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Artificial Intelligence Frameworks for CBCT Image Processing in Clear Aligner Fabrication: Mini Review

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Abstract

Clear aligner therapy increasingly relies on accurate digital models to improve the predictability of complex tooth movements; however, conventional workflows based on intraoral scans lack root and alveolar bone information that is critical for biomechanical planning and risk assessment. Cone-beam computed tomography (CBCT) can provide this anatomical detail but is limited in routine use by time-consuming segmentation, artifact management, and registration processes. This mini review synthesizes current evidence on artificial intelligence (AI), particularly deep learning–based frameworks, applied to CBCT image processing for clear aligner fabrication and digital orthodontic workflows. A targeted literature search identified studies evaluating AI-driven CBCT segmentation, multimodal fusion with intraoral scans, artifact handling, and clinically relevant applications such as root-aware planning, midpalatal suture maturation staging, and automated assessment of orthodontically induced root resorption. Across predominantly retrospective and laboratory-based studies published between 2021 and 2025, deep learning models—most commonly U-Net–based architectures—demonstrated high segmentation accuracy (often exceeding 90%) while substantially reducing processing time from hours to minutes. Multimodal CBCT–intraoral scan fusion emerged as a key advance for generating anatomically complete crown–root–bone models that may enhance aligner planning and monitoring. Despite promising technical performance, clinical translation remains constrained by small datasets, heterogeneous reference standards, limited external validation, and a lack of prospective outcome-focused studies. Overall, AI-enabled CBCT processing shows strong potential to streamline digital orthodontic workflows and improve anatomical fidelity in clear aligner therapy, but further multi-center validation and clinical effectiveness studies are required before widespread adoption.

Keywords: Cone-beam computed tomography; deep learning; tooth segmentation; intraoral scan; multimodal fusion; clear aligners; 3D printing; digital orthodontics

Introduction

Clear aligner therapy has become a mainstream orthodontic modality because it is esthetic and facilitates oral hygiene, yet complex movements (e.g., torque control, bodily root movement, and transverse corrections) remain challenging and often require refinements [1-3]. In parallel, digital manufacturing is rapidly shifting from thermoforming to direct 3D printing, which increases demand for anatomically precise digital models and repeatable workflows [1,4-6]. Compared to fixed braces, clear aligners often finish treatment several months faster and manage segmented tooth movements better, although they showed weaker control over torque, posterior occlusal contacts, transverse widening, and long-term stability [2].

Most commercial aligner setups are based on surface geometry from intraoral scans (IOS). Surface scans accurately represent crowns but lack information about roots and alveolar bone structures that can constrain tooth movement, influence attachment design, and drive adverse events such as dehiscence or external apical root resorption (10). Cone-beam computed tomography (CBCT) provides a detailed three-dimensional visualization of dental and skeletal structures, enabling assessment of crown morphology, root position, and alveolar bone architecture. CBCT is currently the only practical clinical modality that captures these structures in 3D at chairside resolution [7]. However, conventional CBCT workflows require manual or semi-automatic segmentation, artifact management, and registration between CBCT volumes and IOS meshes steps that can take hours and may be difficult to reproduce [8]. CBCT-based analysis has revealed clinically relevant discrepancies between predicted and achieved tooth movements in aligner therapy, particularly for root apices and posterior teeth, highlighting the importance of incorporating root-level information into treatment planning [9-11]. As direct aligner printing becomes more widespread, demand has increased for automated, fast, and anatomically precise CBCT processing pipelines capable of supporting real-time clinical decision-making.

In this context, artificial intelligence (AI), particularly deep learning (DL), has emerged as a promising approach for automated CBCT segmentation, landmark detection, multimodal data fusion, and treatment outcome prediction [12]. In medical imaging, DL is commonly implemented with CNN-based models; U-Net variants are widely used for segmentation, and transformer-based approaches are increasingly adopted for capturing global 3D context [12]. Recent studies suggest that DL-based frameworks can substantially reduce manual processing time while maintaining high segmentation accuracy, potentially enabling real-time or near-real-time reconstruction of crown–root–bone models for aligner fabrication [8,13,14]. Despite this rapid technical progress, the extent to which these systems are clinically validated and ready for routine orthodontic application remains unclear.

Therefore, the aim of this mini review is to synthesize current evidence on deep learning–based real-time CBCT image processing frameworks and evaluate their performance, clinical relevance, and limitations within the context of clear aligner fabrication and digital orthodontic workflows.

Methods and Materials

We performed a targeted literature review to discover publications evaluating the use of AI to CBCT for activities relevant to clear aligner processes, including tooth, root, and bone segmentation or reconstruction, management of CBCT artifacts, and multimodal fusion or registration of CBCT with IOS. Searches were performed in PubMed, MEDLINE, Scopus, Web of Science, and Google Scholar up to December 2025 using combinations of keywords and synonyms related to CBCT, orthodontics/aligners, segmentation, registration/fusion, and deep learning (including “CBCT” AND “tooth segmentation” OR “root segmentation” OR “alveolar bone” OR “U-Net” OR “deep learning” OR “multimodal fusion” OR “registration” AND “clear aligner” OR “orthodontic”). Reference lists of included articles and relevant reviews were also screened to capture additional studies.

Eligibility criteria included original research reporting AI-based analysis of CBCT volumes for segmentation/reconstruction of teeth/roots/bone, CBCT–IOS fusion or registration, or CBCT-based AI applications used to support aligner planning, monitoring, or assessment of adverse events. The exclusion criteria contained studies that did not utilize CBCT imaging, used purely non-AI methodologies, focused exclusively on non-orthodontic applications unrelated to aligner workflows, consisted of editorials or opinion pieces, and included duplicates.

Titles and abstracts were screened, followed by full-text review to confirm eligibility. From each included study, we extracted the clinical task, dataset type and size, imaging inputs (CBCT/IOS), model family (such as CNN, U-Net, transformer), reference standard, evaluation metrics (such as Dice, IoU, AUC, ICC), and processing time when reported. Given heterogeneity in datasets, outcomes, and reporting, findings were synthesized qualitatively and organized by workflow stage with emphasis on reported performance and barriers to clinical translation.

Results

The final selection comprised a limited number of studies directly addressing deep learning–based processing of CBCT data for applications relevant to clear aligner therapy (Table 1). Most eligible studies were published between 2021 and 2025 and consisted primarily of retrospective or laboratory-based investigations. Only a small number included prospective clinical data. The dominant research themes included automated segmentation of dental structures, multimodal fusion of CBCT and intraoral scans, and predictive modeling of orthodontic outcomes. Sample sizes varied substantially across studies, and reporting of dataset composition, annotation protocols, and validation strategies was heterogeneous.

Segmentation Accuracy and Model Performance

Across studies summarized in Table 1, deep learning models consistently demonstrated high accuracy for automated segmentation of dental and skeletal structures from CBCT volumes. Multimodal deep learning systems integrating CBCT and intraoral scans achieved Dice similarity coefficients typically above 90%, with Jin et al. reporting Dice values of 94% for full crown–root–bone reconstruction, while reducing processing time from approximately five hours of manual work to about 20 minutes [15].

Deleat-Besson et al. similarly showed effective machine learning-based segmentation of dental root canals integrated with crown morphology, facilitating the generation of anatomically full tooth models appropriate for aligner design [16]. Zheng et al. exhibited intraclass correlation values surpassing 0.95 for volumetric root measurements in root resorption analysis, with automated classification accuracy reaching 0.8 for the severity grading of orthodontically caused root resorption[17].

Most segmentation pipelines utilize convolutional neural network designs, especially U-Net variations. Recent research has increasingly adopted multimodal and hybrid deep learning frameworks to enhance resilience under varying imaging circumstances.

Multimodal Fusion and Registration

Multimodal fusion of CBCT data with intraoral surface scans represented a central methodological trend (Table 1). D'Alessandro et al. and Jin et al. demonstrated that deep learning–based fusion frameworks enable automatic registration of root and bone information from CBCT with high-resolution crown surfaces from IOS [15,18]. These systems facilitated the construction of anatomically complete digital models and supported the realistic simulation of complex root movements and torque control that cannot be achieved using surface scans alone.

In addition to orthodontic applications, CBCT-based fusion and registration approaches were extended to other dental fields. Fan et al. applied mixed-reality navigation based on CBCT registration for implant placement, achieving spatial deviations of approximately 1.5 mm, illustrating the broader feasibility of real-time CBCT processing in clinical environments [19].

Clinical Applications in Clear Aligner Workflows

Several studies applied AI-driven CBCT analysis to clinically relevant aligner workflows (Table 1). Wang et al. introduced a multimodal deep learning system (DeepMSM) for staging midpalatal suture maturation using CBCT data, reporting classification accuracy of approximately 85%, exceeding the performance of junior clinicians and supporting improved timing of expansion prior to aligner therapy [20].

Predictive modeling was also explored. Li et al. developed a machine learning model for forecasting open gingival embrasures after aligner treatment, achieving an area-under-the-curve value of 0.88 based on treatment-planning variables and patient characteristics [21]. Ruiz et al., in a large scoping review, reported segmentation accuracies approaching 98% across commercial and experimental AI systems, confirming the rapid expansion of AI-driven digital setups in orthodontics [13]. Although Shangyou et al. used CBCT superimposition without AI, their findings highlighted the limited predictability of certain aligner movements, particularly posterior extrusion, reinforcing the need for more advanced AI-based biomechanical modeling [22].

Evidence Gaps and Validation Limitations

Despite strong technical performance documented in several studies, clinical validation is still limited. Most studies depended on limited or institution-specific datasets and lacked external validation. The evaluation measures, annotation standards, and reference methods exhibited significant variability, limiting direct comparisons among models. Few prospective clinical studies evaluated patient outcomes, therapeutic efficacy, and long-term safety. Moreover, while several studies have indicated near-real-time processing rates, the practical use in standard orthodontic practice remains predominantly unverified, and the regulatory frameworks for the clinical installation of AI-driven CBCT systems are not yet distinctly defined.

Discussion

This mini review indicates that deep learning–enabled CBCT processing is progressing toward clinically relevant performance for clear aligner workflows. Clear aligner therapy has become widely used due to esthetics and oral-hygiene advantages, yet biomechanical limitations and variable predictability, particularly for complex movements, remain well recognized in the broader aligner literature [23,24].

Across the included studies, the most consistent signal is that AI can substantially reduce the time and operator burden associated with CBCT segmentation and model reconstruction while maintaining high quantitative performance. In particular, multimodal fusion approaches that integrate CBCT with intraoral scans appear to address a central limitation of surface-only digital setups by combining high-resolution crown morphology with root and alveolar bone information, enabling the generation of anatomically complete models within clinically practical time frames [13,15,16]. In particular, multimodal fusion approaches that integrate CBCT with intraoral scans help address a key limitation of surface-only setups by combining high-resolution crown morphology with root and alveolar bone information, supporting anatomically complete models within clinically practical time frames [15,16,18].

Table 1. Review of CBCT, artificial intelligence, and clear aligners.

Study ID	Year	Technology Focus	CBCT Use	Clear Aligner Role	Key Result
Fan et al. [19]	2023	Mixed Reality navigation	Pre-op planning	Implant path guidance	1.5 mm accuracy with HoloLens
D'Alessandro et al. [18]	2023	CBCT + IOS fusion	Root + bone imaging	Accurate root torque with aligners	Successful complex root movement
Li et al. [21]	2025	ML prediction model	No (ClinCheck only)	Predict open gingival embrasures	AUC 0.88 combined nomogram
Ruiz et al. [13]	2025	AI in clear aligner therapy	Some studies	Segmentation, setup, monitoring	AI rising, 98% seg. accuracy
Wang et al. (DeepMSM) [20]	2025	Multimodal DL	MPS staging	Indirect (expansion planning)	85% accuracy > junior clinicians
Jin et al. (DDMA) [15]	2022	Multimodal DL CBCT+IOS fusion	Full tooth-bone segmentation	High-fidelity crown-root-bone model	Dice 94%, 20 min vs 5 h manual
Shangyou et al. [22]	2025	CBCT superimposition (non-AI)	Pre-/post-treatment CBCT	Quantifying tooth movements with aligners	52.9% predictability of Curve of Spee leveling; substantial posterior overtreatment required
Zheng et al. [17]	2025	Deep learning OIRR quantification	Full CBCT-based 3D root volume analysis	Root resorption monitoring during aligner therapy	ICC >0.95; automatic OIRR detection with >0.8 severity classification accuracy
Deleat-Besson et al. [16]	2021	ML root-canal segmentation + crown merging	CBCT root canal segmentation + IOS crown fusion	Supports aligner planning via root anatomy visualization	Automated root-canal segmentation + crown/root model integration for improved root-position awareness

Note: AI: Artificial Intelligence; ML: Machine Learning; DL: Deep Learning; CBCT: Cone-Beam Computed Tomography; IOS: Intraoral Scan; MPS: Midpalatal Suture; CVM: Cervical Vertebral Maturation; MTM: Mandibular Third Molar; AUC: Area Under Curve; Dice: Dice Similarity Coefficient; IoU: Intersection over Union; mIoU: mean Intersection over Union; OGE: Open Gingival Embrasure; LASSO: Least Absolute Shrinkage and Selection Operator; ABO: American Board of Orthodontics; DDMA: Deep Dental Multimodal Analysis; DeepMSM: Deep Midpalatal Suture Maturation model.

From a clinical perspective, the most immediately applicable use cases for AI-driven CBCT analysis appear to be root-aware planning and risk monitoring in situations where CBCT is clinically justified. Automated three-dimensional quantification of orthodontically induced root resorption has been demonstrated with high reliability and clinically relevant severity classification performance, supporting standardized monitoring of an adverse event that remains a concern in aligner therapy [10,17]. In addition, multimodal CBCT-based models have been applied to diagnostic staging tasks that can influence treatment timing, such as midpalatal suture maturation staging [25].

At the workflow level, the broader scoping literature describes expanding AI adoption across segmentation, digital setup, monitoring, and prediction, while emphasizing that true end-to-end automation remains uneven across commercial and academic systems [13,26]. Complementary orthodontic and biomechanical studies also underscore why improved anatomical modeling matters: CBCT-based assessments have shown discrepancies between planned and achieved tooth movement and have provided quantitative movement evaluation, while finite element studies continue to refine force systems and attachment design in aligner biomechanics [27-30]. In parallel, "AI outside CBCT" is rapidly entering aligner care through treatment outcome prediction, remote monitoring, and workflow support. Machine-learning prediction of outcomes and complications (for example, open gingival embrasures and treatment outcome prediction) and AI-based remote monitoring have been reported, although these tools require careful clinical oversight and validation [31-33]. Broader perspectives on AI-supported aligner technology and clinical integration further reinforce that imaging, biomechanics, and monitoring must be evaluated as a connected system rather than isolated modules [34,35].

Significant evidence gaps remain. Much research on CBCT/AI are either retrospective or laboratory-based, lacking external validation and exhibiting inconsistent annotation standards and performance reporting, which restricts comparability and generalizability. Secondly, the quality of real-world CBCT is inconsistent (due to motion, metal artifacts, and variations in voxel size), and models developed on curated datasets can lose performance without domain adaption and strict quality assurance. The clinical advantages includes more than just technical accuracy; it depends on provable enhancements in significant outcomes, like reduced refinements, enhanced predictability of root control, reduced adverse events, and quantifiable efficiency, all while maintaining safety standards. Safety and materials considerations also remain relevant as aligner manufacturing evolves. Systematic reviews and materials-focused analyses have raised ongoing questions about polymer behavior and potential chemical release, and evidence in growing patients remains comparatively limited, issues that become more critical when new printable resins and manufacturing pathways are introduced [3-6,36,37]. Finally, although not aligner-specific, mixed-reality CBCT registration work in implant navigation illustrates the broader feasibility of near-real-time CBCT-based guidance systems, which may inform future orthodontic implementations [14].

Future research would benefit from multi-center datasets with transparent curation and governance; standardized benchmarking protocols (including external validation across scanners); and prospective clinical studies that quantify downstream impacts on treatment planning decisions, workflow time, and patient-centered outcomes [13,38]. As the field continues to mature, emerging perspectives propose expanding AI-driven CBCT interpretation to better capture biological variability and material-related uncertainty across digital orthodontic workflows [39,40].

Conflict of interest

The authors declared no conflict of interest.

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