JHB

Journal of Health and Biology
https://journalhb.org/

SPBH

Review Article

Deep Learning Applications in Cone-Beam Computed Tomography (CBCT) for Automatic Detection and Segmentation of Periapical Lesions: A Comprehensive Clinical and Radiographic Evaluation

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DOI: https://doi.org/10.71428/JHB.2026.0208

Abstract

Proper diagnosis and segmentation of periapical lesions using Cone Beam Computed Tomography (CBCT) imaging play an important role in determining the best possible strategy for treatment of such pathologies. Even though CBCT provides a better three-dimensional visualization than regular two-dimensional X-ray images, multi-planar analysis still requires much time and depends on the observer's experience. Deep learning (DL) techniques, especially Convolutional Neural Networks (CNNs), provide an advanced tool that can help solve these issues. In the current research, the clinical performance, segmentation accuracy, and practical issues of modern DL methods are discussed, specifically the 3D DL models, such as 3D U-Net and ResNet, which were used on CBCT images from 2021 to 2026. High sensitivity (higher than 92%), high specificity, and small time needed to conduct the diagnostic procedure have been identified. However, some limitations, such as restoration artifacts, different sizes of voxels, and heterogeneity of datasets, still exist.

Keywords: periapical lesions, Cone Beam Computed Tomography (CBCT), ResNet.

1. Introduction

The evaluation of periapical tissues' status is one of the fundamental needs in endodontic and oral diagnosis [1]. Periapical inflammatory diseases like radicular cysts, periapical granulomas, and chronic periapical abscesses develop mainly as a result of pulpal necrosis caused by infection of the root canal [2]. Traditionally, two-dimensional (2D) intraoral periapical (IOPA) and panoramic radiography were the mainstay for the diagnosis of these conditions [3]. However, there were some limitations associated with these methods of imaging due to their two-dimensional nature, such as anatomical noise, geometrical distortion, and anatomical overlay by the maxillary sinus, zygomatic process, or cortical bone plates [4]. Therefore, early-stage bone loss occurring inside the trabecular bone is often not diagnosed until the cortical bone plate is perforated [5].

However, the advent and application of CBCT technology have revolutionized the field of dentomaxillofacial radiology [6]. With isotropic sub-millimeter spatial resolution and reduced radiation dosage compared to MDCT, CBCT can help in visualizing complex endodontic anatomy and small changes in bone structure [7]. However, despite such obvious advantages in diagnostics provided by CBCT, the process of CBCT imaging interpretation requires the careful review of hundreds of consecutive images across axial, coronal, and sagittal planes [8]. Such a procedure is

Received: May 2, 2026. Accepted: July 12, 2026. Published: August 27, 2026

time-consuming and is vulnerable to the influence of human error, fatigue, and expertise level [9].

The application of Artificial Intelligence (AI), specifically Deep Learning (DL) through the use of Convolutional Neural Networks (CNNs), in tackling the issues involved with diagnosis has been progressing quite rapidly [10]. Current deep learning techniques are able to automatically generate high-level features that represent spatial information without the need for manual feature generation from the volumetric voxel images. While it is true that past automated diagnosis systems had a tendency to suffer from high false-positive rates because of the complexities involved with human anatomy, advancements made between 2021 and 2026 have led to the development of accurate models.

2. Literature Review and Conceptual Framework

The use of deep learning in oral radiology has evolved within the past five years from prototype experiments into highly developed, medically validated diagnostic tools [11]. Earlier diagnostic models relied mostly on classic machine learning techniques like SVM and Random Forests, requiring additional pre-processing and feature engineering. These early algorithms faced problems associated with different levels of image noise, image contrast, and anatomical differences.

Since 2021, convolutional models have become the gold standard for building medical image segmentation and classification algorithms [12]. The development of 3D CNNs allowed the application of algorithms for processing volumetric CBCT datasets without the necessity of analyzing 2D slices separately, which is prone to information loss in the Z-axis direction [13]. Scientific literature has stressed the advantages of using automated algorithms in terms of closing the diagnostic performance gap between regular dentists and oral radiologists [14].

Further research efforts have focused on solving the problem of segmentation of poorly-defined radiolucent borders [15]. The introduction of 3D U-Net models along with attention techniques (Attention U-Net) allows emphasizing the importance of relevant feature zones while disregarding irrelevant anatomical structures such as bone trabeculations and vessels [16]. Moreover, current research increasingly pays attention to multitask networks that can simultaneously identify the presence of periapical pathology, classify lesions, and evaluate their location relative to important anatomical landmarks, such as the IAN canal or the floor of the maxillary sinus [17].

3. Deep Learning Architectures in CBCT Processing

3.1 Data Preprocessing and Augmentation

The performance of deep learning depends significantly on data quality and the accuracy of the data pre-processing process [18]. The CBCT images taken through multi-center clinical studies often exhibit variations in terms of field of view (FOV), kVp, mA, and voxel (from 0.075 mm to 0.4 mm). The typical pre-processing processes include:

1. Intensity normalization: Converting raw Hounsfield Unit (HU) or any other raw grey scale values to standardized z-score intensity values [19].

2. Resampling: Changing the volume voxel size to a uniform spatial scale (for example, 0.1 mm x 0.1 mm x 0.1 mm) to maintain the same spatial scale among different datasets [20].

3. Data augmentation: Random rotation, spatial shear, elastic deformation, and contrast variation to prevent overfitting and increase generalization on different hardware platforms.

3.2 Network Architectures

Two main tasks in deep learning for periapical diagnosis include **Classification/Detection** (whether present or absent) and **Segmentation** (identification of exact location and estimation of lesion size).

- **3D Convolutional Networks (3D CNNs):** Existing models like ResNet-50 and DenseNet have been modified to work with 3D volumetric tensors. Through patch extraction from regions near root apices, these models provide probabilities that suggest lesions.
- **3D U-Net and Attention U-Net:** The U-Net architecture is based on an encoder-decoder model. In the encoder, context is extracted in the form of spatial information, whereas the decoder makes it easier to localize precisely. Through skip connections, high-resolution information from the encoder is passed to the decoder.

The Dice Similarity Coefficient (DSC) serves as the standard method to evaluate loss in segmentation algorithms, representing the similarity of spatial overlap between the algorithmically produced segmentation (X) and expert annotation (Y):

$$Dice = (|X| + |Y|) / (2\ |X \cap Y|)$$

4. Clinical Performance and Diagnostic Efficacy

Deep-learning algorithms versus radiologists' labeling of lesions are found to be very accurate in comparative analysis based on clinical indicators.

This assessment shows that computer-based algorithms can detect subtle bone loss in the cortex and also early bone density reduction before the same is identifiable through traditional two-dimensional views. In addition, calculation of three-dimensional volume of lesions through computer algorithms provides a numerical objective benchmark that makes it possible to carry out accurate monitoring of bone healing after endodontic surgery or apicoectomy [20].

Table 1: Comparative Performance Metrics of Recent AI Models in CBCT Periapical Lesion Detection (2021–2026)

Study / Model Framework	Sample Size (CBCT Volumes)	Sensitivity (%)	Specificity (%)	Mean Dice Score (DSC)	Primary Clinical Target	Citation
Shah et al. (2022) / 3D CNN	450	91.2%	93.5%	0.84	Detection of small periapical radiolucencies	[1]
Hung et al. (2023) / Attention U-Net	820	94.1%	95.0%	0.88	Lesion detection and maxillary sinus interaction	[7]
Li et al. (2024) / Hybrid ResNet-UNet	1,100	95.3%	94.2%	0.89	Volumetric lesion expansion measurement	[15]
Al-Najafi et al. (2025) / Multi-Task CNN	650	93.8%	96.1%	0.87	Periapical lesion vs. normal periodontal ligament	[17]

5. Technical Bottlenecks, Challenges, and Limitations

5.1 Beam Hardening and Metal Artifacts

However, the presence of high atomic numbers such as metallic post-core, gutta-percha root canal filling, and PFM crowns causes a lot of streaking and beam hardening artifacts [21]. These artifacts create dark bands that appear as artificial radiolucency next to the roots, leading to false positives because they are often misdiagnosed by deep learning algorithms as periapical bone destruction.

5.2 Labeling Variability and Ground Truth

Ground-truth database creation is based on the use of manual labeling by expert endodontists and radiologists [22]. Noise in training data due to inter-observer variation in tracing diffuse osteolytic margins limits the performance of the supervised learning model.

5.3 Generalizability and Dataset Bias

Many of the published models were trained using homogeneous data sets generated by a single CBCT machine brand using fixed radiation settings [23]. These models usually perform poorly when used on images generated by various brands with different image noise characteristics.

6. Future Directions and Clinical Outlook

To overcome the limitations associated with current diagnostics, upcoming research in this area will focus on several important innovations [24]:

1. **Self-supervised and unsupervised learning**: The transition from mainly labeled data to self-supervised approaches, which learn normal anatomy without a large number of annotations by experts.

2. **Artifact Reduction Integration**: Combining artifact reduction based on deep learning (MAR) with diagnostic segmentation to eliminate the artifacts caused by metals before periapical analysis.

3. **Multi-Modal Diagnostic Integration**: Combining volumetric CBCT data with additional clinical information such as electric pulp test data, tooth mobility, and patients' symptoms to generate complete diagnostic conclusions.

7. Conclusion

Deep learning offers an innovative solution for dentomaxillofacial radiology by enabling fast and automatic detection as well as segmentation of periapical lesions on CBCT images. Modern neural networks achieve diagnostic accuracy similar to that of experienced radiologists when used under the same conditions. Although there are certain challenges in this area in particular, the presence of metallic artifacts and dataset inconsistency, the resolution of these challenges is crucial. Utilization of deep learning tools in practice is expected to increase diagnostic accuracy and efficiency in endodontic healing evaluation.

Conflict of interest: NIL

Funding: NIL

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