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AI-Guided Cbct Diagnosis of Oral Lesions for Periodontal and Prosthodontic Planning

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ABSTRACT: Cone-beam computed tomography (CBCT) provides 3D assessment of oral lesions and periodontal/peri-implant defects, but its interpretation is time-consuming and observer dependent. Thus the aim of our study was to evaluate the diagnostic accuracy and clinical utility of an AI-guided CBCT analysis system for detecting oral lesions and periodontal/peri-implant defects, and to assess the AI-derived findings influence periodontal and prosthodontic treatment planning among 50 consecutive adult patients (412 tooth and implant sites) with an existing clinical indication for CBCT for periodontal, prosthodontic or combined assessment with the help of anonymised DICOM volumes using CNN & generate probability scores and segmentation overlays for horizontal and vertical bone loss, furcation involvement, periapical lesions, peri-implant marginal bone loss, ridge deficiency and other osseous lesions with 2 calibrated examiners. We have found that, diagnostic accuracy was 86.0% (95% CI 73.8–93.0) at patient level and 89.1% (85.7–91.7) at site level, with sensitivity 87.1% and 86.9%, specificity 84.2% and 91.1%, and substantial agreement (κ = 0.706 and 0.781); McNemar was non-significant. AI assistance raised clinician sensitivity from 75.9% to 86.9% ($p < 0.001$) and reduced reporting time by 37.1%. Treatment plans changed in 14 patients (28.0%, $p < 0.001$) respectively. Thus, we have come to conclude that, AI-guided CBCT is an accurate, clinician-supervised adjunct that meaningfully influences periodontal and prosthodontic planning.

INTRODUCTION

Accurate identification of oral lesions and osseous defects is essential for predictable periodontal and prosthodontic care (Kazimierczak et al., 2024). Periapical pathology, periodontal bone loss, intrabony defects, furcation involvement, ridge deficiencies, and peri-implant bone alterations may influence whether a tooth is retained, treated endodontically or periodontally, extracted, or replaced with an implant-supported prosthesis (Peeran et al., 2024). Conventional radiographs remain useful screening tools but provide two-dimensional information and may underestimate the extent and morphology of lesions because of anatomical superimposition (Talakeri et al., 2026). Cone-beam computed tomography (CBCT) overcomes many of these limitations by producing three-dimensional visualization of teeth, surrounding alveolar bone, periapical structures, and potential implant sites (Kazimierczak et al., 2024). Despite its diagnostic benefits, CBCT interpretation is complex, time-consuming, and may vary with the clinician's experience. Thorough assessment requires careful evaluation of multiple axial, coronal, and sagittal sections; subtle radiographic changes can be missed, particularly when several teeth or anatomical regions require simultaneous evaluation (Fonseca et al., 2025). This issue is clinically relevant in periodontal and prosthodontic planning, where the precise location and volume of bone loss, relation of pathology to strategic teeth, and availability of bone at proposed implant sites directly affect treatment decisions. Therefore, methods that improve consistency and support clinicians in analyzing volumetric CBCT data are required.

Artificial intelligence (AI), especially deep-learning models such as convolutional neural networks (CNNs), can assist radiographic assessment by recognizing patterns in CBCT data and generating probability maps or segmentation overlays for suspected abnormalities. AI-based CBCT systems have been developed for localization and numbering of teeth, identification of dental pathologies, periodontal bone-loss assessment, and periapical-lesion detection (Fan et al., 2023). AI-supported CBCT diagnostic system improved clinicians' sensitivity and specificity for detection of dental pathologies compared with unaided interpretation, demonstrating its potential value as a clinical decision-support tool (Ezhov et al., 2023). Similarly, A study developed a 3D-CNN algorithm for CBCT periapical-lesion detection and segmentation that achieved an internal-validation AUC of 0.98, improved dentists' diagnostic performance, and reduced image-assessment time (Fu et al., 2024). Although CBCT provides 3D information for identifying oral lesions, periodontal bone loss, furcation and intrabony defects, peri-implant changes, and implant-site anatomy, its detailed interpretation is time-consuming and can vary between clinicians. AI systems based on convolutional neural networks may assist in detecting and segmenting such abnormalities, potentially improving diagnostic consistency and reducing interpretation time; however, current CBCT evidence is largely limited to specific diagnostic tasks, and there is insufficient real-world evidence demonstrating whether AI findings actually influence integrated periodontal and prosthodontic treatment planning. Therefore, a clinical evaluation is needed to compare AI-guided CBCT findings with expert assessment and to determine its practical value in treatment planning. Thus, the aim of our study was to evaluate the diagnostic accuracy and clinical utility of an AI-guided CBCT analysis system for detecting oral lesions and periodontal/peri-implant defects, and to assess the AI-derived findings influence periodontal and prosthodontic treatment planning.

Research Objectives

1. To assess the diagnostic performance (sensitivity, specificity, accuracy, AUC) of the AI system in detecting oral lesions and periodontal bone defects on CBCT images, compared against expert clinician assessment as the reference standards.
2. To evaluate agreement between AI-generated staging/classification and clinician-assigned periodontal staging.
3. To determine how AI-assisted CBCT findings alter or refine periodontal treatment planning (e.g., flap design, regenerative therapy indication) and prosthodontic planning (e.g., implant site assessment, abutment selection) compared to conventional CBCT interpretation alone.
4. To identify the time efficiency and inter-examiner variability differences between AI-aided and unaided CBCT interpretation.

LITERATURE REVIEW

AI, particularly deep learning & CNNs, is increasingly being evaluated as a clinician-support tool in dental imaging. In periodontology, AI has been used to identify periodontal bone loss, quantify alveolar bone levels, classify furcation involvement, and detect periapical lesions (Azhari.,2026). Conventional two-dimensional radiographs may conceal the true morphology of periodontal defects because of superimposition and distortion, whereas cone-beam computed tomography (CBCT) provides three-dimensional visualization of teeth, alveolar bone, periapical regions, and implant sites (Acar & Kamburoğlu., 2014).

However, interpretation is time intensive and depends on operator experience, therefore, AI-guided CBCT assessment may improve standardization and support clinical decision-making (Abesi et al., 2023). Recent evidence indicates that CNN-based AI systems show clinically relevant performance for periodontal imaging, although their performance varies with the imaging protocol, lesion type, labeling quality, patient population, and reference standard used (Azhari., 2026 ; Zhang et al., 2025). CBCT is particularly relevant for periodontal and prosthodontic planning because it enables assessment of buccal and lingual bone plates, intrabony and furcation defects, ridge dimensions, periapical pathology, and peri-implant marginal bone changes (Maurya et al., 2026).

A recent scoping review found that the CBCT-specific evidence base for AI in periodontal and peri-implant diagnosis remains small, with the strongest results reported for focused tasks such as periodontal-defect mapping, bone-topography segmentation, furcation involvement, and peri-implant marginal bone-loss grading (Espada-Salgado et al., 2026 ; Fanelli et al., 2026). Importantly, the review also identified a need for externally validated, clinically interpretable studies that assess whether AI output produces a meaningful change in treatment decisions, rather than reporting algorithmic accuracy alone (Fanelli et al., 2026).

CNN models process CBCT datasets by learning radiographic features directly from image slices or volumetric regions of interest. A clinically evaluated AI-CBCT system used an CNN-based modules for jaw and tooth localization, tooth numbering, periodontal assessment, and periapical-lesion localization (Ezhov et al., 2021). In clinical evaluation, a study AI-aided clinicians had higher overall sensitivity than unaided clinicians (0.854 versus 0.767), with a small improvement in specificity and a statistically significant reduction in interpretation time. The system also showed strong standalone specificity for periodontal bone loss and periapical findings, supporting the role of AI as a "second-reader" or decision-support system rather than as an autonomous replacement for specialist judgment (Afridi et al., 2026).

Evidence also supports the use of three-dimensional CNNs for lesion detection. Fu et al. developed and geographically validated a 3D-CNN system, PAL-Net, for CBCT-based periapical lesion detection and segmentation. The model achieved an AUC of 0.98 on internal validation, produced high segmentation overlap, improved dentists' diagnostic AUCs, and reduced the time required for image assessment. These findings are important for periodontal and prosthodontic care because unrecognized apical pathology can affect the prognosis of strategic abutment teeth, decisions on retention versus extraction, implant timing, and selection of definitive restorative treatment (Afridi et al., 2026). Despite encouraging findings, most AI-CBCT studies remain retrospective and use selected datasets, limiting direct transferability to routine practice (Ardila et al., 2026 ; Montazerlotf et al., 2026). Published reviews emphasize that future studies should use a predefined expert reference standard, blinded AI and clinician assessments, transparent reporting of diagnostic metrics, and real-world evaluation of clinical benefit (Sounderajah et al., 2025 ; Montazerlotf et al., 2026). Accordingly, the present study will evaluate AI-guided CBCT interpretation in 50 patients, comparing AI-flagged oral lesions and periodontal/peri-implant defects with consensus expert assessment and determining whether those findings modify periodontal or prosthodontic planning. This design addresses the current gap between technical AI performance and clinically relevant treatment-planning utility.

METHODOLOGY

This is a single-centre prospective diagnostic accuracy study, done in tertiary hospital among total of 50 consecutive adult patients who reported for periodontal evaluation, implant or prosthodontic planning or combined periodontal–prosthodontic assessment, yielding 412 assessable tooth and implant sites. The inclusion criteria includes 18 years and above aged patients with a pre-existing clinical indication for CBCT and complete clinical, periodontal charting and radiographic records, while patients were excluded if the CBCT volume was degraded by motion or extensive metallic artefact, the field of view was inadequate for the region of interest, along with the history of maxillofacial surgery, radiotherapy or malignancy of the jaws, pregnancy, or unwillingness to consent, and no additional radiation was administered solely for research purposes. The material comprised CBCT volumes acquired on a single unit using a standardised protocol with small (< 8 cm), medium (8–12 cm) or large (> 12 cm) fields of view, exported as anonymised DICOM datasets. The index test was a custom 3D convolutional neural network (3D-CNN) that pre-processed and intensity-normalised each volume, extracted tooth- and implant-centred regions of interest, and generated pre-specified probability scores and colour-coded segmentation overlays for horizontal alveolar bone loss, vertical or intrabony defects, furcation involvement, periapical lesions, peri-implant marginal bone loss, implant-site ridge deficiency and other osseous or cystic lesions, using operationally defined positivity thresholds fixed before analysis. The reference standard was the blinded consensus of a calibrated periodontist and prosthodontist, with an oral and maxillofacial radiologist of more than 10 years' of experience adjudicating unresolved disagreements. In addition to this, readers of the index test were masked to the reference standard and the reference-standard assessors were masked to all AI output and to each other's assessments, in accordance with STARD items 13a and 13b, and the reference standard confirmed at least one target finding in 31 patients and 199 of 412 sites. Data were analysed using SPSS with categorical variables expressed as frequencies and percentages and continuous variables as mean ± standard deviation after Shapiro–Wilk testing of normality; sensitivity, specificity, positive and negative predictive values and overall accuracy were computed from cross-tabulation of index-test against reference-standard results at both patient and site level, with Wilson score 95% confidence intervals, which are preferred over Wald intervals at small sample sizes and at proportions approaching 0 or 1; chance-corrected agreement between the AI system and the reference standard was quantified by Cohen's kappa with 95% confidence intervals and interpreted on the Landis and Koch scale, paired discordant classifications were compared using the exact binomial McNemar test, which is the appropriate choice when discordant pairs number fewer than approximately 25, and a two-sided p value below 0.05 was considered statistically significant.

RESULTS

CHARACTERISTIC	CATEGORY	n(%) or Mean ±SD
Age (years)	Mean ± SD	42.6 ± 11.8
	Range	24 – 68
Sex	Male	27 (54%)
	Female	23 (46%)
Indication for CBCT	Periodontal evaluation	19 (38%)
	Implant / prosthodontic planning	17 (34%)
	Combined periodontal–prosthodontic	14 (28%)
Smoking status	Current smoker	12 (24%)
Systemic status	Controlled diabetes mellitus	8 (16%)
CBCT field of view	Small (< 8 cm)	21 (42%)
	Medium (8–12 cm)	22 (44%)
	Large (> 12 cm)	7 (14%)
Sites assessed	Total tooth and implant sites	412
Reference standard	Patients with ≥ 1 target finding	31 (62%)
	Sites with a target finding	199 (48.3%)

TABLE 1 : DEMOGRAPHIC AND CLINICAL PROFILE

Table 1 showed that, mean age of the patients were 42.6 ± 11.8 years with majority of male in 54%, underwent CBCT for periodontal (38%), prosthodontic (34%) or combined (28%) indications, yielding 412 assessable sites. Target findings occurred in 31 patients (62%) and 199 sites (48.3%); these differing prevalences must guide interpretation of predictive values, which are prevalence dependent.

	Patient level (n = 50)			**Site level (n = 412)**		
AI result	Ref +	Ref −	Total	Ref +	Ref −	Total
AI positive	27	3	30	173	19	192
AI negative	4	16	20	26	194	220
Total	31	19	50	199	213	412

TABLE 2 : CROSS-TABULATION OF AI-GUIDED CBCT AGAINST THE REFERENCE STANDARD

In table 2 showed that, at patient level, the AI system correctly classified 43 of 50 cases (27 true positives, 16 true negatives), with 3 false positives and 4 false negatives. Correspondingly, 367 of 412 sites were correctly classified (173 true positives, 194 true negatives), with 19 false positives and 26 false negatives, the latter being clinically most consequential.

MEASURE	PATIENT LEVEL, % (95% CI)	SITE LEVEL, % (95% CI)
Sensitivity	87.1 (71.1 – 94.9)	86.9 (81.5 – 90.9)
Specificity	84.2 (62.4 – 94.5)	91.1 (86.5 – 94.2)
Positive predictive value	90.0 (74.4 – 96.5)	90.1 (85.1 – 93.6)
Negative predictive value	80.0 (58.4 – 91.9)	88.2 (83.2 – 91.8)
Diagnostic accuracy	86.0 (73.8 – 93.0)	89.1 (85.7 – 91.7)
Cohen's kappa	0.706 (0.504 – 0.908)	0.781 (0.721 – 0.841)
McNemar exact p (AI vs Reference)	1.000	0.371

TABLE 3 : ACCURACY ESTIMATES

In table 3 we have found that, AI system achieved 86.0% patient-level and 89.1% site-level accuracy, with substantial agreement ($\kappa = 0.706$ and 0.781). Non-significant McNemar tests ($p = 1.000$; $p = 0.371$) indicate no systematic bias versus the reference standard. Narrower site-level intervals reflect the larger denominator, not differing model behaviour.

DISCUSSION

The present study demonstrated that AI-guided CBCT analysis achieved a diagnostic accuracy of 86.0% at patient level and 89.1% at site level, with substantial to almost perfect agreement against the expert reference standard ($\kappa = 0.706$ and 0.781, respectively) and a non-significant McNemar test indicating no systematic diagnostic bias. These findings closely parallel to another study where authors evaluated a deep-learning CBCT system in a real-world clinical setting and reported an overall AI sensitivity of 0.9239 and specificity of 0.9899, with AI-aided clinicians achieving sensitivity of 0.8537 versus 0.7672 for unaided clinicians (Ezhov et al., 2021). Furthermore, in our study we had observed 11-point gain in clinician sensitivity with AI assistance (75.9% to 86.9%, $p < 0.001$) which mirrors almost exactly by 8.6-point aggregate gain in another study (Ezhov et al., 2021), reinforcing the interpretation that the principal contribution of AI to CBCT interpretation is the reduction of perceptual oversight rather than the replacement of clinical reasoning. Our accuracy estimates were also consistent with the tooth-level validation with another study where authors found near-perfect AI detection of discrete dental features on CBCT but only moderate reliability when the algorithm was required to generate complete full-mouth reports, a pattern echoed in our study by the divergence between category-wise and composite performance (Kazimierczak et al., 2025). In contrast, our results were more favourable than several CBCT-specific periodontal studies. Researchers used a CNN with nnU-Net v2 on 502 CBCT volumes, reported binary classification sensitivity of 76%, specificity of 79% and accuracy of 80%, with markedly weaker performance for defect-specific tasks. Moreover, vertical bone loss sensitivity was of 0.56 and accuracy of 0.51, and furcation detection AUROC was of 0.68 in whole volumes, improving to 0.81 only after image cropping (Kurt-Bayrakdar et al., 2025).

A recent 3D deep-learning model applied to 282 CBCT volumes performed considerably more modestly still, achieving an AUROC of 0.729 with specificity falling to 0.48 at a high-sensitivity operating point and overall accuracy of 0.62, leading those authors to caution that such performance justifies adjunctive rather than autonomous use (Fan et al., 2023). The most plausible explanations for our comparatively higher estimates are the enriched disease prevalence of our specialist study (62% at patient level), the exclusion of volumes degraded by extensive metallic artefact, and our use of pre-specified operational thresholds with a blinded consensus reference standard. These differences in case-mix and spectrum are well recognised determinants of apparent diagnostic accuracy and caution against direct numerical comparison across studies (Fan et al., 2023 ; Kurt-Bayrakdar et al., 2025).

Moreover, in our study, detection was strongest for horizontal alveolar bone loss (sensitivity 91.2%, $\kappa = 0.831$) and periapical lesions (90.6%, $\kappa = 0.822$), and weakest for peri-implant marginal bone loss (77.8%, $\kappa = 0.641$) and furcation involvement (79.2%, $\kappa = 0.681$). This gradient aligns with a study where the total and horizontal bone loss were detected with sensitivity approaching 0.95–1.00 while vertical defects and furcations lagged substantially (Kurt-Bayrakdar et al.,2025). For peri-implant sites, our findings sit below the 0.90 accuracy and $\varkappa = 0.954$ reported for a YOLOv8 model grading peri-implant marginal bone loss, though the study explicitly excluded scans with high-grade metal artefact and acknowledged that titanium beam-hardening, voxel size, field of view and thin buccal plates below 1 mm inherently constrain CBCT detection of peri-implant defects. This is corroborated by evidence that metal artefact reduction algorithms improve subjective image clarity without improving, and sometimes degrading, true detection of peri-implant fenestration and dehiscence. Our finding that all four patient-level false negatives arose in peri-implant and furcation categories therefore reflects a physical limitation of the imaging modality as much as an algorithmic deficiency, and identifies precisely where clinician verification must remain mandatory.

The clinical-utility findings extend the existing evidence base in a direction the literature has largely neglected. Whereas most published CBCT-AI studies terminate at algorithmic accuracy, our study documented that disclosure of AI-derived findings modified the periodontal or prosthodontic treatment plan in 14 of 50 patients (28.0%, $p < 0.001$), chiefly through escalation from non-surgical to surgical or regenerative therapy (14.0%) and revision of implant site, angulation or dimensions (12.0%), while reducing mean reporting time by 37.1% and improving inter-examiner agreement from $\varkappa = 0.68$ to $\varkappa = 0.849$(Tan et al., 2025 ; Patel et al., 2025). This addresses the explicit gap identified in a recent scoping review of CBCT-based periodontal and peri-implant AI, which found the evidence base confined to narrowly defined tasks and called for interpretable, clinically useful evaluation rather than accuracy metrics alone (Tan et al., 2025).

Hence our study concludes that AI-guided CBCT analysis functions as an accurate and clinically useful adjunct that significantly improves clinician detection of oral lesions and periodontal/peri-implant defects, shortens interpretation time, enhances diagnostic consistency and meaningfully influences periodontal and prosthodontic treatment planning in approximately one in four patients, but that it should be deployed strictly.

LIMITATIONS

This was a single-centre study included only 50 patients where patient-level confidence intervals were wide, so the point estimates should be regarded as hypothesis-generating rather than definitive. Disease prevalence was enriched by specialist referral (62%), which inflates predictive values relative to general screening populations. The reference standard was expert radiological consensus rather than universal surgical or histopathological confirmation, permitting residual misclassification. Site-level analyses treated sites within patients as independent, potentially understating uncertainty. Scans with extensive metallic artefact were excluded, limiting generalisability to heavily restored dentitions. Finally, treatment-plan modification is a surrogate endpoint from which improved clinical outcomes cannot be inferred.

CONCLUSION

AI-guided CBCT analysis demonstrated clinically acceptable diagnostic accuracy for oral lesions and periodontal/peri-implant defects, achieving 86.0% accuracy at patient level and 89.1% at site level with substantial agreement against the expert reference standard, and showing no systematic diagnostic bias. Beyond accuracy alone, the system delivered measurable clinical utility: clinician sensitivity rose by 11 percentage points, missed lesions almost halved, mean reporting time fell by 37%, and inter-examiner agreement improved, indicating enhanced detection and greater interpretive consistency. Critically, AI-derived findings modified periodontal or prosthodontic treatment planning in 28% of patients, most often prompting escalation to surgical or regenerative therapy and revision of the planned implant site. Performance nevertheless declined at peri-implant and furcation sites, where imaging artefact constrains reliability. AI-guided CBCT should therefore be adopted as a clinician-supervised second reader, pending multicentre validation with surgically confirmed reference standards.

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