

Original Research

Received 28 May 2026

Revised 08 July 2026

Accepted 22 July 2026

Natural Resources for Human
Health 2026, Vol. 6 (13s): 1568–1576

KEYWORDS:

Artificial intelligence, Cone-beam
computed tomography, Machine
learning, Oral lesions,
Prosthodontics.

CBCT versus Machine-Learning Artificial Intelligence for Detecting and Characterizing Oral Lesions in Prosthodontic Patients

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ABSTRACT: Prosthodontic patients often have undetected oral hard- and soft-tissue lesions that can end up hidden beneath a prosthesis. Interpreting CBCT depends on the observer and takes time, so machine-learning-based AI may offer a useful alternative. Thus, the aim of our study was to interpret and compare the diagnostic efficacy of CBCT-based evaluation versus machine-learning-based AI analysis in the detection and characterization of oral lesions among prosthodontic patients among 100 prosthodontic patients with suspected oral lesions, who were randomly allocated into two groups of 50 each. In Group 1, two blinded, calibrated oral radiologists interpreted the CBCT scans. In Group 2, a validated convolutional neural network-based model analysed the imaging and clinical datasets. We have found that, AI showed higher sensitivity (91.67% vs 85.71%), specificity (85.71% vs 80.00%) and accuracy (90.00% vs 84.00%) than CBCT, with a significantly greater AUC (0.887 vs 0.829; $p = 0.041$). Agreement with the gold standard improved from $\kappa = 0.68$ to $\kappa = 0.83$. AI reduced interpretation time (1.24 vs 8.46 min; $p < 0.001$) and measurement deviation (1.08 vs 1.62 mm; $p = 0.001$), and was more reproducible (ICC 0.98 vs 0.86). Therefore we have found that, Machine-learning analysis is a rapid, reproducible and accurate adjunct to CBCT interpretation for pre-prosthetic assessment of oral lesions.

INTRODUCTION

Prosthodontic rehabilitation is frequently undertaken in an older, partially or completely edentulous population in whom the oral mucosa and residual alveolar bone are already subject to age-related change, chronic denture trauma, and functional

overload (Mubarak et al., 2019). Denture-related and non-denture-related oral mucosal lesions such as denture stomatitis, traumatic ulcers, inflammatory papillary hyperplasia, epulis fissuratum, and angular cheilitis are reported in a substantial proportion of prosthesis wearers, with a prevalence of 20.5% documented among patients attending for prosthodontic care (Somaraj et al., 2023). In addition to this, those who were equally important were lesions like periapical pathology, residual and odontogenic cysts, retained roots, antral and bony changes, that lie directly within the intended prosthetic field, and which may compromise abutment survival, implant osseointegration, and long-term prosthesis stability if overlooked during pre-prosthetic assessment (Siminiuc et al., 2025).

Conventional clinical examination and two-dimensional radiography are inherently limited by superimposition, geometric distortion, and the inability to appreciate buccolingual extent, and therefore under-detect early osseous pathology (Talakeri, et al., 2026). Cone-beam computed tomography has consequently become the reference imaging modality in pre-prosthetic and implant planning, offering isotropic voxel resolution and multiplanar reconstruction at a comparatively low radiation dose, with a reported overall diagnostic accuracy of up to 95% for detection of periapical lesions and a demonstrated superiority over panoramic radiography in differentiating osteonecrotic and inflammatory jaw lesions (Venkatesh and Elluru., 2017). Notably, a retrospective analysis of 404 implant-planning CBCT scans identified incidental findings in 82% of volumes, a considerable proportion of which were clinically actionable, underscoring how much pathology exists in an apparently asymptomatic prosthodontic population (Biel et al., 2024). Yet, CBCT interpretation remains observer-dependent, time-intensive, and vulnerable to perceptual error, satisfaction-of-search bias, and fatigue, particularly when large volumes are reviewed for a purely prosthetic indication (Waite et al., 2017).

Artificial intelligence, and specifically convolutional neural network-based machine learning, has emerged as a promising adjunct capable of automated detection, segmentation, and probabilistic classification of maxillofacial lesions (Visconti et al., 2016). A deep-learning neural network applied to panoramic and CBCT images achieved an area under the receiver operating characteristic curve of 0.914 for CBCT-based diagnosis of cystic lesions, while a dedicated model for detection and three-dimensional segmentation of maxillofacial bone lesions in CBCT correctly classified all test cases for the presence or absence of a lesion (Lee et al., 2020). A systematic review and meta-analysis on AI-based detection and segmentation of oral and maxillofacial structures on CBCT further confirms consistently high pooled performance across architectures, and on the soft-tissue side, AI-assisted imaging for oral potentially malignant disorders and oral cancer has shown a summary ROC area of 0.9758 (Sahoo et al., 2024). Beyond accuracy, such models offer near-instantaneous reporting and near-perfect reproducibility, attributes that address precisely the limitations of human interpretation (Dinga et al., 2019).

Despite this expanding evidence base, almost all available literature evaluates artificial intelligence in radiology, oral medicine, or endodontic cohorts, where lesion detection is itself the presenting complaint. Data are conspicuously lacking for the prosthodontic patient a population characterized by a high burden of incidental and asymptomatic pathology, frequent denture-induced mucosal change, and a real risk that an undiagnosed lesion is subsequently concealed beneath a fixed, removable, or implant-supported prosthesis, delaying diagnosis of potentially malignant or malignant disease. Furthermore, direct head-to-head comparisons of expert CBCT interpretation against machine-learning analysis of the same datasets, benchmarked against a histopathological or composite clinico-radiographic gold standard and simultaneously assessing diagnostic accuracy, characterization agreement, measurement precision, reproducibility, and reporting time, remain scarce in a single-centre clinical setting. The present study was therefore undertaken to interpret and compare the diagnostic efficacy of CBCT-based evaluation versus machine-learning-based artificial intelligence analysis in the detection and characterization of oral lesions among prosthodontic patients, with the intention of defining whether AI can serve as a rapid, reproducible screening adjunct within routine pre-prosthetic workflow rather than a replacement for radiological expertise.

Research Objectives

1. To detect and characterize oral lesions in 50 prosthodontic patients (Group 1) by CBCT interpretation by two blinded calibrated oral radiologists.
2. To detect, segment, and classify oral lesions in 50 patients (Group 2) using a validated convolutional neural network-based machine-learning model
3. To compare the diagnostic efficacy of both modalities against the histopathological or composite clinico-radiographic gold standard

4. To compare the lesion characterization accuracy, interpretation time, and reproducibility between CBCT-based and AI-based analysis

LITERATURE REVIEW

Prosthetic patients constitute a high-risk population for oral mucosal and osseous pathology, yet the burden is frequently underestimated in routine pre-prosthetic assessment. A PRISMA-compliant systematic review of 28 cross-sectional studies comprising 4,243 participants reported denture stomatitis in 59% of 3,789 removable denture wearers, with a worldwide prevalence range of 20–67% (Perić et al., 2024), while a records-based study at a tertiary dental teaching hospital documented denture-related stomatitis in 25.76% of 396 edentulous patients, with the palate and tonsillar area most frequently involved (40.2%) and nocturnal denture wear strongly associated with disease (adjusted OR 10.34; $p < 0.0001$) (Adam et al., 2021). Denture-related lesions were similarly identified in 20.5% of 210 prosthetic attendees (Mubarak et al., 2015). Critically, the lesion spectrum is not confined to benign denture-induced change: a retrospective analysis of 354 elderly patients reported an overall mucosal lesion prevalence of 54.7%, including leukoplakia in 19.5%, lichen planus in 17.8%, and frank malignancy in 13.0%, with denture use itself significantly associated with lesion presence ($p = 0.04$), and a hospital-based survey of 3,749 patients found 61.8% presenting with lesions attributable to tobacco use or denture wearing (Mubarak et al., 2015).

In addition to above, conventional two-dimensional radiography under-detects this pathology, whereas cone-beam computed tomography has emerged as the reference three-dimensional modality. In a cross-sectional comparison of 45 teeth, sensitivity was 82% for both periapical and panoramic radiography versus 100% for CBCT, with two-dimensional techniques missing 8 of 45 radiolucencies and significantly underestimating vertical lesion dimension ($p < 0.05$) (Ramis-Alario et al., 2019), and a comparative clinical study reported CBCT sensitivity of 96%, specificity of 94%, and accuracy of 95% against 75%, 70%, and 73% for conventional radiography. CBCT also improves characterization, raising first-differential diagnostic accuracy from 64.4–70.2% to 78.7% across 225 biopsy-proven intraosseous jaw lesions ($p < 0.001$) (Mao et al., 2021), although the same study exposed poor inter-modality agreement for diagnostically decisive descriptors such as cortical destruction ($\kappa = 0.061$), cortical thinning ($\kappa = 0.074$), and border continuity ($\kappa = 0.165$), confirming the observer dependence of radiographic feature extraction. The diagnostic yield of prosthetic CBCT is substantial: incidental findings were present in 82% of 404 implant-planning scans, prompting further dental treatment in 31% and referral in 5% (Biel et al., 2024), while 78.6% of 374 consecutive scans harboured findings of which 38.6% required treatment (Braun et al., 2022), and in 300 pre-implant scans the intended treatment plan was amended or aborted in 12% of cases (Braun et al., 2022).

Moreover, machine learning has consequently been investigated as a means of standardizing this interpretation (Kenge, 2020). A GoogleNet Inception-v3 model applied to odontogenic cystic lesions achieved sensitivity of 96.1%, specificity of 77.1%, and an AUC of 0.914 on CBCT, significantly outperforming its panoramic counterpart (AUC 0.847; $p = 0.014$), and a deep-learning algorithm trained on 82 CBCT scans correctly classified every test case for lesion presence, with detection sensitivity of 95.9%, precision of 98.9%, and a mean Dice coefficient of 83.5% for three-dimensional segmentation. Pooled analyses corroborate these findings, reporting overall recall of 0.91 (95% CI 0.87–0.94) and precision of 0.93 (95% CI 0.88–0.95) for AI applied to CBCT and pooled accuracy of 0.893 for classifying odontogenic keratocysts versus ameloblastomas, with superior performance on CBCT compared with panoramic data (Lee et al., 2020). On the soft-tissue side, AI-assisted imaging for oral potentially malignant disorders and oral cancer achieved a summary ROC area of 0.9758, though pooled specificity remains modest at 0.58–0.62 despite sensitivities of 0.90–0.94, and performance degrades appreciably on external validation (Sahoo, et al., 2024).

Importantly, the most methodologically relevant evidence positions AI as an adjunct rather than a substitute was found in an eight-reader multireader multicase crossover study against a CBCT-proven reference standard, deep-learning assistance improved localization performance from an AFROC-AUC of 0.822 to 0.892, an 8.6% gain ($p = 0.005$) (Hamdan et al., 2022). Within prosthetics, however, artificial intelligence has been applied almost exclusively to design and prediction tasks for crown debonding prediction with 98.5% accuracy, marginal adaptation assessment at 96.2%, and radiographic tasks at 82–89% (Kong and Kim, 2024). While on the other hand, a narrative review of removable prosthetics identified applications limited to denture design, arch classification, and outcome prediction, with no lesion-interpretation application reported (Jayasheelan et al., 2026). Diagnostic AI and prosthetic AI have therefore developed as separate literatures, and existing validation cohorts derive from radiology, oral medicine, or endodontic populations in whom lesion detection is the presenting indication rather than an incidental discovery within the intended prosthetic field (Thurzo et al., 2022). No published protocol prospectively compares expert CBCT interpretation with machine-learning analysis of identical datasets in prosthetic

patients while simultaneously reporting diagnostic accuracy, characterization agreement, measurement precision, interpretation time, and reproducibility against a histopathological gold standard the specific gap the present study was designed to address.

METHODOLOGY

This prospective comparative study was conducted in a tertiary care hospital over a period of 12 months, wherein total of 100 patients who reported for fixed, removable, or implant-supported prosthodontic rehabilitation with clinically or radiographically suspected oral hard- or soft-tissue lesions were enrolled by consecutive sampling and randomly allocated using a computer-generated sequence into two equal groups of 50 each; patients aged 18–70 years of either sex who required prosthodontic rehabilitation, presented with detectable oral lesions in the maxillofacial region, had adequate imaging quality with an available gold-standard diagnosis, and were willing to attend follow-up were included, whereas pregnant or lactating women, patients with a history of head and neck radiotherapy or chemotherapy, previously treated or operated lesions at the same site, known malignancy, uncontrolled systemic disease, antiresorptive therapy producing confounding osseous changes, syndromic or developmental craniofacial anomalies, scans with motion, metallic, or beam-hardening artifacts, and those who refused biopsy or were lost to follow-up were excluded; Group 1 underwent cone-beam computed tomography using a standardized unit and exposure protocol (site-specific field of view, voxel size 0.2–0.3 mm), and the DICOM datasets were independently interpreted in axial, coronal, sagittal, and three-dimensional reconstructed views by two blinded calibrated oral radiologists for lesion presence, site, size, borders, internal density, cortical involvement, root resorption, and proximity to vital structures, while in Group 2 the identical imaging and clinical datasets were processed through a validated convolutional neural network–based machine-learning model (trained and internally validated on an annotated oral lesion dataset with an 80:20 training-to-testing split and pre-processing comprising resizing, normalization, and augmentation) that generated lesion detection, segmentation, and probabilistic classification into benign, potentially malignant, or malignant categories, with histopathological examination or a composite clinico-radiographic diagnosis at 6 months serving as the gold standard for both groups, and all findings, observer agreement, and reporting time were recorded on a pre-designed structured proforma; the collected data were compiled in Microsoft Excel and analyzed using SPSS version 26.0 (IBM Corp., Armonk, NY), with the sample size derived at 80% power and 5% level of significance from previously reported diagnostic accuracy differences, descriptive statistics expressed as mean $\pm$ standard deviation for continuous variables and frequency with percentage for categorical variables, normality assessed by the Shapiro–Wilk test, intergroup comparison of lesion dimensions and interpretation time performed using the independent samples t-test or Mann–Whitney U test as appropriate, categorical outcomes such as lesion detection and classification compared using the Chi-square or Fisher's exact test, diagnostic performance of both modalities evaluated against the gold standard by calculating sensitivity, specificity, positive and negative predictive values, overall accuracy, and area under the receiver operating characteristic curve with paired AUC comparison, and inter-modality as well as inter-observer agreement determined using Cohen's kappa and the intraclass correlation coefficient interpreted per Landis and Koch criteria, with all tests two-tailed at 95% confidence intervals and a p-value $\leq$ 0.05 considered statistically significant.

RESULTS

TABLE 1 : Demographic & Clinical Profile Study

VARIABLE	GROUP 1	GROUP 2	TEST VALUE	P-VALUE
Age (years, mean $\pm$ SD)	44.62 $\pm$ 11.24	45.94 $\pm$ 10.71	t = 0.601	0.549
Gender – Male	27 (54.0%)	25 (50.0%)	χ^2 = 0.160	0.689
Female	23 (46.0%)	25 (50.0%)		
Fixed prosthesis	21 (42.0%)	19 (38.0%)	χ^2 = 0.412	0.814
Removable prosthesis	18 (36.0%)	21 (42.0%)		
Implant-supported prosthesis	11 (22.0%)	10 (20.0%)		
Lesion site – Maxilla	26 (52.0%)	24 (48.0%)	χ^2 = 0.336	0.845
Mandible	20 (40.0%)	22 (44.0%)		
Lesion site – Soft tissue/mucosa	4 (8.0%)	4 (8.0%)		

Table 1 showed that, both groups were statistically comparable at baseline, with no significant difference in mean age (44.62 ± 11.24 vs 45.94 ± 10.71 years; $p = 0.549$), gender distribution ($p = 0.689$), type of prosthodontic rehabilitation ($p = 0.814$), or lesion site ($p = 0.845$). The maxilla was the commonest site in both groups, and soft-tissue lesions were least frequent (8.0% each). This baseline homogeneity confirms effective randomization, ensuring that subsequent differences in diagnostic outcomes reflect the interpretation modality rather than sample-related confounding.

TABLE 2 : Distribution Of Oral Lesions According To Gold-Standard Diagnosis

GOLD- STANDARD DIAGNOSIS	GROUP 1	GROUP 2	TOTAL
No lesion / normal variant	15 (30.0%)	14 (28.0%)	29 (29.0%)
Benign lesion (cyst, benign tumour, reactive)	19 (38.0%)	18 (36.0%)	37 (37.0%)
Potentially malignant disorder	9 (18.0%)	11 (22.0%)	20 (20.0%)
Malignant lesion	7 (14.0%)	7 (14.0%)	14 (14.0%)
$\chi^2 = 0.318$, $df = 3$, $p = 0.957$ (NS)			

Table 2 showed that, the spectrum of confirmed pathology was almost identically distributed between the two groups ($\chi^2 = 0.318$, $df = 3$, $p = 0.957$). Benign lesions predominated overall (37.0%), followed by no lesion/normal variants (29.0%), potentially malignant disorders (20.0%), and malignant lesions (14.0%), with comparable proportions in Group 1 and Group 2. Since diagnostic accuracy indices are prevalence-sensitive, this equivalent case-mix and disease prevalence across both arms permits a valid, unbiased head-to-head comparison of CBCT-based and machine-learning-based interpretation.

TABLE 3 : Comparative Diagnostic Performance

PARAMETER	GROUP 1	GROUP 2	P- VALUE
True positive	30	33	-
False negative	5	3	-
True negative	12	12	-
False positive	3	2	-
Sensitivity	85.71% (95% CI 69.7–95.2)	91.67% (95% CI 77.5–98.2)	0.446
Specificity	80.00% (95% CI 51.9–95.7)	85.71% (95% CI 57.2–98.2)	0.673
Positive predictive value	90.91%	94.29%	0.579
Negative predictive value	70.59%	80.00%	0.541
Diagnostic accuracy	84.00%	90.00%	0.352
Area under ROC curve (AUC)	0.829 (95% CI 0.712–0.945)	0.887 (95% CI 0.789–0.984)	0.041

Table 3 showed that, higher sensitivity (91.67% vs 85.71%), specificity (85.71% vs 80.00%), and overall diagnostic accuracy (90.00% vs 84.00%) than conventional CBCT interpretation. Although individual indices did not differ significantly, the paired ROC comparison revealed a significantly greater area under the curve for AI (0.887 vs 0.829; $p = 0.041$), indicating superior discriminatory ability. Importantly, AI produced fewer false negatives (3 vs 5), which is clinically critical in prosthodontic patients where undetected lesions may remain masked beneath a planned prosthesis.

TABLE 4 : Accuracy Of Lesion Characterization

LESION CATEGORY	GROUP 1	GROUP 2	P- VALUE
Benign lesions	16/19 (84.21%)	17/18 (94.44%)	0.605
Potentially malignant disorders	6/9 (66.67%)	9/11 (81.82%)	0.617
Malignant lesions	6/7 (85.71%)	7/7 (100%)	1.000
Overall characterization accuracy	28/35 (80.00%)	33/36 (91.67%)	0.184
Agreement with gold standard – Cohen's kappa (κ)	0.68 (substantial)	0.83 (almost perfect)	-

Table 4 showed that, machine-learning analysis achieved higher category-wise accuracy than CBCT across benign (94.44% vs 84.21%), potentially malignant (81.82% vs 66.67%), and malignant lesions (100% vs 85.71%), with overall characterization accuracy of 91.67% versus 80.00%; however, these differences were not statistically significant ($p > 0.05$). CBCT performed weakest for potentially malignant disorders, where early mucosal and subtle osseous changes are radiographically inconspicuous. Agreement with the gold standard improved from substantial ($\kappa = 0.68$) to almost perfect ($\kappa = 0.83$), indicating that AI adds greatest incremental value in diagnostically ambiguous lesions.

TABLE 5 : Comaprative Measurement

PARAMETER	GROUP 1	GROUP 2	TEST VALUE	P- VALUE
Mean interpretation time per case (min)	8.46 $\pm$ 1.92	1.24 $\pm$ 0.31	t = 26.24	< 0.001
Mean lesion dimension recorded (mm)	12.84 $\pm$ 4.16	12.31 $\pm$ 3.98	t = 0.652	0.516
Mean deviation from gold-standard dimension (mm)	1.62 $\pm$ 0.74	1.08 $\pm$ 0.51	t = 3.58	0.001
Inter-observer agreement / reproducibility (ICC)	0.86 (95% CI 0.76–0.92)	0.98 (95% CI 0.96–0.99)	-	-
Inconclusive/indeterminate reports	5 (10.0%)	2 (4.0%)	Fisher's exact	0.436

Table 5 showed that, ML analysis reduced mean interpretation time nearly seven-fold compared with radiologist-based CBCT reporting (1.24 $\pm$ 0.31 vs 8.46 $\pm$ 1.92 min; $p < 0.001$), offering a substantial workflow advantage. Absolute lesion dimensions recorded by both modalities were statistically comparable ($p = 0.516$), confirming measurement validity, yet AI deviated significantly less from gold-standard dimensions (1.08 $\pm$ 0.51 vs 1.62 $\pm$ 0.74 mm; $p = 0.001$), reflecting greater metric precision. Reproducibility was excellent for AI (ICC = 0.98) versus good for CBCT (ICC = 0.86), and indeterminate reports were fewer (4.0% vs 10.0%), though non-significant ($p = 0.436$).

DISCUSSION

The present study demonstrated that machine-learning-based analysis outperformed conventional CBCT interpretation in the detection of oral lesions among prosthodontic patients, with sensitivity of 91.67% versus 85.71%, specificity of 85.71% versus 80.00%, overall accuracy of 90.00% versus 84.00%, and a significantly greater area under the receiver operating characteristic curve (0.887 versus 0.829; $p = 0.041$). These values align closely with the pooled evidence for artificial intelligence applied to cone-beam computed tomography, where overall recall of 0.91 (95% CI 0.87–0.94) and precision of 0.93 (95% CI 0.88–0.95) have been reported across twelve eligible studies, and with the pooled accuracy of 0.893 (95% CI 0.832–0.954) documented for AI-based classification of odontogenic cysts and tumours, in which accuracy was likewise higher on CBCT than on panoramic data (Tobias et al., 2024). The sensitivity obtained in the present series was, however, marginally lower than the 96.1% reported

for a GoogleNet Inception-v3 architecture applied to CBCT images of odontogenic cystic lesions, although the specificity achieved here (85.71%) was appreciably higher than the 77.1% reported in that study, and the AUC values were comparable (0.887 versus 0.914) (Lee et al., 2020). This divergence likely reflects a prospective, clinically enrolled, histopathologically anchored studies with a mixed hard- and soft-tissue lesion spectrum, as opposed to curated retrospective datasets enriched for well-defined cystic pathology (Tobias et al., 2024). In contrast to the near-perfect standalone performance reported by some algorithm-development studies which includes deep-learning model that classified all 82 test CBCT scans correctly with detection sensitivity of 95.9% and precision of 98.9%. The more modest accuracy observed here is consistent with the well-documented performance decrement encountered when models move from internal validation to real-world clinical data, where sensitivity has been shown to fall from 48.0% to 22.0% on external datasets (Aloufi., 2026).

The diagnostic performance recorded for CBCT in the present study (sensitivity 85.71%, specificity 80.00%, accuracy 84.00%) was lower than the 96% sensitivity, 94% specificity, and 95% overall accuracy reported in a comparative clinical evaluation of CBCT versus conventional radiography, and below the 100% sensitivity reported when CBCT detected all 45 periapical radiolucencies in a cross-sectional comparison against periapical and panoramic radiography (Ramis-Alario et al., 2019).

In addition to above, past studies had mainly evaluated radiographically & histologically (Mao et al., 2021; Suomalainen et al., 2015; Mozzo et al., 1998) while on the other hand, in our present study we have included mucosal, potentially malignant, and osseous pathology of heterogeneous conspicuity. These studies figures obtained here correspond far more closely to the 78.7% first-differential diagnostic accuracy achieved by two experienced oral radiologists across 225 biopsy-proven intraosseous jaw lesions on CBCT, which represents a methodologically analogous scenario of mixed pathology validated against histopathology (Mao et al., 2021; Suomalainen et al., 2015; Mozzo et al., 1998). Moreover, lesion characterization accuracy in the present study improved from 80.00% with CBCT to 91.67% with AI, and agreement with the gold standard rose from substantial ($\kappa = 0.68$) to almost perfect ($\kappa = 0.83$), with the widest margin observed in potentially malignant disorders (66.67% versus 81.82%). The observation that human interpretation is weakest precisely in this category corroborates the finding that panoramic CBCT observer agreement is only poor to fair for the descriptors most relevant to lesion classification, including cortical destruction ($\kappa = 0.061$), cortical thinning ($\kappa = 0.074$), expansion ($\kappa = 0.200$), and border continuity ($\kappa = 0.165$). The superiority of the model for potentially malignant and malignant lesions is further consistent with the summary receiver operating characteristic area of 0.9758 reported for AI-assisted detection of oral potentially malignant disorders and oral cancer. It is notable, however, that the specificity gain observed in the present study contrasts with the meta-analytical pattern of high sensitivity paired with distinctly modest specificity for oral malignant lesion detection (sensitivity 0.90 with specificity 0.62 for the lesion versus no-lesion task, and sensitivity 0.94 with specificity 0.58 for referral triage), which plausibly reflects the multimodal CBCT-plus-clinical input used here rather than photographic images alone (Sahoo et al., 2024). A further contrast arises with an auto-adapting multi-scaled U-Net trained on 300 CBCT volumes, which raised clinicians' mean diagnostic accuracy only marginally from 53.21% to 55.71% (Huang et al., 2024), whereas the present study evaluated the model as an independent interpreter rather than as an overlay on clinician judgement.

Further, the most pronounced difference in the present study was operational rather than purely diagnostic as the mean interpretation time fell nearly seven-fold from 8.46 ± 1.92 minutes to 1.24 ± 0.31 minutes ($p < 0.001$), reproducibility improved from good (ICC 0.86) to excellent (ICC 0.98), deviation from gold-standard lesion dimensions decreased significantly (1.08 ± 0.51 mm versus 1.62 ± 0.74 mm; $p = 0.001$), and indeterminate reports were halved (4.0% versus 10.0%). The measurement precision achieved was congruent with the mean Dice similarity coefficient of 83.5% reported for three-dimensional segmentation of maxillofacial bone lesions on CBCT, and the reduction in false negatives from five to three carries particular clinical weight in this population, given that incidental findings are present in 82% of implant-planning CBCT scans and necessitate further dental treatment in 31% and referral in 5% (Biel et al., 2024), and that the intended prosthetic treatment plan was amended or aborted in 12% of pre-implant cases following radiographic review. These findings assume additional relevance in light of the substantial mucosal disease burden in prosthesis wearers, with denture stomatitis prevalence ranging from 20% to 67% worldwide and overall oral mucosal lesion prevalence of 54.7% including 13.0% malignancy in elderly patients (Perić et al., 2024). Importantly, the present results should not be construed as endorsing autonomous machine interpretation, since the strongest available comparative evidence shows that deep learning delivers its benefit as an adjunct, improving eight readers' localization performance from an AFROC-AUC of 0.822 to 0.892 against a CBCT-proven reference standard ($p = 0.005$). Within prosthodontics specifically, artificial intelligence has to date been confined to design and prediction applications

such as crown debonding prediction and marginal adaptation assessment, and the present study accordingly extends the discipline's AI evidence base from prosthesis fabrication into pre-prosthetic lesion diagnosis.

Henceforth, a single-centre design and modest sample size, machine-learning-based analysis proved to be a faster, more reproducible, and diagnostically equivalent for potentially malignant lesions superior interpretive tool compared with conventional CBCT evaluation, and therefore it is considered to be the best positioned due to its screening reliability adjustment rather than replacing expert radiological interpretation in the pre-prosthetic assessment of oral lesions.

LIMITATIONS

The single-centre design and modest sample of 100 patients (50 per group) may limit generalizability and statistical power, which is reflected in the non-significant differences in individual diagnostic indices. The machine-learning model was only internally validated and was not tested externally across multiple centres. Some cases used a composite clinico-radiographic diagnosis instead of histopathology, which may introduce reference-standard bias. AI performance also depends on the quality of the training dataset, and differences in CBCT units, exposure parameters and artifacts may affect reproducibility. Larger multicentre studies are recommended.

CONCLUSION

Machine-learning-based analysis detected and characterized oral lesions in prosthodontic patients better than conventional CBCT interpretation. It showed higher sensitivity, specificity and overall accuracy, and a significantly greater area under the ROC curve. AI also agreed more closely with the gold standard, especially for potentially malignant disorders. It measured lesions more precisely, was more reproducible, and cut interpretation time roughly seven-fold. Machine-learning analysis is therefore best used as a rapid, reliable screening aid alongside expert CBCT interpretation during pre-prosthetic assessment, not as a replacement for it.

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