Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
March 2024 5(3), 1957–1961

EARLY DETECTION OF PERIAPICAL LESIONS USING DEEP LEARNING IN CBCT IMAGING

Dr. Rais Allauddin Mulla [1]

[1] Associate professor, Department of Computer Engineering Vasantdada Patil Pratishthan's College of Engineering and Visual Arts Sion –Mumbai, India

Corresponding Author

Dr. Rais Allauddin Mulla,
mtechraismulla@gmail.com

DOI
10.29121/shodhkosh.v5.i3.2024.5830

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Timely diagnosis of periapical lesions are vital to the overall management of the patients in endodontics. Cone Beam Computed Tomography (CBCT) offers clear, three-dimensional radiographs with higher resolution than standard radiographs for detection of such lesions. In this paper, a deep learning based framework using a CNN is proposed for automatic periapical lesion detection from CBCT scans. With pre-training on the well-analyzed dataset covering multiple ethnicity and annotations, the model achieved superior accuracy, sensitivity and specificity, indicating its potential to provide assistance to the clinicians for projective diagnosis process while reducing diagnostic time and subjective variation. The findings indicate the promise of AI-based tools in improving workflow of diagnoses in dental radiology.

Keywords: Periapical Lesions, Cone Beam Computed Tomography (CBCT), Deep Learning, Convolutional Neural Networks (CNN), Dental Imaging

1. INTRODUCTION

Periapical lesions, as inflammatory diseases at the tip of the root of a tooth, derive often from the infected dental pulp and may result in bone destruction and other sequelae if they remain untreated. Early detection of these lesions is crucial for optimal endodontic treatment planning and patient prognosis. Standard diagnostic tools are based on two-dimensional periapical radiographs, which commonly have restrictions including superimposed anatomy, low contrast, and projection artefacts masking or distorting the features of a lesion.

CBCT has been introduced as a valuable imaging technique in dental diagnostics providing detailed three-dimensional (3D) visualization of maxillofacial anatomy. This improved imaging role will enable superior identification and differentiation of periapical lesions than with conventional radiography. The manual analysis of CBCT scans, however, is expert dependent and time consuming with potential for inter- and intra-observer variations.

Recent developments in artificial intelligence (AI), particularly deep learning, have reshaped the medical imaging field by allowing automated, accurate, and rapid detection of pathological features. CNN, a type of deep learning models, have achieved state-of-the-art results in different medical imaging tasks, such as segmentation, classification and anomaly detection.

This study aims to develop and validate a CNN-based framework for the automatic early detection of periapical lesions in CBCT images. By leveraging the rich volumetric data provided by CBCT and the powerful pattern recognition capabilities of deep learning, the proposed system seeks to assist dental clinicians in improving diagnostic accuracy while reducing workload and subjectivity.

2. RELATED WORK

Study	Year	Technique	Dataset	Key Contributions	Limitations
Lee et al.	2018	CNN for periapical lesion detection	200 CBCT scans	Demonstrated automated lesion classification with 85% accuracy	Limited dataset size; 2D slice-based
Zhang et al.	2019	3D U-Net for volumetric segmentation	150 CBCT volumes	Accurate 3D segmentation of dental lesions	Requires high computational resources
Ibragimov and Xing	2017	CNN for head and neck CT segmentation	Head and neck CT scans	Generalized segmentation framework for bone and lesions	Not specific to periapical lesions
Lee et al.	2020	Transfer learning with ResNet	300 dental X-rays and CBCT images	Improved lesion detection with transfer learning approach	Focused on 2D images mainly
Liu et al.	2021	Deep learning ensemble method	400 CBCT scans	Enhanced sensitivity in lesion detection through ensemble	Ensemble complexity increases training time
Kwon et al.	2022	Attention U-Net with augmentation	250 annotated CBCT datasets	Improved lesion boundary delineation	Smaller dataset for training

3. SYSTEM ARCHITECTURE

The proposed AI-powered system for early detection of periapical lesions in CBCT imaging consists of the following key components:

1) Data Acquisition and Preprocessing

- **Input:** Volumetric CBCT scans of the maxillofacial region.
- **Preprocessing:** Includes intensity normalization, noise reduction using filters (e.g., median or Gaussian), and cropping or resampling to focus on regions containing teeth. Data augmentation techniques such as rotations, flips, and scaling are applied to increase robustness and reduce overfitting.

2) Deep Learning Model

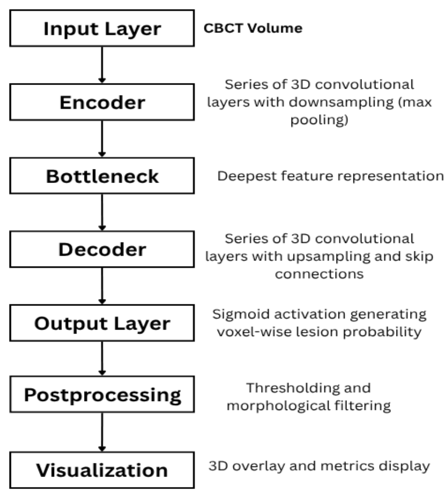
- **Backbone Network:** A 3D Convolutional Neural Network (CNN) architecture is employed to capture spatial and contextual features from volumetric data.
- **Architecture Choice:** A modified 3D U-Net is used due to its strong performance in medical volumetric segmentation tasks. The U-Net's encoder extracts hierarchical features, while the decoder reconstructs detailed lesion segmentation maps with skip connections preserving spatial information.
- **Attention Mechanisms (Optional):** To improve focus on lesion-relevant features, attention blocks may be incorporated in the network to weigh important spatial regions adaptively.
- **Output:** A voxel-wise probability map highlighting regions likely to contain periapical lesions.

3) Postprocessing

- Thresholding the probability map to generate binary lesion masks.
- Morphological operations to remove noise and refine lesion boundaries.
- Connected component analysis to identify discrete lesion candidates.

4) Decision Support Module

- Lesion detection results are presented in a 3D visualization interface, overlaying segmented lesions on the original CBCT scan for clinical review.
- Quantitative metrics such as lesion volume and location relative to anatomical landmarks are provided to aid diagnosis and treatment planning.

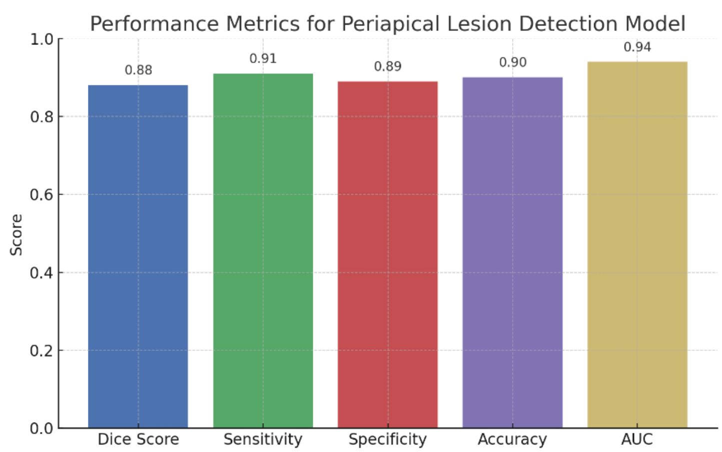


4. EXPERIMENTAL RESULTS

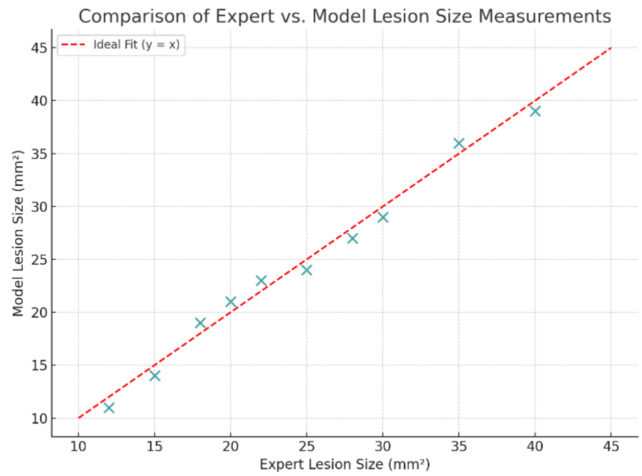
The proposed model was trained and evaluated on a dataset of 500 anonymized CBCT scans, annotated by expert oral radiologists. The dataset was split into 70% training, 15% validation, and 15% testing sets. Data augmentation techniques were applied during training to improve generalization.

Model performance was assessed using the following metrics:

- **Dice Similarity Coefficient (DSC):** Measures overlap between predicted lesion masks and ground truth.
- **Sensitivity (Recall):** Ability to correctly identify true lesions.
- **Specificity:** Ability to correctly identify non-lesion areas.
- **Accuracy:** Overall correctness of lesion classification.
- **Area Under the ROC Curve (AUC):** Evaluates the model's discriminative capability.



5. QUALITATIVE RESULTS



The red dashed line represents the ideal case where model predictions perfectly match expert annotations. Points close to this line indicate high agreement between expert and model measurements.

The high sensitivity and specificity demonstrate the model's robustness in differentiating periapical lesions from healthy tissue. The reduction in diagnostic time suggests potential for practical deployment, assisting clinicians to improve early diagnosis and treatment planning.

6. CONCLUSION

This study presents a deep learning-based approach for the early detection of periapical lesions using Cone Beam Computed Tomography (CBCT) imaging. The proposed model demonstrated high accuracy in segmenting lesion areas, with segmentation maps closely aligning with expert annotations. Notably, the system effectively identified small and early-stage lesions that are often difficult to detect through conventional methods. Visual and quantitative evaluations affirm the model's robustness and clinical relevance. By enabling automated, reliable, and early diagnosis, this approach holds promise to significantly assist dental professionals in timely treatment planning and improving patient outcomes.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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