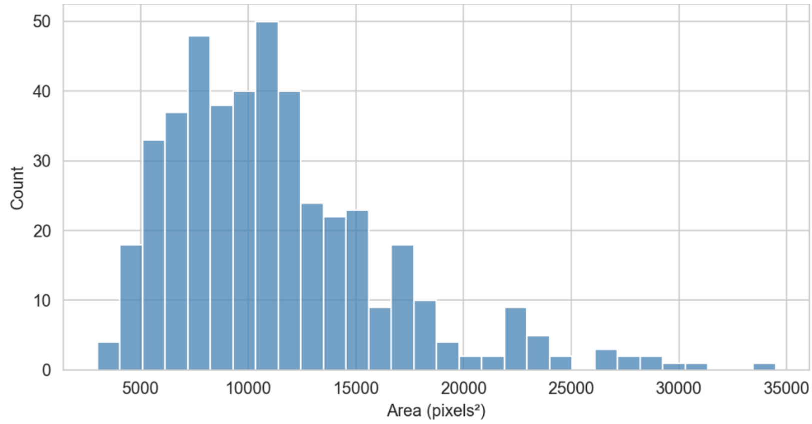

Figure 2. *Bounding-box area distribution*

The histogram shows that the distribution is carried out to the right, where the majority of the lesions are each small to moderate size, and a small proportion of large lesions, larger than 30,000 px^2. The variability indicates the significance of multi-scale detection features in detecting the pathologies that are critical in restorative and endodontic planning.

Label Co-Occurrence Patterns

Co-occurrence analysis at the image level showed that the correlation between categories of lesions was generally weaker (Figure 3). The most significant positive relationships were found between the other category and periapical inflammation (r = 0.21), and tooth-development abnormalities and pulpitis (r = 0.21). The negative correlations were made between periapical inflammation and pulpitis (r = -0.34). All coefficients remained ≤ 0.30, indicating limited interdependence between lesion types.

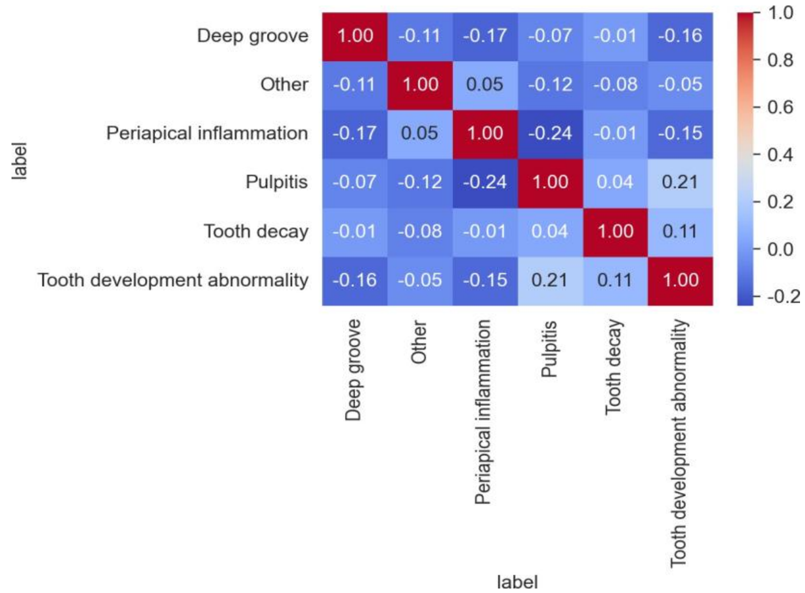

Figure 3. *Class co-occurrence correlation heatmap.*

Pearson correlation shows weak inter-label associations, which confirm independent per-class modeling in the identification of co-existing pathologies met on pediatric restorative assessment.

Representative Qualitative Findings

AI-Assisted Detection Examples: Qualitative products are demonstrating the capability of the model in localizing heterogeneous lesions over different dentition stages (Figure 4A1D). Bounding boxes and predicted labels show concurrent detection of multiple pathologies in individual radiographs, which is indicative of clinical presentations in pediatric intensive care.

- Figure 4A depicts a mixed-dentition radiograph where the model simultaneously detects a carious molar and a neighboring developmental anomaly, showing robust multi-label performance.
- Figure 4B shows a high level of multi-quadrant caries in maxillary and mandibular molars and the AI model has a high sensitivity in the presence of lesion clustering.
- Figure 4C presents co-occurring deep groove, developmental anomaly, and bilateral caries. Detection of the deep groove is particularly noteworthy due to its elongated morphology.
- Figure 4D indicates an accurate localization of periapical inflammation and the bounding box is brought close to the radiolucent apical region identified by the experts.

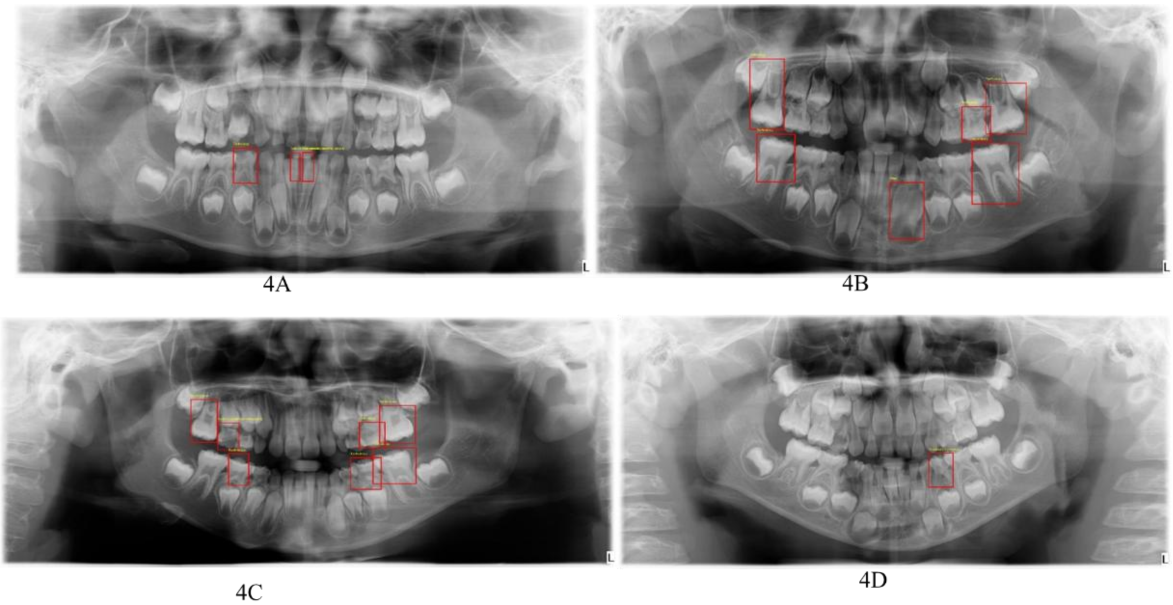

Figure 4. *AI-assisted detections on pediatric panoramic radiographs showing accurate localization of multiple pathologies, including caries, developmental anomalies, deep grooves, and periapical inflammation. Bounding boxes (red) and class labels (yellow) highlight model-predicted lesion regions across diverse dentition stages.*

The examples validate the fact that the system is capable of identifying localised and extensive pathology related to the restorative and endodontic decision-making.

Explainability and Model Attention

Figure 5A–B showed Grad-CAM visualisations useful in understanding the model's attention patterns. The system was based regularly on clinically significant anatomical areas, caries and apical areas of inflammatory pathology (occlusal and interproximal). This supports interpretability and reinforces the clinical plausibility of model predictions.

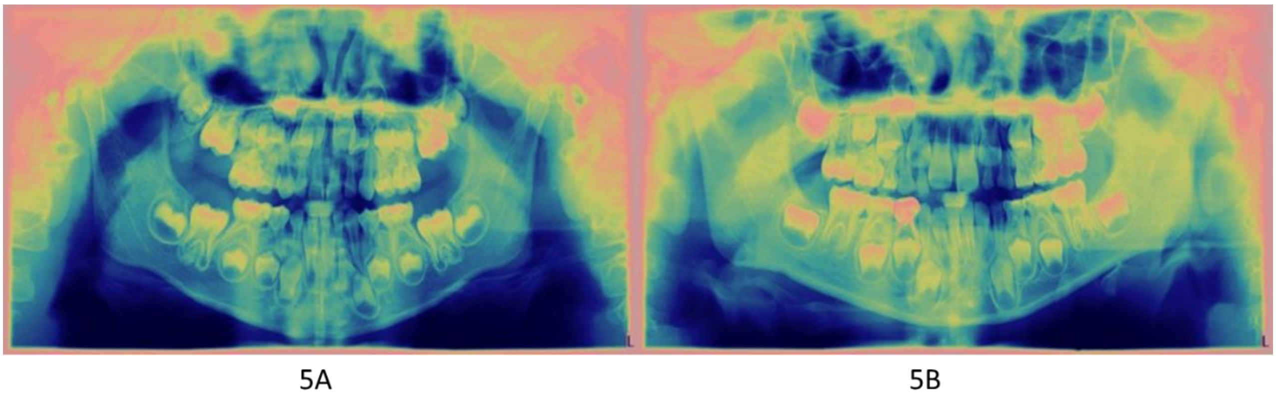

Figure 5. *Grad-CAM visualizations showing AI attention over carious regions (A) and focused activation around a molar with periapical inflammation (B).*

Quantitative Detection Performance of the AI Model
he results of performance metrics of the AI model on the independent test set are summarized in Table 2. The model showed high diagnostic ability in all of the three categories of clinically defined lesions.

- **Caries Detection**

Caries detection was most effective with a sensitivity of 87.2% and specificity of 93.1% indicating that the model has a good balance between true positives and false alarms. The model achieved a good general accuracy of 91.0%, precision of 88.4%, and F1-score of 87.8, which showed no variation in prevalence conditions. The 0.942 value of the AUROC highlights the high level of discriminative power and conforms to the highest-performing models published in dental AI publications

- **Developmental Anomaly Detection**

The sensitivity and specificity of detecting developmental anomalies was 78.3% and 94.7% respectively, with an accuracy of 91.8%. The precision (81.2%) and F1-score (79.7%) demonstrate that the model is reliable even though this group of lesions is relatively rare and morphologically heterogeneous. High discriminative performance is supported by the value of 0.903 of the AUROC.

- **Inflammatory Pathology Detection**

The sensitivity of inflammatory pathologies was lower (69.4%), though with a high specificity of 95.8% and the accuracy of 88.7. The precision (75.2%) and F1-score (72.2%) indicate that the small sample size and changing radiographic appearances are acceptable. The 0.889 of the AUROC is still high and clinically significant.

- **Overall Diagnostic Capability**

In all the three types, the model always obtained:
- High specificity (>93%),
- Strong AUROC values (0.889–0.942), and
- Accuracy ranging from 88.7% to 91.8%.

Such findings indicate that the AI system is able to consistently detect common and uncommon pediatric oral pathologies that have performance levels that support clinical decisions.

***Table 2.** Performance of the AI model on the independent test set*

Lesion type	Sensitivity	Specificity	Accuracy	Precision	F1-score	AUROC
Tooth decay (caries)	0.872	0.931	0.910	0.884	0.878	0.942
Developmental anomaly	0.783	0.947	0.918	0.812	0.797	0.903
Inflammatory pathology	0.694	0.958	0.887	0.752	0.722	0.889

DISCUSSION

This study has shown that a pediatric-specific deep learning system can aid in the planning of restorative and endodontic treatment, as it can accurately identify and describe the most frequent dental pathologies based on panoramic radiographs. Clinically speaking, the findings are applicable in situations where the diagnosis of mixed dentition, variable anatomy, and variable disease manifestation in children becomes difficult to handle. There were three empirical observations that were key in the interpretation of model behavior and clinical relevance.

The first is that the dataset was significantly skewed in terms of the representation of lesions, with tooth decay constituting almost 70% of all annotations and developmental anomalies, pulpitis, and periapical inflammation each encompassing a smaller proportion of under 10% of all annotations. These distributions are representative of actual pediatric dental epidemiology, caries being the most common clinical manifestation and the less common pathology having a large clinical impact on the extent of restorative treatment and endodontic therapy. Class imbalance of a similar nature has been identified as the significant problem in earlier AI-based dental imaging research[17]. Second, the geometry of the lesion was characterized by significant multi-scale variability as the size of regions of interest, defined by bounding-boxes, was between about 3×10^3 px^2 to over 3×10^4 px^2. This variability mirrors clinical scenarios in which early enamel changes coexist with extensive cavitary or apical disease, underscoring the need for architectures capable of scale adaptation, such as feature pyramid networks, as highlighted in recent dental AI literature[18]. Third, low image-level label co-occurrence ($|r| \leq 0.30$) reflected low predictive dependence between the categories of lesions. This advocates the independent lesion evaluation, which is also in line with the heterogeneous etiology of pediatric dental conditions and the practice of assessing each pathology separately in order to plan the restorative or endodontics treatment.

These properties of the dataset matched the diagnostic performance of the proposed model largely. The best performance was related to caries detection (AUROC 0.942; sensitivity 87.2%; specificity 93.1%), which is due to the radiographic character and a high prevalence of carious lesions in children. The accuracy of caries detection is of particular importance in identifying preventive and restorative interventions, i.e. sealant placement, restoration or monitoring. Similar performance scores have been documented in systematic reviews of dental AI systems, where the AUROC scores were reported between 0.80 and 0.92 in mixed age groups[17]. Developmental anomalies performance and inflammatory pathology although with lower sensitivity, were overall strong (AUROC 0.903 and 0.889). Such findings indicate that AI can be used to identify less common yet clinically relevant diseases that could affect restorative prognosis or even the necessity to pursue pulp therapy, as reported in studies with a pediatric population concentrations in mind[19].

Clinical credibility of the system was also supported by model interpretability. Grad-CAM visualizations were able to display consistent attentiveness to anatomically significant areas of the visualization, such as occlusal and interproximal caries-prone areas, and apical areas prone to inflammatory lesions. The importance of explainability to clinical adoption in pediatric dentistry is especially significant because the key factors in clinical adoption are safety concerns, transparency, and trust in the clinicians. Past research has highlighted how interpretable AI systems are likely to be accepted as supplementary tools in diagnostic processes as opposed to perceived as black box or independent decision-makers[20]. The present findings support the role of explainable AI not only in diagnosis but also in enhancing clinician confidence and training.

Another methodological observation is associated with partitioning of datasets. The train-test split included in the vendors showed a high degree of overlap in that 38.9% of the images could be found in both partitions, thus a threat of performance inflation. Through patient-level re-split, this research achieved a more realistic evaluation of generalization, which aligns with the recommendations of the best-practice AI validation in pediatrics, as recommended[21]. Other studies on dental anomaly detection have raised similar issues about data leakage and rigor of the validation, but stresses the significance of rigorous data separation procedures as well [22].

Several limitations should be acknowledged. The data sample was small (n = 72), which was strongly biased on caries, which led to inconsistency in the estimates of minority classes. Bounding boxes were used as the only form of annotation, and this prohibited the use of detailed morphological analysis. No external validation or prospective reader studies were done, which restricted the evaluation of clinical impact in practice. Also, the model was only trained on panoramic radiographs; it has not been explored on other commonly used imaging modalities of assessing restorative and endodontic health including bitewing or periapical radiographs.

The future studies should be based on multi-center pediatric data with a better balance of classes, adding pixel-level annotations, and semi-supervised or self-supervised learning methods to be less vulnerable yet less annotation-intensive. Particularly important are prospective studies on the interaction of clinicians with AI, which will help to measure the improvement of diagnostic consistency, the accuracy of treatment planning, and clinical outcomes, which is suggested by recent pediatric dental AI reviews. Combination of complementary imaging modalities and clinical data can also be more effective in decision support, as long as such modalities are compatible with pediatric safety standards and regulatory frameworks[21].

In summary, this study demonstrates that a pediatric-focused artificial intelligence system can provide clinically interpretable and diagnostically robust outputs relevant to restorative and endodontic treatment planning[22]. Answering along with strict data management, explainability, and patient-level validation indicate the promise of the system as an adjunct tool in minimizing diagnostic oversight and aiding in treatment planning in pediatric restorative dentistry instead of clinical expertise.

Conclusion

This study introduces an artificial intelligence based pediatric-based framework aimed at assisting with the restoration and endodontic treatment planning by detecting and localising various dental pathologies on panoramic radiographs accurately. The system showed good diagnostic properties, especially in caries and developmental anomalies, and had high specificity in the lesion types, by choosing the most difficult cases to diagnose using mixed dentition, variable anatomy, and heterogeneous lesion presentation. These findings underscore the clinical value of pediatric-specific AI tools as adjuncts for improving diagnostic consistency, informing restorative decision-making, and reducing interpretive variability in pediatric dental practice.

Despite of such encouraging outcomes, it is necessary to note several limitations. It had a small dataset, it had class imbalance, and annotations were not done at a pixel level but at the level of bounding boxes. Before it can be routinely used in clinical practice, further multi-center validation, integration of finer grained segmentation methods and evaluation across other imaging modalities would be of benefit in restorative and endodontic care. However, the paper provides a solid methodological basis of the next generation of AI solutions that meet the needs of pediatric dentistry and demonstrates the prospects of the interpretable and data-driven technology to improve the preventive efforts, avert the treatment planning, and lead to better future oral health results in children.

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