Medical Science

To Cite:
Papierz J, Cybulska K, Banaszczyk J, Górski E, Janczarski S, Królczyk G, Pietrzyk A, Krajewski M. Digital Transformation in Dental Radiology: How AI and Modern Technologies are Reshaping Diagnostics – A Literature Review. *Medical Science* 2026; 30: e170ms3952
doi: https://doi.org/10.54905/disssi.v30i174.e170ms3952

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Peer-Review History
Received: 12 February 2026
Reviewed & Revised: 07/March/2026 to 06/August/2026
Accepted: 16 August 2026
Published: 27 August 2026

Peer-review Method
External peer-review was done through double-blind method.

Medical Science
pISSN 2321–7359; eISSN 2321–7367

DISCOVERY SCIENTIFIC SOCIETY

Digital Transformation in Dental Radiology: How AI and Modern Technologies are Reshaping Diagnostics – A Literature Review

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ABSTRACT

The field of contemporary dentistry is experiencing fast development in its approach to diagnostics, which shifts from two-dimensional imaging to three-dimensional imaging techniques, artificial intelligence, and non-ionizing diagnostics. These innovations improve the precision of diagnosis, minimize human factor influence, and decrease radiation dose. The objective of this literature review is to present the latest updates on the influence of artificial intelligence models such as ULDCBCT and GNN, as well as other imaging technologies such as OCT, MRI, and ultrasonography, on dental radiology. Analysis of relevant literature in different fields of medicine reveals the latest trends, the existing problems, and future perspectives. The latest research shows that CNN is as sensitive and specific in diagnosing dental caries, apical lesions, and marginal bone loss as experienced dentists. Furthermore, DL-based metal artifact reduction and automatic 3D tooth segmentation provide much better CBCT image analysis. Ultradose imaging allows volumetric examination with radiation doses close to traditional 2D exams. Non-ionizing diagnostic methods can also be used for high-resolution visualization of soft tissue changes and early structural alterations without any risk of radiation exposure. Still, the issues of data bias, black box problems, and legal liability remain. Transformation of dental radiology through digital means provides accurate clinical significance with the use of certified software and practitioners' supervision. Artificial intelligence works well as a "second opinion," but not as an independent decision maker.

Keywords: dental radiology; artificial intelligence; deep learning; cone-beam computed tomography; digital workflow; explainable AI

1. INTRODUCTION

The acquisition of high-quality diagnostic images forms an important component in successful treatment planning in all branches of dentistry (Srivastava et al., 2023). Various radiographic techniques, such as bitewing, periapical, and panoramic radiography, have been used in disease diagnosis for a long time (Ali et al., 2025).

Nevertheless, conventional 2D radiography is associated with some limitations, including superimposition, geometrical distortion, and interpretative variability (Krois et al., 2025). CBCT is a real game-changer, as it makes it possible to generate 3D images of the maxillofacial area (Jacobs et al., 2018).

Although this is the case, dentists face difficulties in analyzing the vast amount of imaging data promptly (Hung et al., 2020). The rapid incorporation of AI, especially deep learning and CNN, has paved the way for automated diagnostic solutions (Schwendicke et al., 2020). Such technologies analyze the radiographic images to detect caries, measure periodontal bone levels, and pinpoint the uninstrumented root canals (Ossowska et al., 2022). Moreover, advances in ULD CBCT techniques and AI have been developed to ensure that patients are exposed to the lowest dose of radiation possible (Pinsky et al., 2021; Zhang et al., 2026).

In addition to X-ray-based imaging, non-ionizing technologies like OCT, MRI, and ultrasonography are becoming more widespread (Reddy et al., 2022). The use of these devices in an integrated digital process involving CBCT three-dimensional imaging with optical intraoral scans enables the creation of the "Virtual Dental Patient" (Lanza et al., 2021).

This review article explores the influence of AI and modern imaging technologies on the future of dental radiology. The clinical aspects of use, technical and biomechanical innovations, and ethical and regulatory issues associated with clinical implementation are discussed.

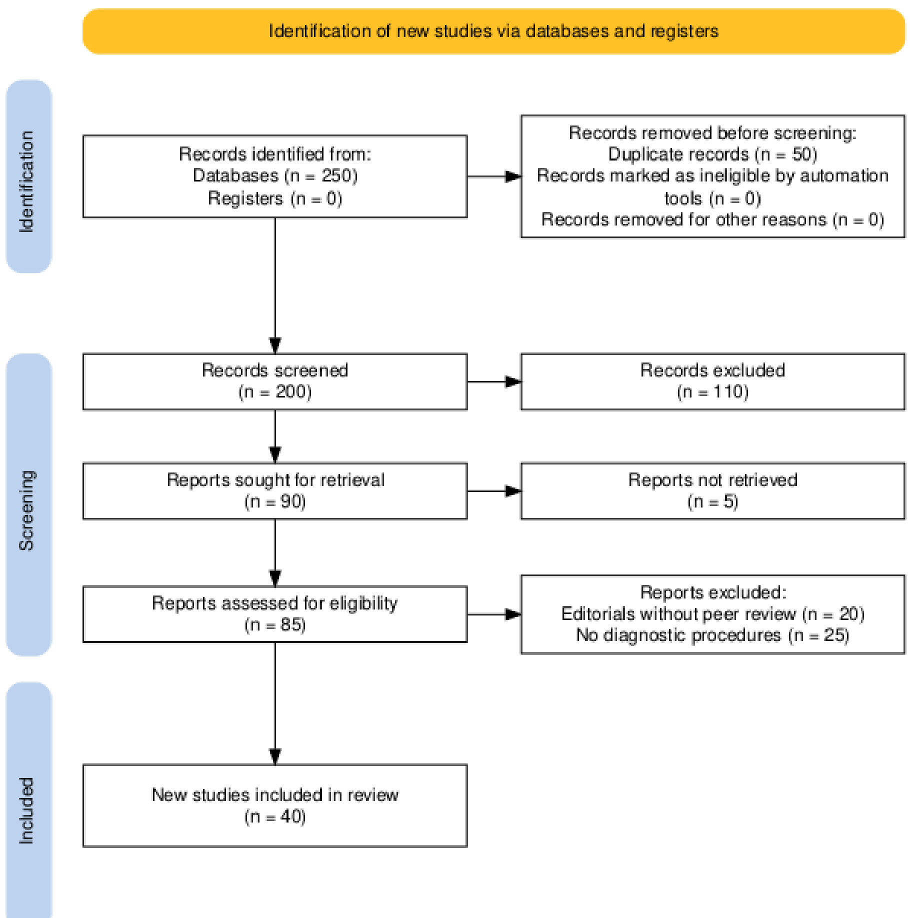

Figure 1. PRISMA flow diagram detailing the literature search and selection process.

2. REVIEW METHODS

In the present literature review, different databases have been searched for relevant information. These include PubMed, Google Scholar, and ScienceDirect. The keywords used in the search are as follows: "dental radiology," "artificial intelligence," "deep learning," "cone beam computed tomography," "optical coherence tomography," and "digital workflow."

The selection criteria involved peer-reviewed papers, reviews, and studies related to the use of digital technologies in dentistry, diagnostic validity, and software validation in dental imaging. Editorials that had not undergone peer review and papers without diagnostic procedures were excluded. In all, 40 papers were selected for qualitative analysis. The detailed study selection process is illustrated in the PRISMA flow diagram (Figure 1).

3. RESULTS AND DISCUSSION

AI-Assisted Detection in 2D and 3D Dental Radiography

Algorithms related to deep learning, specifically Convolutional Neural Networks (CNNs), have shown significant effectiveness in the automated diagnosis of pathology in two-dimensional intraoral and panoramic radiography (Cantu et al., 2020). Early diagnosis of interproximal caries in bitewing radiography in operative dentistry is highly vulnerable to inter-rater variability. Deep learning models using CNNs with annotated large datasets show high sensitivity and specificity for diagnosing the condition, as early lesions in enamel and dentine can be detected even before human visualization (Lee et al., 2018; Hung et al., 2023).

For endodontic and periodontic studies, the output of automated tools provides reliable measures related to spatial analyses. In endodontic cases, alveolar bone loss is quantified in relation to the cementoenamel junction through training of deep learning algorithms based on panoramic radiographs. As a result, the described software allows for the efficient detection of periodontitis following international standards (Krois et al., 2019; Bayrakdar et al., 2021). Similarly, automatic apical periodontitis recognition and evaluation of endodontic treatments help avoid diagnostic errors using panoramic and periapical X-rays (Ekert et al., 2019; Sadr et al., 2021; Ezhov et al., 2021). Two-step detection pipelines help deep learning algorithms identify and assess pathology in each tooth (Chen et al., 2021; Zadrozny et al., 2022).

Innovations in CBCT, Artifact Reduction, and Generative AI

Despite being highly useful for generating three-dimensional images for diagnosis, CBCT images may suffer from streak artifacts due to the high density of metallic restorations, posts, and dental implants (Murtadha et al., 2024). MAR methods that involve deep learning techniques serve as a good solution for reducing beam hardening noise without altering the osseous structures neighboring metal objects (Celik et al., 2022). Radiation safety is taken care of in ULD CBCT imaging systems, which allow for 3D imaging with similar levels of radiation as 2D panoramic imaging (Pinsky et al., 2021; Kilcoyne et al., 2023). The use of generative artificial intelligence through GANs and diffusion models allows for the creation of high-quality 3D images using low amounts of radiation data. This is an important step that is in accordance with the appearance of the ALADA model (Zhang et al., 2026).

The comprehensive workflow is depicted in Figure 2. The integration of hard-tissue DICOM data from low-dose CBCT and STL surface mesh data from an intraoral optical scanner is used for the creation of the Virtual Dental Patient. This model facilitates automated segmentation and lesion detection using XAI heatmaps and AR/VR navigation. This process is illustrated in Figure 2. A summary of the accuracy and limitations of AI and modern diagnostic techniques is presented in Table 1.

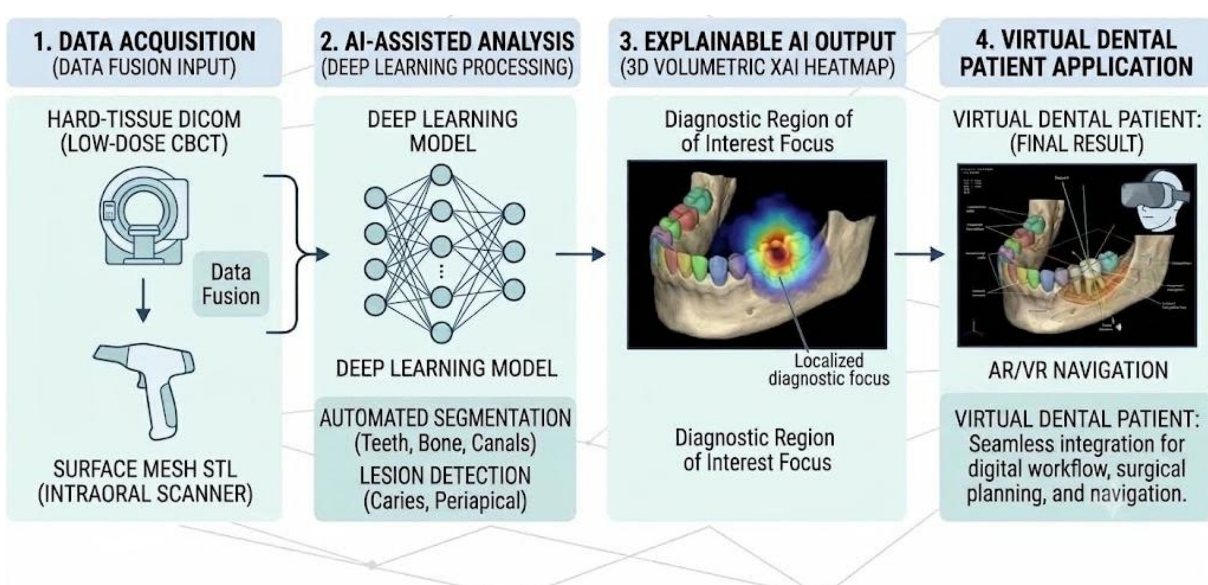

Figure 2. Combination of digital data fusion and AI-assisted analysis for virtual dental patient modeling.

Table 1. Accuracy of artificial intelligence and modern diagnostic techniques in dental radiology together with their limitations and applications.

Modality / Algorithm	Clinical Applications	Performance Metrics & Diagnostic Capabilities	Key Limitations & Constraints	Primary References
Convolutional Neural Networks (CNNs)	Detection of proximal caries, periapical lesions, and alveolar bone loss	Sensitivity: 85–94%; Specificity: 88–96%; High reproducibility in 2D radiographs	Susceptible to image noise, artifacts, and training dataset bias (*data bias*)	Cantu et al., (2020); Krois et al., (2019)
Ultra-Low-Dose (ULD) CBCT Protocols	Orthodontic assessment, airway analysis, guided implant planning	Radiation dose reduction up to 70–85% compared to standard CBCT protocols	Increased image noise affecting soft tissue visualization and subtle bone changes	Pinsky et al., (2021); Kilcoyne et al., (2023)
Generative AI (GANs / Diffusion Models)	Image denoising, super-resolution reconstruction, radiation dose minimization	Generates diagnostic-quality 3D volumes from low-dose acquisition data	Risk of hallucinating synthetic anatomical features or blurring micro-structures	Zhang et al., (2026)
Deep Learning Metal Artifact Reduction (MAR)	Image restoration around dental implants, metallic crowns, and root posts	Increases Signal-to-Noise Ratio (SNR) by filtering beam-hardening streak artifacts	May smooth adjacent fine trabecular bone patterns if over-filtered	Celik et al., (2022); Murtadha et al., (2024)
Automated 3D Segmentation & Landmark Identification	Cephalometric analysis, tooth isolation, nerve trajectory mapping	Reduces manual processing time from hours to <3 minutes; high spatial precision	Requires high contrast between bone and dentin; sensitive to severe crown crowding	Wang et al., (2022); Nishiyama et al., (2023)

Non-Ionizing Modalities and Digital Workflow Integration

The digital revolution in radiology involves non-ionizing imaging systems that reduce the risks of exposure (Reddy et al., 2022). OCT is a technique that uses near-infrared radiation to create detailed sections of the images of the enamel, dentin, and the margin of restoration. This enables minute observation of demineralization and marginal leakage (Hsieh et al., 2013; Machoy et al., 2017; Shim et al., 2021).

In relation to the examination of soft tissues, MRI is the reference standard for TMJ disc displacement and inflammation in the joint (Gaudino et al., 2021). USG can offer real-time visualization of the masticatory muscles, salivary glands, and soft tissue of the periodontium (Marotti et al., 2020). These various imaging modalities have increasingly been combined through data fusion (Data Fusion) (Lanza et al., 2021). Fusion of bone volumes derived from CBCT with optical surfaces from inside the mouth produces a complete "Virtual Dental Patient" that can be used in an AR or VR setting to direct surgical procedures (Joda et al., 2020). A comparative evaluation of these non-ionizing imaging technologies is presented in Table 2.

Table 2. Comparative evaluation of non-ionizing imaging technologies in contemporary dental diagnostics.

Imaging Modality	Physical Principle & Signal Source	Target Anatomy / Tissue Type	Spatial Resolution & Penetration Depth	Specific Clinical Indications	Key Limitations	Primary References
Optical Coherence Tomography (OCT)	Near-infrared light interferometry (non-ionizing)	Enamel, dentin, composite margins, early mucosal lesions	Resolution: ~10–15µm; Depth: 2–3 mm in hard tissues	Micro-leakage detection, early enamel demineralization,	Restricted penetration depth; cannot	Hsieh et al., (2013); Shim et al., (2021)

				crack identification	evaluate deep bone or pulp structures	
Magnetic Resonance Imaging (MRI)	Nuclear magnetic resonance / Radiofrequency pulses	TMJ articular disc, masticatory muscles, trigeminal nerve	High soft-tissue contrast; Variable volumetric resolution	TMJ internal derangement, disc displacement, soft-tissue pathology	High financial cost, accessibility limits, longer acquisition times, motion artifacts	Gaudino et al., (2021); Reddy et al., (2022)
Point-of-Care Ultrasonography (USG)	High-frequency acoustic reflection (7.5–18 MHz)	Salivary glands, masseter muscle, peri-implant mucosa	Real-time dynamic evaluation; Resolution dependent on probe frequency	Peri-implant soft tissue thickness, sialolithiasis, masseter hypertrophy	Inability to penetrate intact cortical bone; operator-dependent diagnostic accuracy	Marotti et al., (2020)

Ethical, Legal, and Economic Aspects

The incorporation of AI in the diagnostic process, from research-based solutions to SaMD implementation, requires FDA approval and MDR compliance as key factors to ensure patient safety (Ramos et al., 2023). One of the challenges associated with integrating AI in the healthcare industry is that deep learning algorithms are complex and often operate as a "black box" (Char et al., 2018). In addition to attempts to make AI more transparent by creating Explainable AI (XAI), saliency maps (Grad-CAM, for example) serve as a way to check the image portions contributing to the algorithm's classification (Tandon et al., 2024). This process is illustrated in Figure 3.

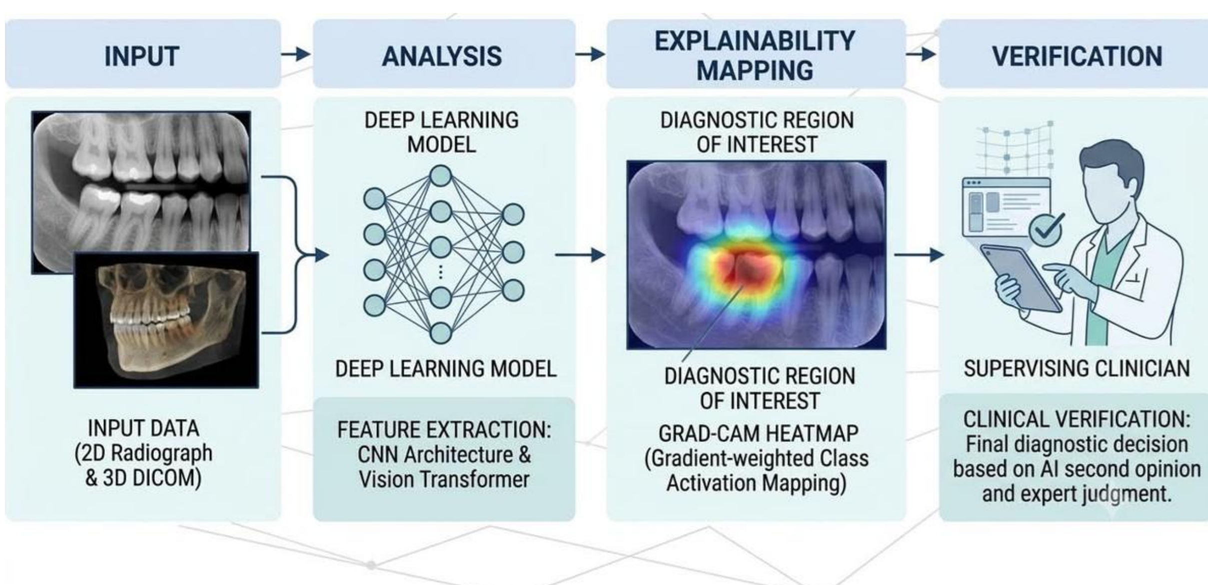

Figure 3. Pipeline to validate Explainable AI (XAI) clinically.

Diagnosis-related legal liability remains the responsibility of the physician providing treatment, with the AI being just an auxiliary diagnostic device and not having autonomy in this process (Pauwels et al., 2021). In addition, issues relating to security of patient data, such as cloud computing of images and DICOM anonymization, also require strict compliance with the privacy requirements (Vanderberghe et al., 2020). According to a health economics study, the use of AI technology in diagnostics is economically efficient due to early identification of lesions and reduced need for invasive techniques in the future (Schwendicke et al., 2021). As the use of the device increases, dental courses are increasingly adding courses on digital imaging and algorithms for risk assessment (Messer et al., 2022; Radosevic et al., 2026).

4. CONCLUSION

The synergy of artificial intelligence with low-dose volumetric and non-ionizing imaging has brought many advancements to the realm of dental radiology. The conclusions drawn from the literature review above include the following points: Artificial neural networks display great accuracy in diagnosing dental caries, periapical lesions, and periodontal bone loss, thereby offering reliable second opinions for clinicians. The use of advanced CBCT image processing technologies such as automatic 3D tooth segmentation, metal artifact elimination, and AI-based reconstruction is beneficial in carrying out volumetric diagnostics and reducing radiation exposure. The application of non-ionizing imaging modalities (OCT, MRI, and ultrasonography) increases the capabilities of X-ray diagnostics by allowing a detailed evaluation of the soft tissues, early pathologic changes, and temporomandibular joint disease.

Acknowledgments

We thank all co-authors and institutional staff for their support during the preparation of this review.

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Informed consent

Not applicable.

Ethical approval

Not applicable. This article does not contain any studies with human participants or animals performed by any of the authors.

Funding

This research did not receive any external funding like specific grant from funding agencies in the public, commercial, or nonprofit sectors.

Conflict of interest

The authors declare that they have no conflicts of interest, competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data and materials availability

All data associated with this study will be available based on the reasonable request to corresponding author.

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