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Review Paper

A Comprehensive Review on Artificial Intelligence Assisted CBCT Analysis for 3D Alveolar Bone Morphometry and Periodontal Diagnosis

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ABSTRACT

Periodontal disease is a chronic inflammation that damages the tooth-supporting structures, i.e., gingiva, cementum, periodontal ligament, and alveolar bone. It is the leading cause of tooth loss across the globe. Evaluation of alveolar bone structure is important in order to estimate the severity and stage classification of periodontal disease, thereby influencing treatment planning and prognosis. Traditional two-dimensional (2D) radiographs, in spite of their widespread use, are limited by structural superimposition and the inability to clearly represent complex three-dimensional (3D) bone disease. Cone-beam computed tomography (CBCT) is better than standard CT in imaging for producing more accurate three-dimensional images of alveolar bone with minimal doses of radiation. Diagnosis based upon CBCT imaging is very helpful in carrying out appropriate treatment of the disease. Advancements in artificial intelligence (AI) and deep learning (DL) technologies, along with the convolutional neural networks (CNNs) and U-Net design have empowered dental imaging to automatically identify, classify, and segment periodontal bone defects with more efficiency. Studies have established that AI-enhanced CBCT evaluation significantly improves diagnostic efficacy and speed and, in some cases, surpasses conventional interpretation. Future projects will focus on developing AI models for local defect detection, multimodal data fusion, and establishing explainable AI to enable individualized periodontal treatment. AI-CBCT is seen in the future to enhance periodontal diagnosis and assist with recovery for patients.

Keywords: Periodontal disease; Cone beam computed tomography (CBCT); Alveolar bone morphometry; Artificial intelligence (AI); Deep learning (DL); Convolutional neural networks (CNNs); Periodontal diagnosis.

INTRODUCTION

Overview of Periodontal Diseases and Clinical Significance of Alveolar Bone Morphology

Periodontal disease is a chronic inflammatory disease that is affecting structures supporting the teeth i.e, gingiva, cementum, periodontal ligament, and alveolar bone, all of which are needed for dental stability and function (Spicer et al., 2012). Various causes like bacterial infection, host immunologic response, and trauma act together to eventually cause tissue loss and hence periodontal attachment loss and tooth loss if not treated (Akcali et al., 2013). Proper evaluation of the alveolar bone shape is important in periodontal disease diagnosis, prognosis, and treatment planning as it determines the selection of regenerative, resective, or combined therapeutic methods (Tonetti et al., 2018; Nibali et al., 2020). Determination of the type and quantity of bone loss, whether it is horizontal bone loss, infra bony defects, or furcation, is very important in directing to the right treatment modalities and achieving acceptable clinical outcomes (Jayakumar et al., 2010; Levine et al., 2024). To maintain the potency of periodontal treatment and the survival of teeth, it is essential to obtain an accurate image of the alveolar bone morphology.

Limitations of Classical 2D Imaging Methods in Periodontal Diagnosis

However, these two-dimensional (2D) imaging methods have some limitations in that they are subject to anatomical structure superimposition, image distortion, and the fact that they cannot effectively represent three-dimensional (3D) alveolar bone morphology (Jacobs et al., 2024). Therefore, they tend to underestimate the extent and magnitude of osseous anomalies, particularly in periodontal complexity cases such as furcation involvement or buccal/lingual deficiencies (Feijo et al., 2012; Songa et al., 2014). These facts point to the necessity of applying state-of-the-art technology imaging equipment to send three-dimensional, high-definition images of periodontal tissues to further confirm diagnosis accuracy. The Cone-beam computed tomography (CBCT) is one of the most notable periodontal disease imaging technologies and much better than the conventional 2D X-rays.

Benefits of 3D CBCT in Periodontal Evaluation

Cone-beam computed tomography (CBCT) generates high-resolution, three-dimensional representations of the alveolar bone and tissues around it with remarkable detail and reduced radiation doses compared to standard CT scans (Macleod & Heath, 2008; Correa et al., 2014).This method of imaging for identification and measurement of horizontal and vertical bone deficits, craters, and furcation involvement, enables diagnostic accuracy and treatment efficiency (Misch et al., 2006; Haas et al., 2018). Scientific literature demonstrates that CBCT is more precise than periodontal probing and 2D radiography in measuring small bone changes and quantifying bone loss (Braun etal., 2014; Anter et al., 2016). Furthermore, the quantitative measurement of bone volume and defect shape enables physicians to make evidence-guided decisions about tooth retention vs. extraction and also optimal resective or regenerative treatment (Zhu & Ouyang, 2016; Suphanantachat et al., 2017). CBCT is the latest periodontal technology for accurate evaluation and use of Artificial Intelligence in Dentistry and Medical Imaging makes the diagnostic process more efficient.

Artificial Intelligence (AI) Emergence in Dentistry and Medical Imaging

Artificial intelligence deep learning has transformed medical imaging, allowing computers to mimic human mental activities like analysis, problem-solving, and learning (Chartrand et al., 2017). Artificial intelligence technology in dentistry possesses a vast power that goes hand in hand with image interpretation and processing hence, it may play a crucial role in making correct clinical decisions and achieving high diagnostic accuracy level (Pesapane et al., 2018; Lakhani et al., 2018). The use of Convolutional neural networks and U-Net networks has helped to very well detect caries which is a diagnosis for root fractures, radiograph periapical lesions, and perform segmentation of the teeth (Devito et al., 2008; Johari et al., 2017; Lee et al., 2018). In addition, 2D imaging information is restricted within the parasagittal plane, and the clinicians cannot fully evaluate the volumetric properties of bone loss (de Faria Vasconcelos et al., 2012). For periodontology, AI-based systems proved to be better than physicians in detecting periodontal bone loss on panoramic radiographs (Kim et al., 2019; Krois et al., 2019). Additionally, the recent developments have significantly improved the 3D CBCT analysis and the AI system has been able to perform the tasks like delineating teeth, detecting the anatomical anomalies in the bone and even classifying the patients correctly in the periodontally healthy and unhealthy groups (Ezhov et al., 2021; Kurt-Bayrakdar et al., 2025). These are, therefore, the factors that underscore the importance of AI for periodontal diagnosis in order to support the establishment of machine-based, precision-facilitated decision-support systems for clinicians.

AIM

The aim of this research is to deliver an expanded perspective of the recent advances in AI-aided CBCT imaging for three-dimensional assessment of the morphology of the alveolar bone and extent of periodontal disease. The aim is to overcome the limitations of conventional 2D imaging, highlight the benefits of CBCT in diagnostic imaging, and explain the use of AI and deep learning technology in diagnosis and decision-making in the clinic. In addition, this article gives a review of some of the new advances in automatic tooth segmentation, periodontal abnormality classification, and disease diagnosis. It also points out the special areas that require attention and suggests new research areas that can be explored more innovatively. The review also has the agenda of revolutionizing the production of diagnostic instruments for periodontal therapy by capitalizing on periodontology, artificial intelligence, and radiography with an eye on patient treatment-efficiency.

OBJECTIVES AND SCOPE OF THE REVIEW

The purpose of the review is to revolutionize the process of designing new diagnostic devices in periodontal treatment by combining the three disciplines of artificial intelligence, radiography, and periodontology to improve patient outcomes.

FUNDAMENTALS OF CBCT IMAGING IN PERIODONTOLOGY

CBCT IMAGING:

Principles and technology:

Cone-beam computed tomography (CBCT), a sophisticated imaging technique, has heavily impacted the three-dimensional (3D) volumetric visualization of maxillofacial tissues and the diagnosis of periodontal disease in dentistry. Cone beam computed tomography (CBCT) projects several with a conical beam of radiation at once and scans the patient in one exam. Three-dimensional volumetric data is created by the integration of this data (Macleod & Heath, 2008). CT scans employ a fan-shaped beam of X-rays. The volumetric data that is generated is in DICOM standardized format. It can then be reconstructed in the form of axial, coronal, and sagittal slices during the study period (Correa et al., 2014).

Advantages of 3D alveolar bone measurement over traditional radiography

The method provides improved spatial resolution and isotropic voxels when compared to the conventional CT and allows hard tissues such as the alveolar bone to be seen in its entirety and without subjecting the patient to unnecessary exposure to radiation (Bornstein et al., 2015). In two-dimensional radiography, anatomical structures superimpose on each other and projection errors conceal significant diagnostic information such that the evaluation of the extent and nature of alveolar bone deficiencies is compromised (Jacobs et al., 2024). However, CBCT takes advantage of these limitations by showing a three-dimensional representation of the supporting periodontal tissues and alveolar bone, hence enabling radiography detection of bone loss in both horizontal and vertical dimensions (Misch et al., 2006). Use of CBCT for periodontal diagnosis in the clinical practice has been underlined by meta-analyses and systematic reviews, which validate its enhanced diagnostic accuracy in the detection of crater-like defects, infra bony and furcation defects (Haas et al., 2018; Anter et al., 2016). Clinicians can now visualize buccal and lingual cortical plates with CBCT, not seen in 2D radiographs because of overlying anatomy (Feijo et al., 2012; Songa et al., 2014).

Diagnostic potential, accuracy, and precision of CBCT for periodontal bone defects

CBCT is also a significant diagnostic tool in periodontitis because it provides a more precise and detailed image of the alveolar bone than regular X-rays. The majority of studies established that CBCT was more accurate in diagnosing periodontal bone disease than other traditional imaging modalities. CBCT precisely measures linear and volumetric bone loss with a difference of less than 0.2 mm from true clinical measures, thus increasing diagnostic accuracy (Misch et al., 2006). The use of CBCT augments periodontal probing and 2D radiographic diagnostic accuracy, especially in difficult furcation cases (Braun et al. (2014)). Zhu and Ouyang (2016) showed that CT scans simplify the identification and classification of maxillary molar furcation anomalies often missed by routine X-rays. Later, CBCT has proved its reliable and precise in the identification and categorization of periodontal bone irregularities.

CLINICAL USE IN DETECTION OF DEFECT MORPHOLOGY, FURCATION, AND BONE LOSS

In the field of periodontics, the application of CBCT became prevalent and it was identified as a therapeutic and diagnostic tool by the intrinsic accuracy support. CBCT is imperative for carrying out the diagnosis that forms the basis of treatment and prognosis (Jayakumar et al., 2010). CBCT can identify fenestrations and buccal dehiscence, which are challenging to diagnose using 2D images, as stated by Suphanantachat et al. (2017). It can elucidate three-dimensional furcation involvement, which is critical for accurate diagnosis and treatment of multirooted teeth (Zhu & Ouyang, 2016). To determine whether restorative or regenerative therapy is needed, evaluate volume, morphology, and depth of surrounding bone walls (Nibali et al., 2020; Levine et al., 2024).

Secondly, the foregoing applications are examples of the effectiveness of CBCT in facilitating accurate diagnosis and treatment planning, hence resultant maximum benefits in periodontal therapy. Artificial Intelligence is a computer program designed to mimic human intelligence, encompassing psychological processes, learning capacity, reasoning, and problem-solving capacity (Chartrand et al., 2017). Machine learning (ML) refers to a form of artificial intelligence which enables computers to learn about patterns from huge datasets and make better decisions over time automatically without being specifically programmed.

Deep learning (DL) is an advanced form of machine learning (ML) that uses multi-layered neural networks to recognize hierarchical features in unstructured input data automatically. This enhances vision significantly (Lakhani et al., 2018). Deep models, particularly CNN-based models, are powerful radiology and pathology tools in clinical settings. Deep models perform sophisticated image analysis, segmentation, and classification (Pesapane et al., 2018). Outcomes are enhanced diagnosis, quicker results review, and reduced errors by less competent or fatigued medical personnel.

DENTAL IMAGING WITH ARTIFICIAL INTELLIGENCE

Overview of medical imaging with artificial intelligence (Ai), machine learning (Ml), and deep learning (Dl)

From being experimental models, AI systems today are indispensable tools for supporting doctors in their decision-making and changing the process of diagnosis (Hung et al., 2022). The true fact that computers are increasingly powerful and more annotated imaging datasets are being made available.

Applying ai in dentistry to detect lesions

From being experimental models, AI systems today are indispensable tools for supporting doctors in their decision-making and changing the process of diagnosis (Hung et al., 2022). The true fact that computers are increasingly powerful and more annotated imaging datasets are being made available.

Transitions from 2D radiograph analysis to 3D CBCT analysis

In the past, ANNs had already been employed in detecting dental caries at a level of accuracy on par with experts (Devito et al., 2008). For optimization of early diagnosis and therapy, convolutional neural networks (CNNs) have been successfully employed for diagnosing periapical lesions (Orhan et al., 2020). For the detection of periodontal bone loss on panoramic radiographs, deep learning algorithms outperform human observers (Kim et al., 2019; Krois et al., 2019). Thanathornwong and Suebnukarn (2020) employed a fast regional CNN (R-CNN) to separate periodontal disease teeth with higher sensitivity and specificity. AI has also been employed to segment teeth automatically, label teeth, determine the root shape, and detect jaw disorders. These procedures become more objective and effective in diagnosis (Schwendicke et al., 2019; Chen et al., 2020). With the result of such scans, AI helps doctors make better diagnoses, decisions, and improve patient treatment for patients who receive dentistry. AI was initially implemented on 2D radiographs as it was available. The deep neural transfer network, DeNTNet, as per the research conducted by Kim et al. (2019), was able to outperform the majority of the doctors with an F1 score of 75% in automatic detection of periodontal bone loss in panoramic radiographs. Krois et al. (2019) were about 81% accurate in the detection of bone resorption using convolutional neural networks with two-dimensional images. The limitations of 2D imaging, which are structural superimposition and reduced spatial resolution, affected the AI's diagnostic performance, that is, the accuracy of the diagnosis was hindered (Jacobs et al., 2024).The use of three-dimensional (3D) CBCT evaluation not only mitigated the challenges but also provided volumetric information for a more precise and accurate assessment of dental and periodontal tissues (Misch et al., 2006; Haas et al., 2018).The latest development in artificial intelligence involves the integration of the technology with cone beam computed tomography (CBCT) whereby automatically rendering the segmentation of teeth, osseous disease identification and differentiating patients between periodontal and non-periodontal disease with the unparalleled accuracy of AI is one of the areas where the technology is applied (Ezhov et al., 2021; Kurt-Bayrakdar et al., 2025).The research by Ezhov et al.(2021) has proven that AI assisted segmentation of periodontal bone loss on CBCT scans was able to provide sensitivity and specificity greater than 0.90. The innovation is a huge advancement from the use of simple 2D diagnostic aid to accurate 3D evaluation and hence facilitating diagnosis and detection of complex periodontal diseases.

Convolutional neural networks (CNNS)

The common artificial intelligence architectures used are U-Net, nnU-Net, and transfer learning architectures. Deep learning models of various types have been key in enabling proper use of dental imaging AI solutions. Convolutional neural networks (CNNs) are extensively used for classification and feature extraction because they can learn spatial hierarchies of image data (Schwendicke et al., 2019). U-Net++, being a modified version of the U-Net model, could acquire dataset-specific features with less hyperparameter tuning and improved-quality segmentation (Kurt-Bayrakdar et al., 2025). The technique promises to provide the highest-class accuracy in segmentation upon being applied to teeth and periodontal bone pathology in CBCT images. Further, the application of transfer learning methods such as fine-tuning of pre-trained networks across dental data has provided the impetus for creating models even if there are few annotated samples (Kim et al., 2019; Danks et al., 2021). Such systems build end-to-end analysis pipelines such as segmentation, classification, feature extraction, and data preprocessing. Periodontal diagnostics have thus been quicker and more accurate. AI continues to advance, and the integration of ensemble methods and explainable AI (XAI) architectures will enable easier interpretation and application of such systems in clinical use. The star feature in AI-assisted CBCT analysis is the collection of good quality data.

CBCT ANALYSIS WITH THE SUPPORT OF ARTIFICIAL INTELLIGENCE FOR PERIODONTAL DIAGNOSIS

AI-aided CBCT image processing workflow

CBCT imaging has highly sophisticated machines like the Planmeca Promax 3D Mid and CS 9600. In order for AI to utilize their images, these devices need to output volumetric data in DICOM format which must then be converted to Neuroimaging Informatics Technology Initiative (NIfTI) format (Kurt-Bayrakdar et al., 2025). Preprocessing is used to scrub the input data quality by removing noise, artifacts, and other unwanted regions. For proper training and evaluation of the model, patient selection criteria such as not including poor-quality images or scans of abnormal bone structure are important (Ezhov et al., 2021). Segmentation and feature extraction Deep learning (DL) models, especially the U-Net architecture-based models and their variations, make segmentation a critical step in the process of detecting anatomical structures such as alveolar bone and teeth independently. nnU-Net v2 brings about a significant improvement in the segmentation quality by tactically exploiting the use of 2D U-Nets for low-resolution, 3D U-Nets, and cascaded 3D U-Nets for high-resolution segmentation with a self-tuning capability (Kurt-Bayrakdar et al., 2025). This multi-phased segmentation method allows precise marking of teeth and periodontal disease contours. Feature extraction includes identifying the structural and textural features unique to each category of defects, for example, bone density slope and defect shape (Hung et al., 2022). The elements are distinctly labeled according to the type of defect or the status of the gums of the oral cavity by convolutional neural networks (CNNs). Classification & Diagnostic Determination Machine learning classification models that are trained using annotated data are capable of differentiating between ill and healthy periodontal conditions (Ezhov et al., 2021). Using probability maps and predictive models, the physician is able to evaluate the extent of the disease, figure out the most effective treatment plans and even estimate the disease progression over time. When we evaluate the diagnostic performance of the model, we measure accuracy, sensitivity, specificity, and area under the curve (AUC) (Kurt-Bayrakdar et al., 2025)

Tooth segmentation and counting models

In AI-assisted CBCT analysis, the tooth segmentation and counting models are very important for enabling the subsequent detection of defects. Kurt-Bayrakdar et al. (2025) quote that the nnU-Net v2 deep learning architecture independently performed excellent segmentation and enumeration of teeth from 3D CBCT data. To get the acceptable segmentation outcomes, the model employs multi-stage U-Net architectures and get dataset fingerprinting. The automatic segmentation model has worked practically flawlessly with 0.99 accuracy and an area under curve (AUC) score of 0.95 (Kurt-Bayrakdar et al., 2025). The detection of dental features is verified in the Dice score (0.78 in the upper left jaw) and the IoU (0.70). Correct tooth segmentation can identify abnormalities and count teeth effectively with the FDI system to enhance diagnostic reporting and clinical communication (Schwendicke et al., 2019).

AUTOMATIC DETECTION AND CLASSIFICATION OF PERIODONTAL BONE PARTICLES

Total loss of alveolar bone

By excluding the factor of human error present in manual segmentation, the automated procedure reduces the workload on physicians and accelerates the diagnosis process. Employing patterns of deviation from the normative position of the alveolar crest, being in a typical position 2 mm apical to the cemento-enamel junction, artificial intelligence models have proven high efficacy in identifying complete alveolar bone loss (Kurt-Bayrakdar et al., 2025). The models were very precise in identifying generalized periodontal disease as reflected by their AUC of 0.8499 for identification of overall bone loss. Supra-bony and infra-bony defects are key terms to understand when planning the therapy. Supra-bony defects are horizontal bone loss over the alveolar crest, and infra-bony defects are vertical bone loss under the crest. Values of AUC equal to 0.5052 for supra-bony defects and 0.5613 for infra-bony defects were obtained from CBCT-trained AI models. AUC for infra-bony defect detection increased drastically to 0.7488 after region cropping was used during training. This proves the value of localized training methods for defect-based segmentation (Kurt-Bayrakdar et al., 2025).

Lesions on the Perio-endo

The performance of the model to detect these complex lesions was proved by the detection of perio-endo lesions, which are characterized by the association of the periodontal pocket with pulp, using an AUC of 0.8893 (Kurt-Bayrakdar et al., 2025). The difference between periodontal disease and perio-endo disorders depends on the correct diagnosis. Due to difficulty to visualize obstructed buccal signs like fenestrations, dehiscence, and multirooted furcation involvement are particularly difficult to detect. For buccal and furcation lesions, The AUC values were of 0.6780 in the first-generation AI models. These values increased to 0.7592 and 0.8087, respectively, following cropping and retraining. This is evidence that localized attention greatly enhances a model's ability to detect minor imperfections (Zhu & Ouyang, 2016; Kurt-Bayrakdar et al., 2025). This breakthrough allows physicians to design treatments in more minute detail, which endulates patients to better results from surgical and regenerative procedures.

Comparative performance of ai models (accuracy, auc, sensitivity, specificity)

Substantial diagnostic performance has been demonstrated by CBCT models assisted with AI in various parameters. In tooth segmentation procedures, the nnU-Net v2 model showed an average accuracy of 0.99 and AUC of 0.95, while the sensitivity of its model ranged between 0.75 and 0.86 in different quadrants (Kurt-Bayrakdar et al., 2025). Total loss of alveolar bone and perio-endo lesions, both, captured higher AUC (0.8499 and 0.8893, respectively) in periodontal defect identification. However, defect-wise, infra-bony defect detection was enhanced from 0.5613 to 0.7488 after image cropping. Accuracy, sensitivity, and specificity scores of the defect detection models were stated to be 0.55–0.81, 0.43–0.60, and 0.99, respectively. This indicates a decreased rate of false positives and suggests that the models were functioning well (Kurt-Bayrakdar et al., 2023). These tests indicate that AI models can compete with, or even outperform, the skill of physicians when it comes to diagnosing, especially detecting subtle mistakes which are hard to notice and understand, according to Ezhov et al (2021).

Detection of healthy vs. Diseased patients with periodontal disease with AI

It is only through CBCT images that AI models can differentiate between patients who have healthy gums and patients with unhealthy gums. They do not need to label them manually. CNN classifiers using TensorFlow and Keras allowed the models to successfully be able to differentiate between healthy individuals and persons with illness 80% and 76% of the cases, respectively

(Kurt-Bayrakdar et al., 2025). The overall F1-score was 0.78 with sensitivity, specificity, and precision at 0.76, 0.79, and 0.80, respectively. The performance of the models to accurately classify 20 of 26 healthy and 19 of 24 ill patients indicates their potential usefulness in automated screening and disease classification. The technologies can help doctors make choices by shortening the list of suspected conditions and allowing doctors to identify and treat matters in time enough (Kim et al., 2019; Ezhov et al., 2021). Using AI-based classification and segmentation models together makes it much easier to establish if a person has periodontal disease.

CLINICAL IMPLICATIONS AND DIAGNOSTIC VALUE

The role of ai in periodontal treatment planning and decision-making

Artificial intelligence can have a significant beneficial influence on periodontal treatment planning by increasing diagnostic consistency, reducing variability, and making treatments patient-specific. Repetitive imaging of alveolar bone shape is very important in tooth extraction, flap procedure, and regenerative or restorative treatment (Nibali et al., 2020; Levine et al., 2024). Additionally, the application of AI-based interpretation of CBCT scans by clinicians can detect subtle periodontal changes and other lesions such as furcation, buccal dehiscence, and horizontal and vertical bone loss (Kurt-Bayrakdar et al., 2025). The precision of such imaging can assist patients with deciding on the suitability of regeneration therapy for conditions such as three-walled vertical lesions or if resective measures are necessary (Jayakumar et al., 2010). Moreover, computer-aided Perio-endo diagnosis allows for discrimination between periodontal and endodontic infection and predicts treatment as a consequence (Zhu & Ouyang, 2016). Therapeutic planning using AI accelerates diagnosis and reduces the risk of errors due to clinician tiredness or inexperience and thereby enhances patient outcomes and long-term periodontal stability (Kim et al., 2019). AI is actually taking over the periodontics clinical pipeline and ushering in an era of high-precision dentistry.

Incorporating ai tools into clinical workflows and decision-support systems

Decision-support systems by AI-based CBCT diagnostic devices are real-time analysis and helping doctors interpret huge amounts of imaging data (Hung et al., 2022). These machine learning algorithms may be integrated into dental software packages, which will automatically identify disparities in disease with CBCT scans, categorize them, and establish their likelihood (Kurt-Bayrakdar et al., 2025).AI algorithms rank the patients, placing the most serious or worsening periodontal conditions first in the treatment queue. AI helps doctors plan treatment more efficiently and interact with patients by avoiding the lengthy endeavor of interpreting images manually. AI systems can relate imaging data with clinical, microbiological, or genetic data and use electronic health records. This would further amplify personalized periodontal treatment (Lakhani et al., 2018). The use of these technologies will lead to a higher number of dentists being comfortable and thus start using them in their daily practice since they are easier to understand and operate. Afterwards, based on the data at hand, the practitioners would have no trouble in making decisions and diagnosing periodontal diseases.

Comparing ai-assisted CBCT analysis with conventional diagnostic approaches

AI-assisted CBCT analysis provides greater diagnostic advantage over conventional approaches, especially regarding accuracy and utility. These traditional methods of periodontal probing and 2D radiography are usually insufficient as they cannot represent the complexity of periodontal structures in three dimensions or the extent of bone loss (Jacobs et al., 2024; Braun et al., 2014). AI makes CBCT to provide precise volumetric information that detects localized pathology, furcation disease, and change in shape (Misch et al., 2006; Haas et al., 2018). Diagnostic performance is to or superior to human physicians is achieved by AI models. Kim et al. (2019) uncovered that an AI model detected periodontal bone loss in panoramic radiographs with F1-score 75% vs. 69% for dentists. Ezhov et al. (2021) identified that AI-assisted CBCT segmentation achieved sensitivity and specificity of more than 0.90 for the detection of periodontal bone loss. Kurt-Bayrakdar et al. (2025) said that AI-based diagnosis using CBCT is able to separate healthy and diseased patients with 80% accuracy and its validity for diagnosis.

CASE STUDIES AND RESEARCH FINDINGS

These findings demonstrate that AI enhances diagnostic accuracy, reduces observer variability, and reduces the time required for diagnosis. AI is capable of accurate diagnosis, reduction of differences between different observers, and speeding up the whole process of diagnosis. The latter presents the traditional ways of doing things as inferior concerning the performance of detailed periodontal examination. Evidence for clinical diagnosis suggests the application of AI-assisted periodontal imaging. The DeNTNet model developed by Kim et al. in 2019 was employed for the detection of periodontal bone loss using panoramic radiography. It was better than the agreement of five doctors. Krois et al. (2019) used convolutional neural networks (CNNs) on 2001 panoramic radiographs at an accuracy, sensitivity, and specificity rate of approximately 81% for the detection of bone loss. Thanathornwong and Suebnukarn (2020) utilized a faster R-CNN model to detect periodontally involved teeth with accuracy, sensitivity, specificity, and F1-score values of 81%, 84%, 88%, and 81%, respectively. Ezhov et al. (2021) created an AI model to automatically detect periodontal bone loss and oral pathology from CBCT images with sensitivity and specificity > 0.90. Dentists using AI-supported CBCT images made significantly superior diagnostic accuracy than the traditional technique. (Kurt-Bayrakdar et al. 2025) enhanced this study with the use of nnU-Net v2 for segmentation of teeth with accuracy 0.99 and AUC 0.95. They further classified six periodontal conditions, for which the total alveolar bone loss had an AUC of 0.8499 and Perio-endo lesions an AUC of 0.8893. The incorporation of cropped images in retraining provided for better identification of errors and thus increased the AUC scores for infra-bony defects to 0.7488 and furcation defects to 0.8087. The CNN-based classifier had an F1-score of 0.78 in discriminating between ill and healthy patients. Research has shown that using AI to support CBCT analysis significantly increases its accuracy, reliability, and efficiency in the detection of various types of periodontal diseases. The technology can support doctors in making decisions, carry out their activities more efficiently, and give patients periodontal treatment founded on the best evidence.

CHALLENGES AND LIMITATIONS

Data quality, diversity, and annotation challenges

The challenging aspect is creating AI-based CBCT systems that are able to detect periodontal disease and perform efficiently might be collecting a large amount of diverse high-quality training data. Large data with lots of notes on them are necessary for AI programs to operate effectively. The majority of currently available datasets are not sufficiently large. This is either because they only include a small number of diseases or because there are not enough people in them (Hung et al., 2022). AI systems would be less successful when applied to new populations because the patients' age, race, bone density, and disease severity are changing (Chartrand et al., 2017). In order to identify any periodontal problems, such as defects above and below the bone, furcation invasion, and Perio-endo lesions, the expert should also look at the hand-scores. This consumes time and may cause discrepancies between observers (Kurt-Bayrakdar et al., 2021). Models can also be less accurate and real when they possess small naming errors. CBCT scans are inaccurate and riddled with defects since the patient can shift, be out of position, or the device is not functioning consistently. This introduces noise into datasets, which complicates models to be trained (Ezhov et al., 2021). To make AI systems more reliable and consistent, we must employ standardized imaging practices, create datasets with multiple focal points, and develop consensus-based standards for annotations. It is difficult to know what AI models can do with medical images aside from what they were instructed, particularly with the diagnosis of gum disease. Models that are constructed on a specific group of people or imaging technique may not be effective with other groups of people, imaging techniques, or regions of the world (Lakhani et al., 2018). Modifying the CBCT scanner settings, voxel dimensions, and reconstruction techniques is likely to significantly influence image quality and contrast, making it more challenging to divide and label images appropriately (Haas et al., 2018). Model estimates can also be influenced by aspects about the patient, such as variation in anatomy, bone density, and patterns of disease, so the models are not as useful in a wide range of clinical applications (Hung et al., 2022).

Model strength and ability to generalize across populations and imaging devices

A model must be trained on plenty of different types of data that illustrate how demographics, diseases, and imaging conditions vary. It is only then that it can be applied to various situations. Domain adaptation and transfer learning are two additional methods through which models can improve in new domains (Kim et al., 2019). To prevent these problems and ensure diagnostic performance is equivalent in multicultural hospitals, we must collaborate with some hospitals and adopt the same imaging techniques. When AI, in a clinical environment, is used to detect periodontal disease, plenty of legal, ethical, and personal concerns need to be considered. AI systems need a lot of image data from patients, which means that institutions often have to share personal health information.

Privacy, legal, and ethical issues with ai-based diagnosis

As Pesapane et al. (2018) say, it is very important to follow data protection rules like HIPAA and GDPR to keep patients' privacy and trust safe. It is also an ethical issue who to hold responsible and blame when a decision is wrong. The responsibility remains unresolved between the doctor, the software developer, or the health care organization (Lakhani et al., 2018). Further, discriminatory training data, as evidenced by underrepresentation of some groups, may result in discriminatory analytical results, exacerbating health care inequities (Hung et al., 2022). This is why decisions by AI must be explained openly and straightforwardly so that doctors can agree with what the software says (Chartrand et al., 2017).

Issues with the affordability and simplicity of using computers in clinical application

These issues may be mitigated through strict validation, regulatory approval, and ongoing monitoring after deployment. This would promote the ethical and safe application of AI in clinical practice. Clinics do not utilize CBCT scanners with artificial intelligence (AI) frequently since they are costly, require powerful computers, and are difficult to implement into current processes. Deep learning models, particularly those applied to 3D CBCT image classification and segmentation, require plenty of computing power for both training and inference in real-time (Kurt-Bayrakdar et al., 2021). This is particularly the case with dental firms that are not rich. The majority of them lack the high-performance GPUs required to host AI systems. Furthermore, integrating AI technologies into highly prevalent dental imaging software and electronic health record systems may develop technological issues and be very expensive (Pesapane et al., 2018). Something else to consider is that physicians must familiarize themselves with

AI-powered systems, which could be more difficult to acclimate to (Lakhani et al., 2018).

CONCLUSION

The cone-beam computed tomography (CBCT) artificial intelligence (AI) partnership is a step forward in the diagnosis of periodontal diseases. Artificial intelligence has made considerable progress in the last ten years, especially with the use of deep learning models like the convolutional neural network (CNN), U-Net, and nnU-Net for intricate tasks like tooth segmentation, defect identification, and periodontal disease stage categorization (Ezhov et al., 2021; Kurt-Bayrakdar et al., 2025).Artificial intelligence- with CBCT evaluation overcomes the constraints of standard 2D assessment through providing the precise three-dimensional impressions of alveolar bone structure, thereby enhances detection of horizontal and vertical bone loss, furcation lesions, buccal lesions, and perio-endo lesions with proper diagnostic precision (Haas et al., 2018; Braun et al., 2014). These methods normalize diagnoses, reduce the frequency of unexpected observations, and allow doctors to create more personalized treatment plans, resulting in improved outcomes (Kim et al., 2019). Even with these advances, problems like data quality, model generalizability, ethics, and implementation problems prevail that inhibit their large-scale usage. Next-generation research must focus on improving segmentation accuracy for lesions within a region, using multimodal genomic and clinical data, and constructing XAI models to regain physicians' trust (Hung et al., 2022; Pesapane et al., 2018). For AI to be utilized in routine clinical processes, the processes of computing and diagnostic equipment that can perform real-time actions have to be extremely rapid. The AI-based CBCT imaging has the potential to success for periodontal disease diagnosis and treatment with enhanced diagnostic precision, diagnosis easily, and provide customized treatment plan and as technology continues to develop and get integrated into our lives, it will become an a very valuable aid for modern periodontology and the basis of the next generation of data-backed and personalized dental care.

FUTURE RESEARCH DIRECTIONS

Enhancing segmentation accuracy for defect detection in target areas

Humans are resistant to change, and they don't want AI to assist them in decision-making. This complicates things for physicians to utilize. We must develop cloud-based, lightweight AI solutions that align with software developers, regulatory bodies, and physicians to ensure they integrate into clinical processes without issues. Such solutions must also be cost-effective and time-effective. Present AI-assisted CBCT machines are capable of detecting extensive bone loss as well as overall AI models that are trained on general traits have trouble with infra-bony defects, buccal fenestrations, and furcation involvement because they are very small and very specific (Kurt-Bayrakdar et al., 2025). Major categories of defects; however, one major research goal is to improve segmentation accuracy to detect localized and small defects. Infra-bony defects, buccal fenestrations, and furcation involvement tend to be millimeter-sized and highly localized, posing challenges for AI models with training over general attributes (Kurt-Bayrakdar et al., 2025). A recent study has also revealed that application of special preprocessing operations, such as cropping specific regions of interest, significantly enhances detection accuracy, demonstrated by the improvement in AUC scores for infra-bony defects from 0.5613 to 0.7488 and for furcation defects from 0.6780 to 0.8087 after retraining (Kurt-Bayrakdar et al., 2025). Follow-up research must stress the optimization of segmentation networks with complex topologies, like attention U-Nets, with context-aware feature learning and 3D patch-based training methodologies for accurate detection of minute morphological alterations (Schwendicke et al., 2019).

Multimodal data fusion: combining cbct with clinical and genetic data

Besides, incorporating more annotated datasets and the integration of other forms of faults could improve the model in identifying more localized periodontal infections. The merging of CBCT with other imaging techniques will significantly boost the precision of AI systems in diagnosing and predicting the future course of diseases. Periodontal disease is a difficult problem because there are so many different factors involved, including the bacteria present, the individual's genetic make-up, overall health, and the environment. Hence, the AI models would need to be trained according to the individual patient's 3D imaging data along with clinical parameters (such as probing depth and bleeding on probing), microbiological characterizations, and genetic markers to provide more precise and customized diagnostic data (Hung et al., 2022).We can establish how a disease will spread, identify those most susceptible to developing severe periodontitis, and develop treatments effective in each patient with this type of data integration (Chartrand et al., 2017). Most significant is the fact that the integration of CBCT with systemic health information, such as inflammation markers or diabetic status, can greatly assist in the early detection of periodontal disease and its systemic links (Pesapane et al., 2018). Future work will have to focus on developing standardized approaches to merging and processing complex data sets, as well as multimodal neural network architectures for handling large numbers of data sources.

Developing explainable ai (XAI) to enable clinicians to trust it

More models of AI have advanced, but they are all "black boxes" at this point, and it is not easy for the doctors to apply them in the clinic. Doctors' ought to be able to see and understand the mechanism of the models if they are going to be able to diagnose what ails the patient. Explainable AI (XAI) seeks to address this deficiency by enabling comprehensible explanations of model predictions, for example, visual saliency maps that identify the most significant areas in defect classification (Lakhani et al., 2018). XAI can allow doctors to understand how AI systems differentiate between different types of defects, decide how severe a disease is, and suggest a treatment. This makes it easier for doctors to rely more on other doctors and enables them to work together to make decisions more comfortably (Hung et al., 2022). Regulatory bodies now expect explainability of clinical clearance. This means that XAI needs to be designed in such a way that it is safe to use AI systems (Pesapane et al., 2018). Future research should try to incorporate XAI frameworks into current AI workflows for CBCT analysis. Moreover, it is vital that the spotlight be on the research of methods such as visualization of attention and rule-based post-hoc explanations as a means of ensuring transparency while still maintaining high levels of accuracy.

Artificial intelligence-assisted diagnosis using chairside periodontal care in real time

The creation of real-time diagnostic tools that are boosted by artificial intelligence and that can be easily included into healthcare procedures is another promising area of study and development. There is a propensity for AI-enhanced CBCT evaluation to require offline processing and substantial calculation at the present time, which makes its incorporation in chairside settings more difficult (Kurt-Bayrakdar et al., 2025). In the event that cloud computing, edge artificial intelligence technology, and improved computers further develop (Pesapane et al., 2018), it will become less difficult to disassemble photos into their component parts and identify issues during office visits. Real-time feedback for medical practitioners would lead to faster treatment decisions, while patients would have more opportunities to communicate and interact with each other. It is possible to incorporate artificial intelligence devices into portable and intraoral CBCT scanners so that they can continuously monitor the periodontium for any changes. Which enables us to treat diseases on a case-by-case basis and react accordingly (Ezhov et al., 2021). Hardware and software advancements of AI technologies will enable real-time application which helps periodontal therapy be evidence-based and preventive rather than reactive.

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