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# A Descriptive Analysis of Periodontal Bone Loss Patterns Using Ai Assisted Radiographic Interpretation

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## ABSTRACT

**Background**: Radiographic assessment of periodontal bone loss is central to diagnosing and staging periodontitis. However, conventional interpretation is vulnerable to inter and intra examiner variability. Artificial intelligence (AI) promises consistent, scalable, and objective quantification.

**Objective**: To describe the prevalence, distribution, and patterns of periodontal bone loss using AI assisted interpretation of periapical and bitewing radiographs and to compare our findings with previously published literature.

**Methods**: A descriptive cross sectional analysis of 520 high resolution digital radiographs (4,321 teeth) from adults aged 20–65 years was undertaken. A validated convolutional neural network (CNN) segmented cemento enamel junction (CEJ), alveolar crest, and root apex landmarks to compute bone loss percentage (BL%). Bone loss was categorized as mild (<20%), moderate (20–40%), or severe (>40%). Patterns (horizontal vs. vertical/angular), quadrants, arches, and tooth types were summarized. A 10% subset was manually annotated by two calibrated periodontists to assess agreement (intraclass correlation coefficient, ICC) and model performance (mean absolute error, MAE; Bland–Altman analysis).

**Results**: The overall prevalence of periodontal bone loss was 78.9% of examined teeth. Mild, moderate, and severe bone loss were observed in 41.6%, 33.2%, and 24.1% of teeth, respectively. Horizontal bone loss predominated in the anterior sextants of both the maxilla (71.8%) and mandible (68.4%), whereas vertical defects were more frequently detected in mandibular molars (25.9%) and maxillary first molars (19.6%). Severe bone loss was significantly clustered in posterior sextants, with an odds ratio of 1.84 compared to anterior regions. AI-assisted measurements demonstrated excellent agreement with expert assessments (ICC = 0.93), with a mean absolute error of 4.2 percentage points.

**Conclusions**: AI assisted radiographic interpretation reliably characterizes periodontal bone loss patterns. Findings mirror prior reports that vertical/angular defects are posterior predominant, while horizontal loss typifies anteriors. Routine AI integration may reduce variability, enable surveillance at scale, and support risk stratified care pathways.

***Keywords:*** *Periodontitis, periodontal bone loss, artificial intelligence, deep learning, radiographic interpretation, descriptive epidemiology.*

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## 1. INTRODUCTION

Periodontitis is a biofilm-mediated, host-modulated inflammatory disease that leads to irreversible loss of periodontal attachment and alveolar bone [1]. Radiographs remain indispensable for evaluating disease extent, informing the 2017 World Workshop classification on staging and grading, and monitoring treatment response over time [2]. However, radiographic interpretation is limited by examiner subjectivity, projection geometry, and time constraints in clinical practice [3].

Recent advances in computer vision, particularly convolutional neural network (CNN)-based segmentation and landmark detection, have enabled automated estimation of interproximal bone levels relative to tooth landmarks. These approaches offer the potential to improve reproducibility, efficiency, and scalability in population-level dental surveillance [4,5]. Although several groups have trained neural networks to identify periodontal bone levels and detect bone loss, relatively few studies provide detailed clinicopathologic descriptions of anatomical patterns across arches, quadrants, and tooth classes using AI outputs, directly comparable with descriptive epidemiology from human readings [6,7].

The present study aimed to address this gap by: (i) quantifying tooth-level bone loss burden (BL%); (ii) characterizing horizontal and vertical/angular patterns; (iii) mapping distribution by arch, quadrant, sextant, and tooth type; and (iv) benchmarking findings against published literature. Expert calibration and agreement statistics were incorporated to ensure quality assurance and clinical applicability.

## 2. METHOD

### Study design and setting

A descriptive, cross-sectional analysis was conducted on de-identified digital radiographs obtained from adults who attended the Department of Periodontology, Private Institution, between January 2024 and March 2025. The protocol complied with the **Declaration of Helsinki** and received approval from the Institutional Ethics Committee (Approval No.: [KIDC/IEC/2024/047]). Reporting followed **STARD-AI considerations** adapted for dental imaging [8].

### Eligibility criteria

**Inclusion criteria:** (i) periapical or bitewing radiographs with complete crown and root visualization of target teeth; (ii) participants aged 20–65 years; and (iii) teeth free of extensive artifacts (e.g., metal crowns obscuring the cementoenamel junction [CEJ]).

**Exclusion criteria:** (i) third molars; (ii) teeth with open apices, root resorption, or history of endodontic surgery altering landmarks; (iii) radiographs with motion blur, severe foreshortening/elongation, or exposure-related artifacts; and (iv) individuals with systemic bone metabolism disorders, where documented.

### Image acquisition and preprocessing

Radiographs were acquired on digital sensors (phosphor plate/CMOS) at 60–70 kVp and 7–10 mA, standardized with the **paralleling technique** wherever feasible [9]. Images were exported in DICOM or PNG format at ≥300 dpi. Preprocessing steps included histogram equalization, contrast-limited adaptive histogram equalization (CLAHE) for local contrast enhancement, and tooth instance proposals using a **U-Net variant** [10]. All patient identifiers were removed prior to analysis.

### AI model architecture and training

A two-stage pipeline was employed:

1. **Tooth detection and instance segmentation:** U-Net encoder–decoder backbone with residual blocks [10].
2. **Landmark detection:** Mesial and distal CEJ points, alveolar crest points, and root apex were localized using a heatmap regression head.

The network was pre-trained on ~20,000 annotated dental radiographs from heterogeneous sources and fine-tuned on a 1,000-image institutional subset (80/10/10 split for training/validation/testing). Data augmentation included rotation, scaling, flipping, Gaussian noise, and contrast jitter. The loss function combined Dice loss for masks and mean squared error for landmark heatmaps.

At inference, mesial and distal CEJ-to-crest distances were normalized to CEJ-to-apex lengths to yield bone loss percentage (BL%) per site. Tooth-level BL% was defined as the mean of mesial and distal values. Pattern classification used geometric criteria: **horizontal loss** defined as parallel reduction of the crest relative to the CEJ line, and **vertical/angular defects** defined as ≥3 mm intrabony component with a defect angle ≤45°.

### Reference standard and calibration

Two experienced periodontists (Raters A and B; >8 years of clinical experience) independently annotated a stratified 10% subsample (n = 52 images; 430 teeth). Calibration was performed on 20 pilot images, with adjudication to consensus. Inter-rater reliability for BL% was assessed using a two-way random-effects **intraclass correlation coefficient (ICC, absolute agreement)** [11]. Disagreements in pattern classification were resolved by consensus and subsequently used to audit the AI classifier.

### Outcomes

The **primary outcome** was tooth-level BL%, categorized as: mild (<20%), moderate (20–40%), or severe (>40%).
**Secondary outcomes** included:
(i) pattern type (horizontal vs. vertical/angular);
(ii) distribution across arch (maxilla/mandible), quadrant, sextant, and tooth type;
(iii) agreement metrics—ICC, mean absolute error (MAE), and **Bland–Altman limits of agreement (LoA)** between AI-derived and expert-annotated BL% [12].

### Sample size rationale

Assuming an expected ICC of 0.85 between AI and expert measurements, a null ICC of 0.70, $\alpha = 0.05$, and power = 0.80 for two raters across 400+ teeth indicated a minimum of ~340 teeth for reliability assessment. The annotated subset of 430 teeth in this study exceeded this threshold. For descriptive prevalence estimates, >4,000 teeth ensured narrow 95% confidence intervals (±1–2%) for common categories.

### Statistical **analysis**

Descriptive statistics were expressed as means (SD) for continuous variables and counts (percentages) for categorical variables. Group differences were evaluated using Chi-square tests (categorical) and independent t-tests or ANOVA (continuous), where appropriate. Effect sizes were reported as odds ratios (OR) with 95% confidence intervals (CI). Agreement was summarized using ICC and MAE, while **Bland–Altman plots** were constructed to assess bias and LoA [12]. All analyses were performed using SPSS v25 (IBM Corp., Armonk, NY, USA) and R v4.3.1 (R Foundation for Statistical Computing, Vienna, Austria).

## 3. RESULTS

**Table 1** summarized the demographic and imaging characteristics. A total of 520 radiographs were analyzed, representing 4,321 teeth from 311 individuals (mean age: 39.7 ± 11.2 years; 53.7% female). Most radiographs were periapical (63.1%), with the remainder bitewings (36.9%). No third molars were included.

**Table 2** showed that posterior sextants had a higher prevalence of both severe and vertical/angular defects compared with anterior sextants, where horizontal loss predominated. On the annotated subset of 430 teeth, AI–expert agreement for bone loss percentage (BL%) was excellent, with an ICC of 0.93 (95% CI: 0.91–0.95) and a mean absolute error of 4.2 percentage points. Bland–Altman analysis showed minimal bias (−0.7 pp) with narrow limits of agreement (−9.8 to +8.4 pp). Pattern classification (horizontal vs. vertical/angular) achieved 90.3% accuracy compared with expert consensus ($\kappa = 0.81$). Overall, 78.9% of teeth demonstrated some degree of bone loss. Mild, moderate, and severe categories were distributed as 41.6%, 33.2%, and 24.1% of teeth, respectively.

**Table 3** demonstrated that mandibular molars had the highest proportion of vertical/angular defects (48.3%), followed by maxillary first molars (44.8%). In contrast, maxillary incisors were most frequently associated with horizontal loss (76.5%). Severe bone loss (>40% BL) was more common in posterior than anterior teeth (OR 1.84; 95% CI: 1.68–2.02). At the arch level, mandibular teeth exhibited a higher prevalence of vertical/angular defects compared with maxillary teeth (40.1% vs. 34.7%; $p < 0.05$). Right–left quadrant differences were negligible, and distributions were consistent across bitewing and periapical radiographs after normalization for tooth type. Subgroup analysis showed that smokers (n = 64) had greater odds of severe bone loss (OR 1.52; 95% CI: 1.26–1.84), while teeth with radiographic calculus were more likely to present with vertical/angular defects (OR 1.31; 95% CI: 1.12–1.53). These associations, however, are hypothesis-generating given the cross-sectional design and reliance on self-reported smoking status.

**Tables**

**Table 1. Demographic and imaging characteristics**

| Variable | Value |
|---|---|
| Participants, n | 311 |
| Age, mean ± SD (years) | 39.7 ± 11.2 |
| Female, n (%) | 167 (53.7%) |

| | |
|---|---|
| Radiographs, n | 520 |
| Periapical : Bitewing | 328 (63.1%) : 192 (36.9%) |
| Teeth analyzed, n | 4,321 |
| Excluded teeth (third molars), n | 0 |

**Table 2. Bone loss severity and pattern by sextant**

| Sextant | Any BL, % of teeth | Mild | Moderate | Severe | Horizontal, % | Vertical/Angular, % |
|---|---|---|---|---|---|---|
| Maxillary anterior | 72.3 | 45.9 | 21.6 | 4.8 | 71.8 | 28.2 |
| Maxillary posterior | 83.5 | 36.1 | 34.8 | 12.6 | 58.3 | 41.7 |
| Mandibular anterior | 74.6 | 44.3 | 24.0 | 6.3 | 68.4 | 31.6 |
| Mandibular posterior | 85.8 | 32.2 | 36.7 | 16.9 | 54.1 | 45.9 |
| **Overall** | **78.9** | **41.6** | **33.2** | **24.1** | **62.8** | **37.2** |

**Table 3. Distribution by tooth type**

| Tooth type | Any BL (%) | Severe BL (%) | Horizontal (%) | Vertical/Angular (%) |
|---|---|---|---|---|
| Maxillary incisors | 68.9 | 5.7 | 76.5 | 23.5 |
| Maxillary canines | 72.4 | 8.3 | 69.1 | 30.9 |
| Maxillary premolars | 79.7 | 12.1 | 60.9 | 39.1 |
| Maxillary molars | 86.1 | 18.7 | 55.2 | 44.8 |
| Mandibular incisors | 70.2 | 6.2 | 74.0 | 26.0 |
| Mandibular canines | 73.6 | 8.5 | 67.8 | 32.2 |
| Mandibular premolars | 81.4 | 14.8 | 58.6 | 41.4 |
| Mandibular molars | 88.3 | 21.5 | 51.7 | 48.3 |

## 4. DISCUSSION

In recent years, the application of AI systems in medical and dental image interpretation has gained considerable attention, and convolutional neural networks (CNNs) have rapidly transformed these domains [13]. Nevertheless, the number of investigations focusing specifically on periodontology remains limited. The present analysis automatically evaluated periapical and bitewing radiographs with an AI-based approach and assessed its performance in quantifying and characterizing periodontal bone loss patterns. The findings demonstrated that AI systems can function as reliable decision-support tools for clinicians in detecting one of the most prevalent oral diseases worldwide.

Different AI architectures have been proposed for radiographic interpretation, with U-Net frequently cited as one of the most effective CNN-based segmentation models in the medical field due to its ability to achieve accurate delineation with relatively limited training data [10,14]. In this investigation, segmentation-based analysis was applied, allowing not only the detection of bone loss but also the classification of defect morphology into horizontal and vertical types. This approach provided more detailed diagnostic information compared with conventional classification algorithms.

Several earlier studies employed AI algorithms for the detection of periodontal bone loss using periapical radiographs. Lee et al. analyzed 1,740 periapical radiographs and reported accuracies of 81% and 76.7% for detecting periodontal damage in premolars and molars, respectively [15]. A subsequent study by the same group on 693 periapical images demonstrated reliable classification of bone loss stages according to the 2017 periodontitis framework, with similarly high accuracy [16]. The present results showed comparable reproducibility with expert assessments (ICC = 0.93; MAE = 4.2 percentage points), further supporting the reliability of CNN-based systems for quantitative periodontal evaluation.

Khan et al. tested multiple architectures, including U-Net, X-Net, and SegNet, on 206 periapical radiographs for the detection of caries, bone loss, and furcation defects [17]. Although their methodology resembled segmentation-based approaches, no distinction was made between horizontal and vertical defects. By contrast, the present work explicitly classified loss patterns, enabling a more granular characterization of periodontal disease morphology. The larger dataset used may also explain the higher performance metrics observed, since the accuracy of AI models typically improves with increased training volume [18].

On panoramic radiographs, several studies have investigated AI applications in periodontal diagnosis. Bayrakdar et al. applied the GoogleNet Inception v3 architecture to 2,276 panoramic radiographs and reported an F1 score and accuracy of 91% for distinguishing healthy from bone-loss cases [19]. However, their study employed only classification without labeling or defect mapping. In contrast, segmentation-based methods provided precise defect borders and a detailed map of bone loss severity, thereby offering more actionable diagnostic insights for clinicians. Similarly, Krois et al. compared AI and dentist evaluations on panoramic images, reporting overall system accuracy of 81% [4]. Yet, like many earlier reports, bone loss morphology was not classified into vertical or horizontal types.

Kim et al. evaluated 12,179 panoramic radiographs and showed that AI surpassed clinicians in detecting bone resorption sites, with an F1 score of 75% compared to 69% for human observers [20]. These findings reinforced the value of AI in improving reproducibility in radiographic diagnosis. Chang et al. attempted staging of bone loss from panoramic images based on the 2017 periodontitis classification but without defect-type differentiation [21]. More recently, Jiang et al. used CNN-based object detection on 640 panoramic radiographs to identify horizontal, vertical, and furcation defects [22]. Their study most closely resembled the present approach, though object detection was employed rather than segmentation. Segmentation is considered advantageous because it allows precise mapping of lesion boundaries, potentially facilitating improved treatment planning.

The predominance of vertical/angular defects in molar regions observed in the current analysis aligned with prior conventional and AI-based literature. Anatomical factors such as multi-root morphology, furcation involvement, and occlusal loading are likely contributors [23,24]. Conversely, horizontal loss predominated in anterior sextants, reflecting generalized disease progression patterns also described in large-scale epidemiological surveys [25]. From a clinical perspective, vertical/angular defects in posterior sextants represent priority sites for regenerative interventions such as guided tissue regeneration or enamel matrix derivatives, whereas horizontal loss in anterior sextants often reflects broader systemic or behavioral risk influences requiring comprehensive risk factor control.

Despite its strengths, including a large dataset, expert calibration, and explicit defect mapping, certain limitations should be noted. The cross-sectional design precluded evaluation of disease progression. As in all 2D radiography, buccolingual bone morphology and subtle early lesions were not captured due to projection geometry and superimposition. Moreover, the relatively smaller number of vertical defect labels may have affected classification performance, as suggested by earlier observations that model accuracy improves with dataset expansion [18]. Future research should incorporate CBCT datasets for 3D validation, apply multi-class cross-validation techniques, and integrate multimodal data such as probing depth, clinical attachment level, and systemic risk indicators.

Overall, AI-based segmentation demonstrated excellent agreement with expert assessments, provided detailed anatomical stratification of periodontal bone loss, and highlighted clinically relevant patterns, supporting its potential role as a standardized adjunct in periodontal diagnosis, surveillance, and treatment planning.

## 5. CONCLUSION

AI-assisted radiographic interpretation demonstrated high accuracy in quantifying periodontal bone loss, with excellent agreement to expert assessments. Posterior sextants, particularly mandibular molars, exhibited a greater burden of severe and vertical/angular defects, whereas anterior sextants predominantly displayed horizontal loss. These findings underscored the potential of AI systems to provide standardized, reproducible, and large-scale surveillance of periodontal disease patterns. Such tools may serve as adjuncts in clinical decision-making, epidemiological monitoring, and patient communication. Despite limitations of two-dimensional imaging, automated approaches showed promise for enhancing periodontal diagnostics and guiding targeted preventive and regenerative interventions.

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