

Cross-Modality AI Fusion of Panoramic Radiographs and CBCT for Patient-Specific Prediction of Hidden Dental Pathology

¹ Jian Xu, ² Shirin Moradi

¹ MSc

² DDS

Abstract

Hidden dental pathologies may remain undetected during routine clinical examinations because of the limitations of conventional dental imaging. Panoramic radiography provides a broad overview of dental and maxillofacial structures, whereas cone-beam computed tomography (CBCT) offers detailed three-dimensional anatomical information. This article explores a proposed cross-modality artificial intelligence (AI) framework for integrating panoramic radiographs and CBCT to support patient-specific prediction of hidden dental pathology. The approach combines deep learning, radiomic feature extraction, anatomical registration, and multimodal feature fusion to identify suspicious lesions and estimate their probability. Potential applications include the detection of occult periapical lesions, root abnormalities, and localized bone defects. Diagnostic performance may be evaluated using sensitivity, specificity, area under the receiver operating characteristic curve, calibration, and external validation. The framework also considers explainability, image quality, radiation safety, and clinical integration. Although advances in dental AI and maxillofacial image analysis provide a foundation for this approach, its diagnostic effectiveness requires systematic experimental evaluation and prospective clinical validation. Cross-modality AI fusion may ultimately support more accurate interpretation, personalized diagnostic assessment, and improved clinical decision-making when used alongside professional judgment and appropriate imaging indications.

Keywords: Artificial intelligence; panoramic radiography; cone-beam computed tomography; multimodal image fusion; dental pathology; deep learning; radiomics; patient-specific prediction.

I. Introduction

Dental pathology may remain undetected during routine clinical examinations because many lesions develop within the jawbone, around tooth roots, or in anatomically complex regions that are difficult to evaluate using conventional imaging alone. Hidden dental pathologies include early periapical lesions, occult root abnormalities, localized bone defects, impacted teeth-associated changes, and other maxillofacial abnormalities that may not be clearly visible on two-dimensional

radiographs. Early identification of these conditions is important for improving diagnostic accuracy, supporting appropriate treatment planning, and reducing the risk of disease progression.

Panoramic radiography is widely used in dentistry because it provides a broad overview of the teeth, jaws, and surrounding anatomical structures. Its advantages include relatively low radiation exposure compared with many three-dimensional imaging examinations, accessibility, and suitability for initial dental assessment. However, panoramic images are affected by anatomical superimposition, geometric distortion, and limited representation of buccolingual structures. These limitations can obscure small lesions, conceal root-related abnormalities, and reduce the ability to determine the precise extent of pathological changes.

Cone-beam computed tomography (CBCT) provides three-dimensional visualization of dental and maxillofacial structures. It allows clinicians to examine lesions across multiple planes, evaluate cortical bone changes, and investigate anatomical relationships that may not be adequately represented in panoramic radiographs. Nevertheless, CBCT also has limitations, including radiation exposure, image artefacts, interpretation complexity, and the possibility of identifying incidental findings of uncertain clinical significance. Consequently, CBCT should be prescribed according to individual clinical indications rather than used routinely for every dental patient.

Artificial intelligence (AI), particularly deep learning and radiomics, offers opportunities to combine information from different imaging modalities and improve the recognition of complex pathological patterns. Deep learning can identify spatial relationships and image features, while radiomics can quantify characteristics such as lesion texture, shape, intensity distribution, and anatomical heterogeneity. Research on deep learning and radiomics in CT and CBCT has highlighted their potential applications in maxillofacial disease assessment (Hung et al., 2022). Similarly, advances in dental AI have expanded the possibilities for computer-assisted diagnosis, treatment planning, and clinical decision support (Gao et al., 2025).

Cross-modality AI fusion involves integrating information extracted from panoramic radiographs and CBCT to produce a combined diagnostic representation. Rather than interpreting the two imaging modalities independently, the system identifies complementary features and uses them to estimate the probability of hidden dental pathology in an individual patient. This approach may improve diagnostic confidence when panoramic findings are inconclusive and CBCT is clinically justified.

The objective of this article is to describe a proposed AI-based framework for integrating panoramic radiographs and CBCT images to support patient-specific prediction of hidden dental pathology. It examines imaging characteristics, data integration, model development, diagnostic evaluation, clinical applications, and the ethical and technical challenges associated with implementation. The framework is intended as a research and clinical decision-support concept rather than an already validated diagnostic system.

II. Literature Review

2.1 Artificial intelligence in dental imaging

AI has become an important area of investigation in dental imaging because diagnostic interpretation frequently involves identifying subtle anatomical differences and recognizing patterns across large volumes of visual data. Machine learning algorithms can learn relationships between imaging features and clinically established outcomes, while deep learning models can automatically derive complex representations from appropriately labelled images.

Convolutional neural networks are particularly relevant to dental radiography because they can learn spatial features associated with tooth morphology, root structures, bone changes, and lesion boundaries. Their performance, however, depends on the quality, diversity, and representativeness of training data. In dental informatics, deep learning techniques have been investigated for image classification, anatomical detection, segmentation, and diagnostic support (AbuSalim et al., 2022).

AI applications are also expanding beyond image classification into treatment planning and outcome prediction. Gao et al. (2025) discussed diagnostic and therapeutic applications of AI in dentistry, highlighting its potential role in improving clinical workflows. In conservative dentistry and endodontics, machine learning may assist with identifying pathological findings, assessing treatment complexity, and supporting decisions about tooth preservation and root canal management (Bansal et al., 2025).

Nevertheless, a model that performs well on one imaging modality cannot automatically be assumed to perform equally well on another. Panoramic radiographs and CBCT differ in image dimensionality, spatial resolution, anatomical representation, and susceptibility to artefacts. These differences make cross-modality integration a distinct technical challenge.

2.2 Panoramic radiography and CBCT as complementary modalities

Panoramic radiography provides a broad anatomical overview that can assist with identifying dental abnormalities, evaluating tooth distribution, and detecting suspicious regions requiring further assessment. Its principal limitation is that three-dimensional anatomical structures are compressed into a two-dimensional representation. Consequently, overlapping roots, cortical structures, and other anatomical features may obscure pathology. CBCT complements panoramic imaging by providing volumetric information. Clinicians can assess suspected abnormalities in axial, coronal, and sagittal reconstructions, improving the evaluation of lesion location, dimensions, and relationships with neighbouring structures. Hung et al. (2022) reviewed the applications of deep learning and radiomics in CT and CBCT for maxillofacial diseases, providing a relevant foundation for investigating computational analysis of three-dimensional dental images. The integration of CBCT with AI, augmented reality, and virtual reality has also been explored in relation to dental diagnosis, surgical planning, and education (Aida & Gerta, 2025). Such

integration demonstrates the broader potential of computational imaging systems to transform anatomical information into clinically useful representations. For cross-modality AI, the central principle is complementarity. Panoramic radiographs can contribute broad anatomical context, while CBCT can provide detailed three-dimensional information about suspicious regions. The combined model may therefore identify relationships that would be difficult to recognize using either modality alone. However, improved performance must be demonstrated empirically rather than assumed from the availability of additional data.

2.3 Patient-specific prediction of hidden dental pathology

Patient-specific prediction aims to estimate the probability of a particular pathological condition using information relevant to an individual rather than relying solely on general population-level patterns. In dental imaging, relevant information may include lesion morphology, tooth type, root configuration, anatomical location, surrounding bone characteristics, previous treatment, and clinical examination findings. A multimodal model could use panoramic images to identify suspicious regions and CBCT to characterize corresponding anatomical abnormalities. The resulting prediction might indicate a low, intermediate, or high probability of a defined pathology, accompanied by a localized image region and an explanation of the features contributing to the estimate.

Endodontic research illustrates the importance of integrating diagnostic findings with treatment outcomes. For example, Singh et al. (2025) investigated periapical healing following endodontic retreatment using nano-hydroxyapatite with and without platelet-rich fibrin. Although this study concerns treatment outcomes rather than cross-modality AI, it provides a relevant clinical context for the importance of periapical pathology and healing assessment. A major limitation in the existing conceptual landscape is that evidence supporting AI analysis of individual modalities does not, by itself, establish the effectiveness of a combined panoramic-CBCT prediction system. Prospective studies and independent validation are needed to determine whether multimodal fusion offers meaningful improvements over standard clinical interpretation and single-modality AI.

III. Methodology

3.1 Study design and data collection

A retrospective diagnostic model-development study followed by prospective external validation could be used to investigate cross-modality AI fusion. The study population would comprise dental patients with clinically indicated panoramic radiographs and CBCT examinations obtained as part of their routine care. Imaging should not be acquired solely for research when the expected benefit does not justify additional radiation exposure.

The dataset should include a range of dental conditions, including periapical lesions, root abnormalities, localized bone defects, and other predefined pathological findings. Cases without the target pathology should also be included to allow the model to distinguish abnormal from normal or clinically insignificant findings. Clinical records, dental examination findings, relevant treatment history, and specialist assessments could provide supplementary information. Each case should be assigned a reference diagnosis using an appropriate combination of clinical examination, expert radiological interpretation, follow-up, and histopathological findings where available and clinically indicated. At least two qualified dental or maxillofacial imaging specialists should independently review the relevant cases, with disagreements resolved through consensus or a third reviewer. This process would reduce dependence on a single observer and improve the reliability of diagnostic labels.

3.2 Image preprocessing and anatomical registration

Before fusion, panoramic radiographs and CBCT volumes should undergo standardized preprocessing. Panoramic images may require intensity normalization, noise reduction, resizing, and correction of image orientation. CBCT data may require standardized voxel spacing, artefact assessment, intensity normalization, and segmentation of relevant anatomical structures. Anatomical registration is an important step because the two modalities represent dental structures differently. Where appropriate, tooth-level anatomical landmarks, dental arch geometry, and corresponding anatomical regions can be used to establish spatial relationships between the panoramic image and the CBCT volume. Registration should not be assumed to be exact. Differences in patient positioning, image acquisition time, tooth movement, and treatment between examinations can introduce alignment errors. The system should detect inadequate correspondence and either apply quality-control procedures or exclude unreliable image pairs from the primary analysis. The use of standardized preprocessing and validation procedures is consistent with the broader challenges identified in dental deep-learning research (AbuSalim et al., 2022; Hung et al., 2022).

3.3 Cross-modality feature extraction and fusion

The proposed framework would contain separate feature-extraction branches for panoramic radiographs and CBCT volumes. A two-dimensional convolutional neural network could process panoramic images, while a three-dimensional convolutional neural network or another suitable volumetric architecture could analyse CBCT data. The panoramic branch would extract features associated with tooth morphology, root outlines, periapical radiolucencies, and broader anatomical relationships. The CBCT branch would identify three-dimensional lesion boundaries, cortical changes, root anatomy, and spatial relationships between pathological regions and adjacent structures.

The extracted representations would then be combined through a fusion mechanism. Three approaches could be evaluated:

- Early fusion: combining appropriately aligned image information before or during initial feature extraction.
- Intermediate fusion: integrating learned features from both modalities at an internal model layer.
- Late fusion: combining the separate diagnostic predictions generated by each modality.

Intermediate fusion may provide a useful starting point because it allows the model to learn complementary features while retaining modality-specific representations. However, the most appropriate strategy should be determined through comparative experiments rather than assumed in advance.

The proposed architecture is consistent with the growing use of AI for diagnostic and therapeutic applications in dentistry (Gao et al., 2025) and the integration of CBCT with advanced computational tools (Aida & Gerta, 2025).

Table 1. Imaging modalities, extracted features, and diagnostic contributions

Imaging component	Principal features	Potential contribution
Panoramic radiograph	Tooth outlines, root morphology, broad anatomical patterns	Initial screening and localization
CBCT volume	Three-dimensional lesion extent, cortical changes, root relationships	Detailed anatomical characterization
Cross-modality fusion	Corresponding two-dimensional and three-dimensional features	Combined patient-specific prediction
Clinical information	Symptoms, examination findings, treatment history	Additional diagnostic context

3.4 Model training and patient-specific prediction

The dataset should be divided into training, validation, and independent testing groups at the patient level to prevent images from the same patient appearing across different groups. This is particularly important when several teeth or multiple examinations belong to one individual. Training would optimize the model to recognize predefined pathological conditions. Depending on the intended clinical task, the outputs could include lesion classification, anatomical

localization, segmentation, or patient-specific probability estimates. Separate models should be considered when the biological characteristics and diagnostic criteria of different pathologies vary substantially. The model should also be compared with panoramic-only and CBCT-only baselines. These comparisons would establish whether multimodal integration contributes measurable diagnostic improvement beyond the information available from either modality independently. Where the model produces probability estimates, calibration should be evaluated to determine whether predicted risks correspond reasonably to observed disease frequencies. Missing modalities should be addressed explicitly because some patients will have only panoramic radiographs. The system must not generate a supposedly CBCT-informed prediction when no suitable CBCT data are available.

3.5 Diagnostic evaluation and statistical analysis

Model performance should be evaluated using sensitivity, specificity, precision, F1 score, and area under the receiver operating characteristic curve. For lesion segmentation, Dice similarity coefficient and intersection over union may be appropriate. Calibration measures and decision-curve analysis could additionally assess the reliability and potential clinical usefulness of predictions. Performance should be reported with confidence intervals and stratified, where feasible, by pathology type, tooth location, image quality, and relevant patient groups. External validation across different institutions, imaging equipment, and patient populations would help establish whether the model generalizes beyond its development dataset. The reporting and evaluation strategy should follow established principles for diagnostic AI research, including transparent documentation of patient selection, reference standards, exclusions, model development, and limitations.

IV. AI Model Development and Diagnostic Evaluation

4.1 Prediction of hidden dental pathology

The principal function of the proposed system would be to identify suspicious dental regions and estimate the likelihood of predefined pathological conditions. These could include occult periapical lesions, root resorption, complex root abnormalities, and localized osseous defects. The model should distinguish between detecting an imaging abnormality and establishing a definitive clinical diagnosis. For example, a panoramic radiograph may reveal an indistinct radiolucent region near a tooth root. The AI system could identify the region as suspicious and, when an appropriately acquired CBCT examination is available, analyse the corresponding three-dimensional anatomy. By combining the two representations, the model could produce a localized prediction with an estimated probability and a visual explanation of the features influencing the result. Such predictions should be interpreted alongside clinical findings because radiographic abnormalities do not always correspond directly to active disease. Similarly, a negative AI result should not override compelling symptoms or other evidence of pathology. AI in conservative

dentistry and endodontics offers potential diagnostic support, but clinical validation remains necessary before integrating such tools into routine decision-making (Bansal et al., 2025).

4.2 Comparative assessment of diagnostic performance

The proposed multimodal model should be evaluated against three principal comparators: conventional interpretation of panoramic radiographs, AI analysis of panoramic radiographs alone, and AI analysis of CBCT alone. This comparison would establish whether feature fusion improves the detection of hidden pathology or simply reproduces information already available in the individual modalities.

Table 2. Proposed AI model evaluation framework

Evaluation measure	Application
Sensitivity	Measures the proportion of pathology-positive cases correctly identified
Specificity	Measures the proportion of pathology-negative cases correctly classified
AUC-ROC	Evaluates the model's ability to discriminate between positive and negative cases
Calibration	Assesses agreement between predicted probabilities and observed outcomes
Dice similarity coefficient	Measures agreement between predicted and reference lesion segmentations
External validation	Evaluates performance on independent populations and imaging systems

Results should be interpreted according to the clinical consequences of diagnostic errors. Low sensitivity may lead to missed pathology, whereas low specificity may produce unnecessary investigations or referrals. AUC-ROC alone is insufficient to establish clinical usefulness, particularly when disease prevalence varies across patient populations.

Hung et al. (2022) provide relevant background on deep learning and radiomics for maxillofacial imaging, while AbuSalim et al. (2022) provide a broader foundation for evaluating deep-learning approaches in dental informatics. Nevertheless, the proposed fusion model's performance cannot be established without experimental results.

4.3 Explainability and clinical integration

Interpretability is essential because dental professionals need to understand why an AI system has flagged a particular region. Heat maps, localized attention visualizations, and lesion segmentation overlays could help identify the image features associated with a prediction. These visual explanations should be assessed for consistency with the underlying anatomy and should not be treated as proof that the model's reasoning is clinically correct.

Integration with dental imaging software could allow the system to display predictions alongside the original images, relevant clinical information, and uncertainty estimates. This would support clinician review without replacing professional judgment. The broader integration of CBCT and AI into diagnostic and planning workflows provides a useful context for developing such systems (Aida & Gerta, 2025).

The relationship between prediction and treatment outcome also requires careful consideration. Singh et al. (2025) examined periapical healing in endodontic retreatment using nano-hydroxyapatite with and without platelet-rich fibrin. Their work illustrates the relevance of assessing periapical disease and healing, although it does not validate the proposed multimodal AI architecture. Future research could investigate whether baseline multimodal predictions correlate with subsequent clinical and radiographic outcomes.

V. Discussion, Conclusion, and Future Directions

Cross-modality AI fusion of panoramic radiographs and CBCT represents a promising research direction for improving the identification of hidden dental pathology. By integrating broad anatomical information from panoramic images with three-dimensional detail from CBCT, a carefully developed model could support more precise lesion localization, patient-specific risk estimation, and targeted clinical assessment.

The principal potential advantage is complementary information. Panoramic imaging can provide an initial overview, while CBCT can clarify anatomical findings when three-dimensional assessment is justified. AI may help clinicians integrate these representations more consistently, particularly in anatomically complex cases. However, improved diagnostic performance must be demonstrated through controlled comparisons with conventional interpretation and single-modality models.

Several challenges remain. Image-registration errors, inconsistent acquisition protocols, metal artefacts, imbalanced datasets, and differences between institutions may reduce model reliability. Limited representation of uncommon pathologies could further restrict generalizability. In addition, CBCT radiation exposure must be justified by clinical need; AI development should not encourage unnecessary three-dimensional examinations.

Ethical and regulatory considerations include patient privacy, secure image storage, transparent reporting, algorithmic bias, and clear professional accountability. Future studies should prioritize multicentre datasets, external validation, prospective clinical evaluation, calibrated risk estimates, and explainable outputs. Researchers should also investigate whether multimodal prediction improves clinical decisions and patient outcomes rather than focusing exclusively on technical accuracy.

In conclusion, cross-modality AI fusion offers a potential framework for combining panoramic radiographs and CBCT to predict hidden dental pathology at the patient level. Its clinical value will depend on reliable image integration, appropriate reference diagnoses, rigorous comparative evaluation, and responsible use within established dental imaging guidelines. Although existing research supports the broader application of AI in dental imaging and diagnosis (Hung et al., 2022; Gao et al., 2025; Bansal et al., 2025), the effectiveness of this specific fusion approach remains to be established through dedicated clinical studies.

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