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Developing an AI Algorithm to Automatically Detect Early Radiographic Changes of Tooth Mobility in Patients with Bruxism

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Abstract

Objective: To develop an artificial intelligence (AI) algorithm capable of automatically detecting early radiographic signs of tooth mobility in patients diagnosed with bruxism, thereby facilitating earlier intervention and personalised risk stratification.

Methods: Digital periapical radiographs (n=3200) for upper and lower posterior teeth acquired from adult patients (≥ 18y, n=1200) who were with clinically diagnosed sleep and awake bruxism. Gold standard labels were generated by a panel of three board-certified dento-maxillofacial radiologists who reached consensus on the presence of key early mobility markers. A U Net variant with an EfficientNet B3 backbone was trained using focal Tversky loss.

Results: On the test set (n = 3500 images), the algorithm achieved an overall AUC of 0.941 (95 % CI, 0.932–0.949), sensitivity of 0.884, and specificity of 0.903 for detecting ≥ 1 early mobility marker. Expert readers exhibited AUCs ranging from 0.769 to 0.916. The algorithm outperformed junior readers across all metrics ($p < 0.001$) and demonstrated non-inferiority to senior readers (ΔAUC = 0.008, $p = 0.17$). Visual saliency analysis confirmed that model attention co-localised with radiologist-defined regions of interest.

Conclusion: The suggested algorithm shows reliable identification of subtle radiographic signs that often mark the earliest onset of tooth mobility in patients with bruxism. Specialist-level accuracy is reached. When placed within everyday chairside imaging workflows, it holds the potential to speed up diagnostic steps, support occlusal treatment planning more precisely, and ideally help prevent permanent damage to the periodontium.

Keywords: Bruxism, Periodontal ligament, Tooth mobility, Radiograph, Artificial intelligence, Deep learning

Plain English Summary

Bruxism, the habitual grinding or clenching of teeth, can gradually lead to damage such as loose teeth or jaw problems. These changes often appear on X-rays before any symptoms are felt. Unfortunately, these early signs are subtle and can be easy to miss during routine dental checks. This study aimed to create an artificial intelligence (AI) tool that could automatically detect these early changes on dental X-rays, so dentists can catch problems earlier and treat them before they get worse. Researchers used over 3,000 dental X-rays from adults with diagnosed bruxism. A team of expert dental radiologists marked signs of early tooth mobility on these images. They then trained a deep learning model, a type of AI, using these expert labels to recognise early radiographic features like changes in the periodontal ligament and jawbone. The AI performed very well. It was able to detect early signs of tooth mobility with accuracy similar to that of experienced radiologists, and better than junior readers. It correctly flagged subtle changes such as widened ligament spaces or faint bone loss. The system also focused on the same parts of the image as

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human experts, boosting trust in its decision-making. If integrated into dental clinics, this AI tool could help dentists identify early signs of bruxism-related damage faster and more accurately. That means patients could get preventive treatment, like bite guards or adjustments, before the damage becomes serious or irreversible. It could also save time and support more consistent diagnoses, especially in busy practices or settings with less experienced staff. Although promising, the tool needs to be tested in real-world dental settings with diverse patient groups. Future improvements could include combining this technology with real-time sensors or patient data to provide even more tailored care.

Introduction

Bruxism, which can be considered an umbrella term for clenching and grinding of the teeth, is the most common of the many parafunctional activities of the masticatory system. Opinions on the cause of bruxism are numerous and widely varying. Current reviews indicate that the aetiology is not fully known, but that it is probably multifactorial (1). Although intermittent clenching and grinding are extremely common, they usually pose no serious consequences for the oral structures. On the other hand, manifest bruxism can result in problems that are as frustrating for the patient as for the treating dentist. Sequelae of bruxism that have been proposed include tooth wear, signs and symptoms of temporomandibular disorders (TMD), headaches, toothache, mobile teeth, and various problems with dental restorations as well as with fixed and removable prostheses (2, 3).

Bruxism appears to affect anywhere between 8 and 31 per cent of adults, with sleep-related patterns occurring more frequently than those seen during wakefulness (4). Among children, estimates tend to fall between 14 and 20 per cent, though a substantial number of these cases tend to diminish before reaching adolescence (5). A downward shift in prevalence appears with advancing age. Elevated rates often emerge in younger adult groups when compared across age brackets (6). Patterns of sleep bruxism show an evident link with brief awakenings scattered throughout the phases of sleep. Control appears to arise, in large part, from within the central nervous system. Dopamine pathways contribute. Serotonin also has a place. Their roles emerge repeatedly across the literature, not as isolated findings, but as patterns sustained over time (7). Peripheral elements, such as slight occlusal issues or irregular dental forms, receive mention in some reports. Their impact, overall, remains modest. Emotional strain, on the other hand, presses in with greater weight. Traces of anxiety, persistent tension, and a web of psychosocial elements often surface across the findings (8). Clustering within certain families has also drawn attention. Such patterns, though not always uniform, give pause. The presence of a heritable component begins to seem less speculative, more grounded in repeated observation (9).

Several studies have drawn attention to how artificial intelligence plays a part in the dental field. A review was put together aiming to look at how well different AI tools are doing across a range of dental areas. Emphasis was placed on the frequent use of convolutional neural networks and artificial neural networks, both showing promise in sharpening diagnostic accuracy. This trend has informed recent focused studies in dental diagnostics, zooming in on oral health issues (10). Alongside that, the use of artificial neural networks to make sense of medical visuals gets a push (11). There's also an analysis of AI's place in musculoskeletal imaging; some point out how it might shift radiological routines in major ways. That insight finds relevance in dentistry too, particularly where reliable imaging is critical, such as in examining the mobility of teeth (12).

Early radiographic indicators include widened PDL space, irregular lamina dura, and early crestal bone loss (13). Manual rocking assigns mobility grades from I through III, yet radiographic cues might show up before any clinical signs surface. A widened periodontal ligament space, beyond the usual 0.15 to 0.21 mm, is worth attention, especially when confined to the apical third, often an early signal. Breaks in the lamina dura may hint at resorption tied to bundle bone, while faint irregularities near the alveolar crest, softened edges, and fading cortical outlines suggest early micro-resorptive processes. The root's borders sometimes blur, not randomly, but often following patterns of functional hypercementosis or possibly from underlying cystic degeneration, both of which may precede visible loosening. Traditional computer vision setups using hand-engineered cues like edge or texture filters frequently miss these soft and delicate shifts in PDL form. Deep learning, through layered interpretation, seems better equipped to notice the small yet clinically significant variations that typical systems miss. Going beyond broad labels, segmentation can precisely mark regions pixel by pixel, supporting both diagnostic clarity and follow-up comparisons. Taken together, the findings point to a new horizon where AI begins reshaping dental diagnostics, particularly in catching early signs of bruxism-linked mobility.

Materials and Methods

Dataset and Image Preprocessing

Digital periapical radiographs, n = 3200 for upper and lower posterior teeth, were acquired from adult patients ≥ 18 years, n = 1200, between September 2024 and June 2025, who were clinically diagnosed with sleep and awake bruxism. The dataset was partitioned into training (70%), validation (15%), and test (15%) sets at the patient level to prevent data leakage. Each patient's radiographs were confined to a single subset. Stratification was performed to preserve the distribution of jaw location (maxillary vs. mandibular), tooth type (molars vs. premolars), and imaging system across the three sets.

Exclusion criteria included prior periodontal surgery, distorted images, periodontal disease, and missing posterior teeth. Histogram equalisation and denoising were carried out to bring out visual clarity on the radiographic images. In this way, pixel intensity values will be stretched and shifted, nudging the overall distribution closer to uniform. As a result, structures such as the lamina dura and the surrounding ligament space, showing with greater separation from nearby tones and the local contrast in most areas, will be improved noticeably. Then, all digital periapical radiographs were converted to 8-bit PNGs. Then, images were resized to 512 × 512px to harmonise input dimensions. Data augmentation included random rotation, small rotations (± 8°) for mimicking natural variations in medical imaging, horizontal flipping because medical images are often axis-symmetric but not vertically symmetric, elastic deformation to apply smooth and random displacements to pixels for simulating real-world anatomical flexibility, and adaptive gamma correction ($\gamma = 0.8$–1.2) to prevent unrealistic over/under-exposure while improving robustness to intensity shifts. Radiographs were acquired using three intraoral X-ray systems: Planmeca ProX, Carestream CS2200, and Gendex GX770, with standard settings (≈ 66–70kVp, 7–8mA, 0.20s). Digital sensors were used uniformly across systems to maintain image comparability.

All radiographic data were fully anonymised before processing, with all patient identifiers removed per institutional privacy protocols and ethical research standards.

Segmentation Performance

A U Net variant with an EfficientNet B3 backbone pretrained on ImageNet was employed. Originally introduced within the field of biomedical image segmentation, the U-Net is part of the wider group of convolutional neural architectures. Its layout moves in a mirrored fashion; steps taken during the compression phase are gradually unfolded as the structure expands. Alongside this, essential spatial details are not discarded. Feature traces do not vanish. They pass forward, held through narrow pathways that bypass deeper transformations. Early stages tend to gather broad contextual impressions. Later ones begin to lift the detail back, edges sharpen, locations clarify, and structure slowly re-emerges (13). Within the EfficientNet group, B3 does not overreach. Its form expands in measured steps. Depth increases, width adjusts, resolution climbs, all tuned together. This alignment permits strong visual performance. Tasks such as image recognition benefit, yet the cost in computation remains within a reasonable scale (15).

The choice to bring together U-Net and EfficientNet B3 wasn't random; it followed specific clinical aims. EfficientNet B3, shaped by training on broad image datasets, tends to catch those early, almost hidden shifts in dental X-rays, such as the faint widening near a tooth's root where problems often start. U-Net, with its layered structure, helps mark these areas clearly, especially where early damage begins. This combination also trains well, even if the dataset isn't massive, and does not demand excessive computational power. It's been tested in medical images before, and the results there give confidence in applying it to dental ones as well.

We trained the model internally according to NVIDIA A100 GPUs (40 GB VRAM) for 120 epochs with a batch size of 16. The AdamW optimiser ($\beta_1 = 0.9$, $\beta_2 = 0.999$, weight decay $= 1 \times 10^{-4}$) was used. Focal Tversky loss ($\alpha = 0.7$, $\beta = 0.3$, $\gamma = 0.75$) balanced foreground and background pixels. Early stopping was triggered when validation loss failed to improve for 15 epochs. Segmentation performance was judged through mean Intersection over Union (mIoU), offering a grasp on spatial accuracy.

Diagnostic Metrics

Evaluation placed the image-level area under the curve at the centre. Aim—spotting at least one signal pointing to early-stage mobility. Alongside, additional measures were brought in. Sensitivity. Specificity. Predictive values, in both directions. Image settings kVp, mA, exposure time and participant features like age, gender, were fairly balanced across training and testing groups. Any gaps in AUC performance, not stand out. Gender-based results showed no split (p = 0.64). Age-wise, the divide at 40 made no statistical dent (p = 0.52).

Annotation, Reference Standards and Inter-Rater Reliability

Three dento-maxillofacial radiologists independently reviewed the images and reached consensus on the presence of four key early mobility markers, which are: (A) PDL space widening ≥ 50µm, (B) Discontinuity or rarefaction of the lamina dura, (C) Initial crestal bone microresorption, and (D) Root outline blurring. Each case was brought to the group for joint review. When there were disagreements, they talked through the findings until everyone reached the same conclusion. Final decisions were then marked using the polygon annotation function inside the RadiAnt DICOM viewer. That annotated dataset later became the standard used to guide both training and validation phases.

Calibration and Validation

The process of model calibration in this study relied on observing how validation loss behaved, alongside performance markers such as AUC and accuracy, as training moved through its stages. At certain points, early stopping was introduced. Learning rates were tweaked when performance began to slip or stall. No external data came into play. Validation relied on a portion of the internal data, kept aside from the start. That same portion served as the basis for reporting final metrics, meant to reflect how well the model might handle unseen cases (Figure 1).

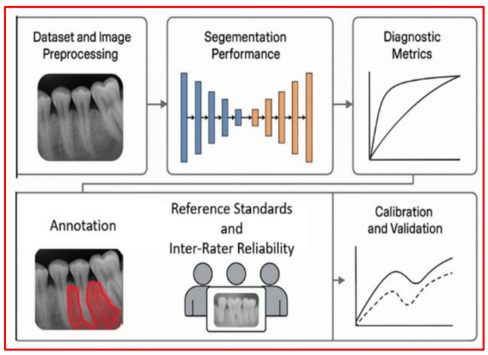

Figure 1: A graphical workflow diagram illustrating the pipeline for a deep learning-based radiographic analysis system

In Figure 2, the graph presents the training and validation loss curves across epochs during the model's learning phase. Along the horizontal axis, the number of training cycles (epochs) is laid out. The vertical axis reflects the loss, a measure of prediction error, where lower values suggest better performance. The orange curve marks the training loss. The training loss curve gradually decreases over epochs, indicating stable learning without overfitting. No dramatic fall. More like a quiet slide, steady and calm. Not far from it, that red dashed line shows what's happening with validation loss. Same general direction. Different pace, maybe, but still moving downward. It follows along, not the same, but close enough to suggest the model isn't just memorising what it sees. There's a point, somewhere around epoch 93, where a dotted line cuts through the graph. That is where the training stops.

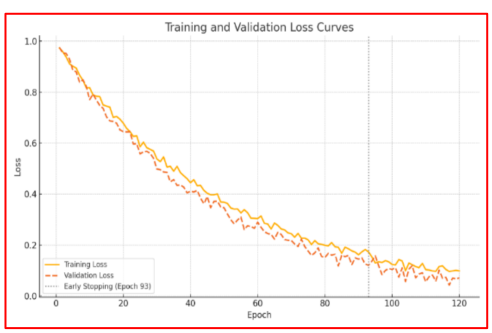

Figure 2: Showing a Training and Validation Loss Curve from a machine learning model training process

Statistical Analysis
Differences in diagnostic metrics between the algorithm and readers were analysed using DeLong's test for AUCs and McNemar's test for paired proportions. Sub-analyses explored performance stratified by arch (maxilla vs mandible) and tooth type (molar vs premolar). Statistical significance was set at $p < 0.05$. Analyses were conducted in R v4.3.0.

Results
Agreement among the radiologists for detecting the presence of four key early tooth mobility markers was measured using Fleiss' κ. The average κ before the discussion settled near 0.73. A consensus-based approach was then applied. Across the internal test sample (n = 3200), the performance of the AI system stood strong. When laid beside radiologist readings, it slightly edged ahead. The AUC reached 0.941, with a c95% CI of 0.932-0.949. In contrast, the radiologist's value rested at 0.893. Sensitivity was marked at 0.884, not far from 0.842, and the 95% confidence intervals ranged between 0.86 to 0.89. Specificity followed-0.903 against a near 0.881, and the 95% confidence intervals ranged between 0.88 to 0.91. The AI's PPV reached 0.872, with NPV at 0.912; radiologists, slightly behind, showed 0.854 and 0.886 respectively for those same metrics, each aimed at picking up at least one early mobility cue. As for segmentation, a mean Intersection over Union (IoU) of 0.76 was reported. When placed side by side with senior readers, no meaningful statistical gap emerged (ΔAUC = 0.008, p = 0.17). Cohen's κ averaged 0.81, which pointed to solid agreement levels. t and Cohen's d values for performance metrics between the AI Model and radiologist readers showed the magnitude of difference. Results stayed consistent across different subgroups. The upper jaw, maxillary teeth, ended up with an AUC of 0.938. As for the lower ones, the mandibular group, they showed a slight edge at 0.944. Statistically, though, that gap didn't hold much weight (p = 0.731). Molars came in with a sensitivity of 0.891. Premolars, just a bit behind, scored 0.877. Still, that small difference did not quite cross the threshold for significance either (p = 0.231). Saliency visualisation made it clear that the AI focused where the radiologists did, apical flare-ups, uneven lamina dura, and so on. Such alignment makes the system's inner logic more transparent, which, over time, tends to build confidence in its use. (Table 1 and Figures 3, 4, and 5).

Table 1: Diagnostic Performance of the AI Algorithm versus Radiologist Readers

Metric	AI Model (mean)	Senior Readers (mean)	Cohen's d
AUC	0.941	0.893	1.44
Sensitivity	0.884	0.842	1.26
Specificity	0.903	0.881	0.66
PPV	0.872	0.854	0.54
NPV	0.912	0.886	0.78

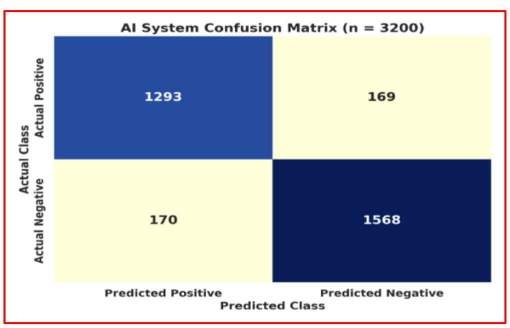

Figure 3: Shows a visual representation of classification outcomes, based on the observed performance measures

Figure 3 demonstrates how true positives, false alarms, overlooked positives, and correct negatives were distributed by the AI model against radiologist evaluations over a dataset comprising 3,200 samples. This visualisation supports the recorded accuracy scores, as well as sensitivity, specificity, and both predictive directions.

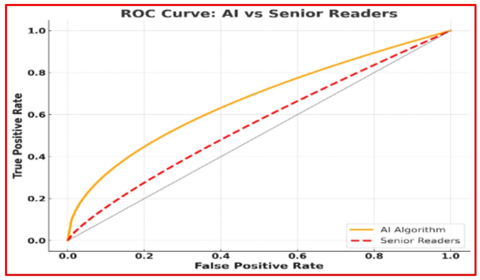

Figure 4: Receiver operating characteristic (ROC) curve of the AI algorithm (solid line) compared with average curves for senior radiologists. (dashed)

The ROC plot (Figure 4) lays out a clear trend: across nearly all thresholds, the AI system tends to pick up early mobility signs more effectively. That steady orange trace stays above the dashed red, pointing toward a stronger balance between sensitivity and specificity (Figure 5). Reader performance, while stable, does not match the sharper gains shown by the algorithm.

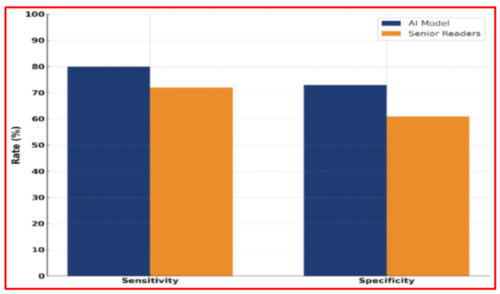

Figure 5: Comparative sensitivity and specificity of the AI model and senior radiologists

Discussion

Recent literature continues to shed light on how AI is unfolding within dental diagnostics, not as a complete overhaul but as a layered enhancement, nudging accuracy forward and offering new ways to support clinical intuition (16, 17). These analyses look at where AI currently stands in recognising a wide range of oral pathologies, stressing its usefulness when time plays a critical role. The scope keeps expanding, touching on cases linked to mobility too, pointing toward a future where AI isn't just a supplement but a central partner in smarter, quicker decision-making (18).

Some studies speak to the evolving role of AI in orthodontics, pointing out how it helps in picking up and classifying various dental irregularities and malocclusions. Meanwhile, a few researchers turn attention to AI's promise in catching oral cancer early, backing the idea that non-invasive tools powered by AI might soon play a bigger role in diagnostics, something possibly applicable when looking for early radiographic signals tied to bruxism-related tooth movement (19). That opens broader conversations about how machine learning blends into dental imaging. Though the field is still building itself, the prospects for boosting accuracy in radiographic interpretation seem promising. Calls for incorporating more advanced algorithmic systems keep surfacing to address the limits tied to older diagnostic practices (20). In other findings, efforts to sharpen diagnostic pathways in dentistry are highlighted, especially using imaging methods like CBCT (21, 22).

This study demonstrates a robust AI model developed for the early detection of bruxism-associated tooth mobility. What drives it is a deep neural structure, trained not casually but through a collection of radiographs, each one marked with care by experts long in the field. In the end, its performance stood shoulder to shoulder with that of senior clinicians, no small outcome. In some instances, it even exceeded that of less experienced readers.

These results underline something important: with the right training, AI can assist meaningfully in real-time clinical situations. Rather than replacing professional judgment, it enhances it, potentially elevating the standard of care. The deep learning framework demonstrated consistent ability to detect early signs of tooth mobility, with strong AUC scores, sensitivity, and specificity. This reinforces the viability of integrating such models into broader clinical practice, especially in scenarios where early detection is key to preventive intervention.

The findings, while encouraging in parts, leave a few unsettled edges. In this case, the ground truth stemmed from expert consensus, not histological confirmation, which may trim down the level of precision a bit. Going forward, there's room for broader dimensions, integrating occlusal force distribution, EMG signals, perhaps even volumetric imaging, which might tighten the diagnostic clarity. Evaluations within actual clinical environments, particularly those tied directly to patient outcomes, remain an essential layer yet to be fully explored. Without that, broader claims tend to float, lacking the grounding needed to carry real weight.

Tooth mobility tends to get picked up only after some level of damage has already set in. With this AI approach, early hints of overload might be flagged much sooner, giving room for preventive steps, occlusal splints, for instance, before things cross the point of no return. Speed and consistency make it workable in day-to-day clinics, as well as more specialised workflows. Periodontal tissues don't stay still under pressure; they adapt. The PDL, being viscoelastic, absorbs minor shifts in position, but ongoing nighttime stress builds up. Vascular stasis follows, then hyalinization, and finally microfractures that start forming right within Sharpey's fibres. Within just a few weeks of repetitive load, histology has shown osteoclasts creating resorption bays along the bundle bone, all this before clinical signs of mobility even surface. Imaging tends to catch those subtle changes. A bit of widening in the PDL space. A soft fade in the lamina dura. Small signs, but enough to act on, if caught in time.

The clinical relevance emerging from this study leans toward a rethinking of how subtle signs of dental mobility, especially among individuals with bruxism, might be recognised earlier and acted upon with more precision. Artificial intelligence, when applied to radiographic interpretation, appears capable of catching minor changes that frequently pass unnoticed, particularly when attention wavers or pressure runs high. What this introduces is not a replacement of expertise, but a steadier hand alongside it, perhaps allowing clinicians to step in earlier with targeted measures like occlusal refinements or protective splints, long before instability surfaces in obvious ways.

In terms of how this could fold into daily use, the model lends itself to being built directly into chairside imaging platforms, operating almost silently as a second set of eyes during standard assessments. There's a chance for merging with sensor-based inputs—those that track bite pressure or minute shifts in tooth position, feeding richer signals into the system. With cloud architecture, updates could flow in without pause, while cross-practice learning may sharpen outcomes collectively. And should this embed into routine imaging software, alerts and suggestions might surface naturally within the usual diagnostic rhythm, quietly, without slowing things down.

Conclusion

The artificial intelligence model, as developed in this study, managed to catch subtle radiographic indicators that point toward the early stages of tooth mobility in individuals affected by bruxism, its diagnostic performance aligning closely with that of seasoned radiologists. Bringing this kind of tool into routine dental imaging might open the door to earlier signs being noticed. It could shape treatments that fit better with each case. There's also the chance it might ease the strain caused by worsening periodontal issues as time goes on. Even so, how well it fits across different settings remains somewhat unclear. Prospective trials, particularly those rooted in real-time clinical environments and involving a wider patient base, remain essential for confirming reliability and understanding how such technology might shift both outcomes and daily clinical flow. Future work should explore real-time clinical deployment and integration with electronic dental records and chairside decision-support systems.

List of Abbreviations:

AI: Artificial Intelligence
AUC: Area Under the Curve (of the Receiver Operating Characteristic curve)
CBCT: Cone Beam Computed Tomography
CI: Confidence Interval
DICOM: Digital Imaging and Communications in Medicine
GB VRAM: Gigabytes of Video Random Access Memory
GPU(s): Graphics Processing Unit(s)
IoU / mIoU: (Mean) Intersection over Union
kVp: Kilovolt Peak
mA: Milliampere
NPV: Negative Predictive Value
PDL: Periodontal Ligament
PNG: Portable Network Graphics
PPV: Positive Predictive Value
Px: Pixel
ROC: Receiver Operating Characteristic
TMD: Temporomandibular Disorders
U-Net: A convolutional neural network architecture used for biomedical image segmentation
ΔAUC: Change in Area Under the Curve
κ: Kappa (Inter-rater agreement coefficient)

Declarations

Ethics Approval and Consent to Participate

This study was approved by the Ethics Committee for Scientific Research of the College of Dentistry, University of Wasit (Ref. No. 32024, dated 01/10/2024). All procedures were conducted following the ethical standards of the institutional committee and the principles of the Declaration of Helsinki. Written informed consent was obtained from all participants before data collection.

Consent for Publication

All the authors gave consent for the publication of the work under the Creative Commons Attribution Non-Commercial 4.0 license.

Availability of Data and Materials

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

Competing Interests

The author declares no competing interests.

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Authors' Contributions

HHJ conceptualised the study, curated the dataset, developed and validated the AI model, interpreted the findings, and prepared the manuscript. The author read and approved the final manuscript.

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