A Deep Learning Approach for Detecting Periapical Lesions on Panoramic Radiographic Images

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ABSTRACT

Objective: To assess the performance of a deep learning method for detecting the segmentation of periapical lesions on dental panoramic radiographs.
Study Design: Observational study.
Place and Duration of the Study: Faculty of Dentistry, Van Yuzuncu Yil University, Van, Turkiye, from March to September 2024.
Methodology: The deep learning model, YOLOv5, based on the YOLO algorithm for periapical lesion segmentation, was further developed using 1,500 anonymised panoramic radiographs. The radiographs were obtained from the Radiology Archive at the aforementioned University. For apical lesion segmentation, YOLOv5 with the PyTorch model was utilised. The dataset was divided into training (n = 1,200 radiographs / 2,628 labels), validation (150 radiographs / 325 labels), and test (n = 150 radiographs / 368 labels) sets. The model's effectiveness was measured using the confusion matrix. Sensitivity (recall), precision, and F1 scores provided quantitative assessments of the model's predictive capabilities.
Results: The sensitivity, precision, and F1 score performance values of the YOLOv5 deep learning algorithm were 0.682, 0.784, and 0.729, respectively.
Conclusion: Periapical lesions on panoramic radiography can be reliably identified using deep learning algorithms. Dental healthcare is being revolutionised by artificial intelligence and deep learning methods, which are advantageous to both the system and practitioners. While the current YOLO-based system yields encouraging findings, additional data should be gathered in future research to improve detection outcomes.

Key Words: *Panoramic radiography, Periapical pathology, Deep learning, Artificial intelligence, Lesion segmentation, YOLOv5*.

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INTRODUCTION

Artificial intelligence (AI) refers to the use of computers and machines to carry out tasks such as problem-solving, recognising words and objects, and making decisions. In recent years, deep learning systems—a specialised branch of AI—have gained significant popularity and are considered highly promising.[1-10] In dentistry, AI, deep learning, and convolutional neural networks (CNNs) are widely applied across various domains, including orthodontic treatment, dental implant design, caries detection, and the diagnosis of oral mucosal diseases.[7]

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The single-stage deep learning method, known as YOLO, detects objects using CNNs.[11,12] In contrast to previous algorithms that use the complete image to identify objects, YOLO divide the image into sections and creates boxes containing objects in each section. The primary distinction between the YOLOv5 model and other YOLO versions lies in its development of library. On custom datasets, YOLOv5 makes inference and training incredibly simple and efficient. It offers quick training with a ready-made dataset in an appropriate format. In essence, it creates a single image by combining four distinct images, allowing the model to learn how to handle challenging and varied images.[11]

Panoramic radiograph is an imaging technique used to visualise the teeth in the upper and lower jaw and the supporting tissues surrounding the teeth. It is frequently used in dental imaging because of its advantages, such as providing a general idea about the jaws and surrounding tissues, relatively low radiation exposure, and fast and easy patient co-operation.[2,8,13]

An acute or persistent inflammatory lesion at the root tip of tooth caused by a polymicrobial infection of the pulp tissue within the root canal system is known as apical periodontitis (AP).[14,15] It usually occurs as a result of deep caries, restoration, or fracture of the tooth. AP can be cured by root canal treatment. However, even in cases where the infection is controlled, inflammation may persist, and the disease may recur.[14]

AI applications in dentistry, particularly in imaging, are fascinating and long-lasting.[2,7] Current investigations include applications such as automatic labelling of anatomical components, detection of dental and gingival disorders, and classification and segmentation of teeth on two- and three-dimensional radiological images.[14] According to the literature, AI has also been used to diagnose a number of disorders affecting the oral mucosa and to facilitate the early screening of oral cancer and cervical lymph node metastases.[5,7,9]

The existing literature includes limited number of studies employing various deep learning algorithms and methods for detecting periapical lesions.[16-18] For instance, Bayrakdar *et al*. developed a segmentation model using the U-Net architecture on panoramic radiographs, successfully identifying 63 apical lesions in 47 radiographs from the test dataset.[18] Notably, there are no prior studies have utilised the YOLOv5 algorithm for this purpose. The study aimed to fill this gap by applying a deep learning approach to detect periapical lesions on panoramic radiographs, thereby contributing significantly to the existing body of literature. It was hypothesised that the deep learning approach could diagnose periapical lesions on panoramic radiographs with an accuracy comparable to that of physicians.

METHODOLOGY

The study was conducted in the Faculty of Dentistry, Van Yuzuncu Yil University, Van, Turkiye, over a seven-month period, from March to September 2024. The inclusion criteria of the study involved orthopantomography (OPTG) images of 1,500 patients aged ≤18 years or older, each with at least 8 existing teeth and with periapical lesions in at least one of these teeth. The number of panoramic radiographs was increased due to the adequate evaluation time available during the project and the increase in success parameters. Individuals under 18 years of age, as well as panoramic radiographs that did not include periapical lesions or were of suboptimal quality, were excluded from the study. All images were obtained from the Radiology Archive of Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Van Yuzuncu Yil University. The usage parameters of the OPTG device (Sirona, Dentsply, Germany) were 60kV, 4mA, and 8 seconds.

The panoramic radiography images included in this study were anonymised to remove all personal information and uploaded to CranioCatch software (Eskisehir/Turkiye) to create the project. The evaluation of the obtained data with the artificial intelligence application and the development of the models were conducted by the CranioCatch software company. A dental student (MYP), who had previously undergone segmentation training to identify periapical lesions, along with two of the authors (HY and AGOT), labelled the patient images using the CranioCatch programme (CranioCatch, Eskisehir, Turkey). Two oral and maxillofacial radiologists (FMNP and GK) examined the labelled periapical lesions.

The dataset was partitioned into three subsets to avoid reusing training images during evaluation: 80% for training, 10% for validation, and 10% for testing. The training set (80%) was used to train the model and comprised the majority of the dataset. The validation set (10%) consisted of images excluded from the training process and was served to evaluate the model during training, helping to determine whether to stop training early or to adjust hyperparameters. The test set (10%) was an independent subset used to evaluate the final performance of the trained model and to compare it with both training and validation results.

The model's effectiveness was measured using the confusion matrix, which summarises real acute and projected circumstances. To evaluate AI model's effectiveness, the true positive (TP), false positive (FP), and false negative (FN) rates were first computed.[19]

TP represented the number of samples correctly identified as positive, FP represented the number of samples incorrectly identified as positive, and FN represented the number of samples incorrectly identified as negative. These TP, FP, and FN values were then used to calculate sensitivity (recall), precision, and F1 score as follows: TP/(TP+FN), TP/(TP+FP), and 2×TP/(2×TP+ FP+FN), respectively.

RESULTS

The YOLOv5 algorithm was used to detect periapical lesions in panoramic radiography using the test dataset (Figure 1). The calculated TP, FP, and FN values were 251, 69 and 117 in 150 test images, including 417 labels, respectively.

As shown in Table I, the corresponding sensitivity, precision, and F1 score were 0.682 (68.2%), 0.784 (78.4%), and 0.729 (72.9%), respectively.

Table I: Precision, sensitivity and F1 scores of the deep learning algorithm.

Measures	Values
Sensitivity (recall)	0.682
Precision	0.784
F1 score	0.729

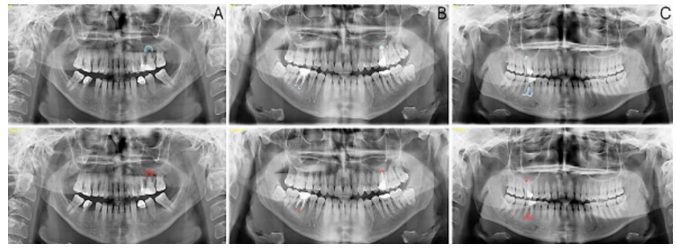

Figure 1: Segmenting the periapical lesions using the YOLOv5 algorithm gives predictions that are impressively close to reality. (The upper row represents ground truth segmentations (manual), and the lower row shows predictions by the YOLOv5 model. Red indicates predicted regions; blue indicates ground truth).

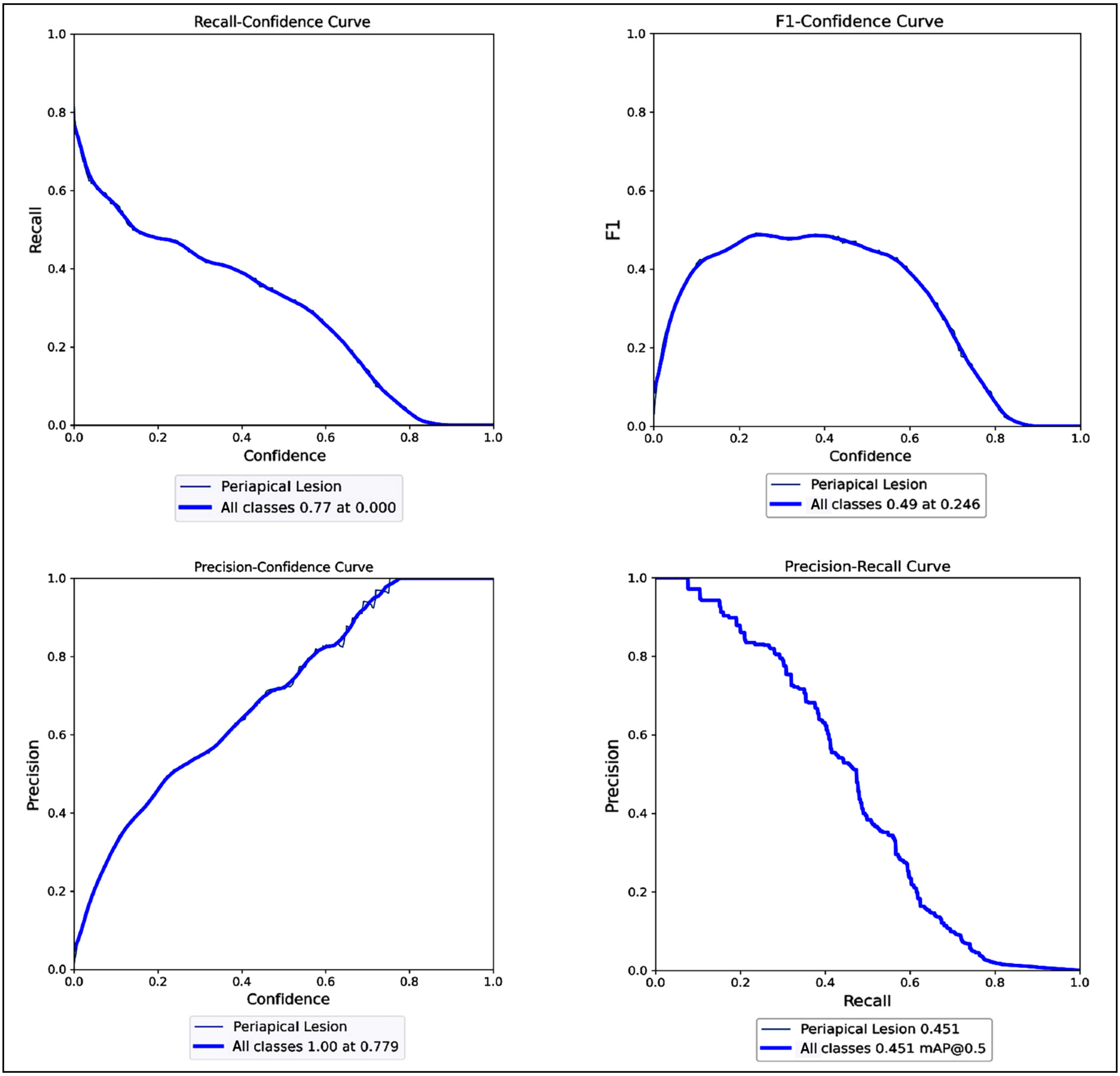

Figure 2: A performance graph of the YOLOv5-based AI model that includes the precision, recall, F1-confidence and Precision-recall curves.

Figure 2 presents the performance graphs for the YOLOv5-based AI model, including the recall-confidence, precision-confidence, F1-confidence, and precision-recall curves. The recall-confidence curve illustrates the model's recall score at varying confidence levels, with the highest recall score of 0.77 achieved at its peak confidence level. The precision-confidence performance graph demonstrates that precision improves as confidence levels increase, reaching a precision of 1.00 at a confidence level of 0.77.

DISCUSSION

Using the CNNs and deep learning models, AI has rapidly enhanced the interpretation of radiographic images. According to the literature, there are only a limited number of studies that have used artificial intelligence and deep learning approaches to periapical lesion detection.[16-18] Ekert *et al*. explored the potential of deep CNN algorithms to detect periapical lesions in panoramic radiographs.[16] Their study demonstrated that CNNs could successfully identify and detect periapical lesions, even with a limited dataset.

Endres *et al*. developed a model using 2,902 de-identified panoramic radiographs. Periapical radiolucencies were assessed on panoramic radiographs by twenty-four oral and maxillofacial surgeons. The deep learning algorithm outperforms 14 out of 24 oral and maxillofacial physicians, according to their findings. The scores of precision and F1 of the deep learning algorithm were 0.60 and 0.58, respectively.[17] The results of the present investigation, however, showed higher performance value scores.

Bayrakdar *et al*. evaluated the effectiveness of a deep convolutional neural network (D-CNN) model in detecting periapical lesions on panoramic radiographs. The D-CNN model, which was based on the U-Net algorithm, was improved using 470 panoramic radiographs. Apical lesion segmentation was performed with the U-Net architecture. In the test dataset, the AI model identified 47 panoramic radiographs containing sixty-three periapical lesions. The U-Net algorithm achieved precision, sensitivity, and F1-scores of 0.92, 0.84, and 0.88, respectively.[18]

The findings demonstrated the potential of AI deep learning systems for clinical dentistry settings. The current study did have a few limitations; however, image acquisition was performed using standard parameters and a single radiographic device. Future research should consider larger sample sizes and incorporate images from multiple radiographic systems to enhance generalisability. Different CNNs should be used in comparative tests, and the performance of AI models should be evaluated against that of various human observers with varying degrees of professional experience.

CONCLUSION

Time-consuming clinical issues may be resolved by AI systems. The assessment of periapical disease using panoramic radiographs may be facilitated by AI. Deep learning AI models allow the assessment of periapical disease on panoramic radiographs. Furthermore, clinicians' workload may be reduced through the use of AI for apical lesion detection and segmentation.

DISCLOSURE:
This study was presented on May 14, 2025, at the Istanbul University-Cerrahpasa Faculty of Dentistry Student Symposium and received the first prize in the poster presentation category.

ETHICAL APPROVAL:
Ethical approval was obtained from Van Yuzuncu Yil University Non-Invasive Clinical Research Ethics Committee (Approval No. 2023/06-24/ dated: 16.06.2023).

PATIENTS' CONSENT:
Due to the retrospective nature of the study, the requirement for patients' informed consent was waived according to the decision of the Ethics Committee.

COMPETING INTEREST:
The authors declared no conflict of interest.

AUTHORS' CONTRIBUTION:
MYP: Conceptualisation, data curation, and manuscript writing.
HY: Manuscript writing.
AGOT: Data curation.
GK: Conceptualisation, methodology, writing of the original draft, and preparation.
FNP: Conceptualisation, reviewing, editing, and supervision.
ISB: Software and statistical analysis.
All authors approved the final version of the manuscript to be published.

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