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Detection of Periapical Lesions on Panoramic Radiographs Using Artificial Intelligence

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Research Article

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ABSTRACT

Objectives: This study aimed to compare the performance of two deep learning models, YOLOv8 and Cascade Mask R-CNN, for the artificial intelligence-assisted automatic detection of periapical lesions in dental panoramic radiographs.

Materials and Methods: A total of 1861 panoramic radiographs were reviewed, and 602 images containing periapical lesions were included in the study. In these radiographs, a total of 1059 lesions were identified. Observer agreement for lesion detection was evaluated using Kappa analysis. The included radiographs were divided into three datasets: training (70%), validation (20%), and testing (10%). The YOLOv8 and Cascade Mask R-CNN models were trained using the PyTorch library. The trained models were then applied to the test dataset, and true positive, false positive, true negative, and false negative outcomes were recorded for periapical lesion detection. Based on these outcomes, accuracy, sensitivity, specificity, precision, and F1 score were calculated for each model.

Results: In the test set comprising 60 panoramic radiographs, a total of 1,707 teeth were present, and apical lesions were found in 101 of these teeth. On this dataset, the YOLOv8 model achieved 96.9% accuracy, 53.5% sensitivity, 90% precision, and an F1 score of 0.671, whereas the Cascade Mask R-CNN model achieved 97.6% accuracy, 76.2% sensitivity, 81.9% precision, and an F1 score of 0.790. The predominance of healthy teeth in the dataset influenced the overall results. Despite the high overall accuracy, sensitivity varied significantly between the models. Although YOLOv8 produced fewer false positives, it failed to detect a considerable number of lesions. In contrast, Cascade Mask R-CNN detected more lesions but generated relatively more false positives.

Conclusions: Artificial intelligence models demonstrated potential as supportive tools in clinical decision support systems based on their accuracy rates. However, the current sensitivity levels were insufficient to reliably undertake diagnostic responsibilities alone, suggesting that these models should not yet be used independently for clinical decision-making.

Keywords: Artificial intelligence, panoramic radiography, periapical periodontitis

Panoramik Radyograflar Üzerinden Yapay Zekâ Destekli Periapikal Lezyon Teşhisi

Araştırma Makalesi

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ÖZ

Amaç: Bu çalışmada, dental panoramik radyografilerde periapikal lezyonların yapay zekâ destekli otomatik tespiti amacıyla iki farklı derin öğrenme modeli olan YOLOv8 ve Cascade Mask R-CNN'nin performansları karşılaştırılmıştır.

Gereç ve Yöntemler: Toplamda 1861 panoramik radyografi incelenmiş ve periapikal lezyon barındıran 602 görüntü çalışma kapsamına alınmıştır. Bu radyograflarda toplamda 1059 lezyonun bulunduğu belirlenmiştir. Lezyon tespiti için gözlemciler arası uyum Kappa analizi ile değerlendirilmiştir. Çalışmaya dahil edilen radyograflar, eğitim (%70), doğrulama (%20) ve test (%10) olmak üzere üç veri setine ayrılmıştır. YOLOv8 ve Cascade Mask R-CNN yapay zeka modelleri PyTorch kütüphanesi kullanılarak eğitilmiştir. Eğitilen modeller test veri setine uygulanmış ve periapikal lezyonlar için gerçek pozitif, yanlış pozitif, gerçek negatif ve yanlış negatif durumları tespit edilmiştir. Bu bulgular üzerinden ise modellere ait doğruluk, duyarlılık, özgüllük, kesinlik ve F1 skoru hesaplanmıştır.

Bulgular: Test veri setinde YOLOv8 modeli %96,9 doğruluk, %53,5 duyarlılık, %90 kesinlik ve 0,671 F1 skoru sunarken; Cascade Mask R-CNN modeli %97,6 doğruluk, %76,2 duyarlılık, %81,9 kesinlik ve 0,790 F1 skoruna ulaşmıştır. YOLOv8 daha az yanlış pozitif üretse de yüksek sayıda lezyonu gözden kaçırmıştır. Cascade Mask R-CNN ise daha fazla lezyonu tespit edebilmiş, ancak nispeten daha fazla yanlış pozitif üretmiştir.

Sonuçlar: Yapay zeka modelleri, doğruluk oranları dikkate alındığında klinik karar destek sistemlerinde yardımcı araçlar olarak potansiyel taşımaktadır. Ancak mevcut duyarlılık oranlarının tanı sürecini güvenle üstlenebilecek düzeyde olmadığı, bu nedenle bu modellerin tek başlarına klinik karar aracı olarak kullanılmaması gerektiği sonucuna varılmıştır.

Anahtar Kelimeler: Yapay zeka, panoramik radyografi, periapikal periodontit

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Introduction

Periapical lesions are pathological conditions that typically develop around the tooth root, mostly as a result of endodontic infections.[1] During this process, structural changes occur in the periapical bone, leading to the formation of characteristic radiolucent areas detectable through radiographic imaging. However, for a periapical lesion to be radiographically identifiable, alveolar bone loss must extend to involve the cortical bone.[2,3] This indicates that unless resorption reaches the cortical plate, the development of a periapical lesion cannot be visualized radiographically.[4] Various imaging modalities, including panoramic radiography, periapical radiography, and cone-beam computed tomography (CBCT), are used for the detection of periapical lesions.[5] CBCT is frequently considered the reference standard for diagnosing periapical lesions. Compared to CBCT, the reported diagnostic accuracies are approximately 71% for periapical radiographs and 66% for panoramic radiographs.[6] Nevertheless, panoramic radiographs remain widely used in dental practice for routine screening and diagnostic purposes, owing to their ability to capture a broad anatomical area in a single exposure and their relatively low radiation dose.

In recent years, the use of artificial intelligence (AI) and deep learning techniques in medical imaging has enabled the automatic detection of pathologies in panoramic radiographs. Artificial neural networks, a subset of deep learning, are capable of recognizing complex patterns in images in a human-like manner after being trained on large datasets. In this field, Convolutional Neural Networks (CNNs) are particularly widely used for object recognition and classification tasks in medical imaging. Reflecting this trend, a growing number of studies have recently focused on incorporating AI technologies into the field of endodontics.[7,8]

The aim of this study was to evaluate the feasibility of automatically detecting periapical lesions on dental panoramic radiographs using artificial intelligence and to discuss its clinical applicability. For this purpose, the performances of two AI models, YOLOv8 and Cascade Mask R-CNN, were compared. YOLOv8 is a recently developed one-stage deep learning model that offers high speed and accuracy, making it suitable for real-time applications. In contrast, Cascade Mask R-CNN is an advanced two-stage model that aims to achieve more precise detection by refining the detection and segmentation steps in a cascaded manner. Both models were trained on the same panoramic radiographic dataset, and their performances in detecting periapical lesions were compared. Our hypothesis is that image processing artificial intelligence models can be utilized for the diagnosis of apical lesions.

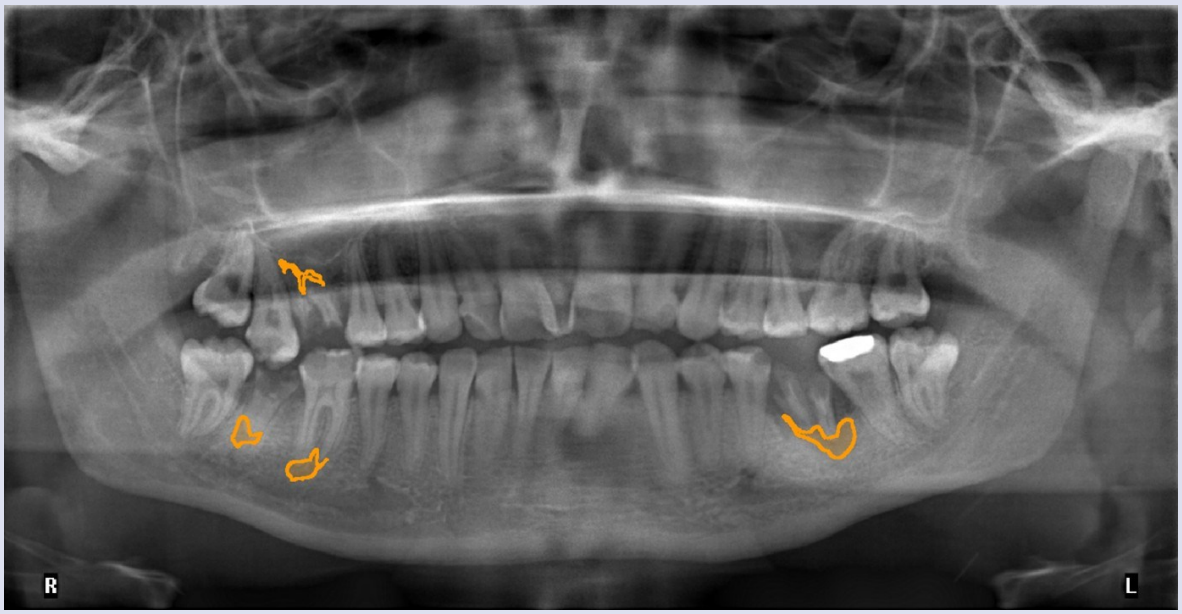


Figure 1. Segmentation of detected periapical lesions on a panoramic radiograph from the training dataset.

Materials and Methods

This study was conducted with the approval of the Ethics Committee of Karamanoğlu Mehmetbey University Faculty of Medicine (Approval No: 09-2024/01). A total of 1861 digital panoramic radiographs obtained from Karamanoğlu Mehmetbey University Faculty of Dentistry, Karaman Oral and Dental Health Center, and the Zenodo database (https://doi.org/10.5281/zenodo.4457647) were reviewed. The use of panoramic radiographs acquired from different populations, captured with various imaging devices, and including both permanent and mixed dentitions was anticipated to enhance the generalizability of the developed model and to contribute to obtaining more reliable results for real clinical applications.

Following the radiographic evaluation by a specialist dentist, periapical lesion findings were detected in 602 of

the 1861 panoramic images. A total of 1059 periapical lesions were identified in these images. During the differential diagnosis, particular attention was paid to exclude cysts (e.g., nasopalatine, lateral periodontal, odontogenic keratocysts), periodontal ligament widening due to orthodontic forces or trauma, radiolucencies associated with developing or erupting tooth germs, and the mental foramen. The identified lesions were annotated using a masking method with careful delineation of lesion boundaries, as illustrated in Figure 1.

To assess the reliability of the lesion annotations, a second independent specialist dentist was consulted. A 10% random sample of the included panoramic images was re-evaluated, and interobserver agreement was assessed using the Kappa coefficient calculated with SPSS software (IBM, Armonk, NY).

Data augmentation techniques were not applied. The original 602 panoramic images were randomly divided into three subsets: 70% (422 images) for model training, 20% (120 images) for validation, and the remaining 10% (60 images) for final testing. The first model compared in this study was YOLOv8. Although the YOLO (You Only Look Once) architecture has undergone continuous development, its eighth version has become widely used in the literature and was therefore selected for this study. The second model, Cascade Mask R-CNN, is a cascaded version of the Mask R-CNN model; in this study, a more recent version employing the ConvNeXt architecture instead of the traditional ResNet backbone was preferred. Training of both models was performed using the PyTorch deep learning framework on an NVIDIA A100 80GB GPU. During this process, fine-tuning was applied to the pre-trained model weights using the prepared dataset to enable the recognition of periapical lesions. Hyperparameters such as learning rate, batch size, and the number of iterations were optimized based on validation set performance. For the Cascade Mask R-CNN, the batch size was set to 2 with a learning rate of 0.0001, whereas for YOLOv8, the batch size was set to 7 and the learning rate was set to auto. Both models were trained for 100 epochs. The model weights from the epoch achieving the highest accuracy on the validation dataset were saved and subsequently used for the evaluation on the test set.

In the 60 radiographs reserved for testing, a total of 1707 teeth were present, among which 101 teeth exhibited apical lesions. The models' performance in detecting periapical lesions was evaluated using metrics calculated from the confusion matrix. In this context; True Positive (TP) refers to a situation where a lesion at the apex of a tooth root is correctly detected. False Positive (FP) refers to a situation where the model incorrectly identifies the presence of a lesion in any area of the panoramic radiograph where no lesion exists. False Negative (FN) refers to a situation where an existing lesion at the apex of a tooth root is not detected by the model. True Negative (TN) refers to a situation in which a tooth does not have an apical lesion, and the model correctly refrains from making a positive prediction for that tooth.

Using these values, performance metrics were calculated. The most fundamental performance indicator, accuracy, represents the proportion of correct decisions made by the model across all cases and is calculated as (TP+TN)/(TP+FP+FN+TN). Recall (sensitivity) measures the proportion of actual lesions correctly identified by the model and is calculated as TP/(TP+FN). Specificity indicates the proportion of non-lesion areas correctly classified as negative and is calculated as TN/(TN+FP). Precision (positive predictive value) measures how many of the lesions detected by the model actually correspond to true lesions and is calculated as TP/(TP+FP). Finally, the F1-score is the harmonic mean of precision and recall, calculated as 2*(Precision * Recall)/(Precision + Recall). The F1-score provides an overall measure of model performance and is often preferred when comparing artificial intelligence models.

Table 1. Performance metrics of the tested artificial intelligence models

Model	TP	FP	FN	TN	Accuracy	Recall	Specificity	Precision	F1 score
YOLOv8	54	6	47	1600	96.9%	53.5%	99.6%	90.0%	0.671
Cascade Mask R-CNN	77	17	24	1589	97.6%	76.2%	98.9%	81.9%	0.790

Results

To assess the consistency of lesion detection among observers, a Kappa analysis was performed, yielding a Kappa coefficient of 0.71. According to the classification by Landis and Koch, this value indicates a "substantial agreement".[9]

Following the training and validation processes, the performances of both models were compared on the test dataset. During the testing phase, detection results were evaluated by comparing model predictions with the ground truth annotations across 60 panoramic radiographs. Of the 101 periapical lesions present in these radiographs, the YOLOv8 model correctly detected 54 lesions but missed 47. In contrast, the Cascade Mask R-CNN model correctly identified 77 lesions while missing 24.

In terms of false positive findings, the YOLOv8 model produced 6 false positives (i.e., areas incorrectly identified as lesions), while the Cascade Mask R-CNN model generated 17 false positives (Figure 2). Based on the calculated TP, FP, FN, and TN values, the performance metrics for each model are summarized in Table 1.

The accuracy rates of the models were found to be relatively close, with 96.9% for YOLOv8 and 97.6% for Cascade Mask R-CNN (Table 1). These high accuracy percentages can be attributed to the predominance of teeth with healthy apical regions compared to those with periapical lesions within the test dataset. However, accuracy alone may not adequately reflect model

performance when dealing with imbalanced datasets. Indeed, despite the high accuracy rate, the YOLOv8 model failed to detect more than half of the lesions. Therefore, additional performance metrics such as sensitivity and precision offer a more distinctive assessment of model success.

Overall, the Cascade Mask R-CNN model demonstrated higher sensitivity compared to YOLOv8. Cascade Mask R-CNN correctly identified approximately 76% of the lesions present in the test radiographs, while YOLOv8 detected only 53.5%. In other words, the YOLOv8 model missed nearly one out of every two lesions, whereas Cascade Mask R-CNN missed approximately one out of every four.

When evaluated in terms of precision, an opposite trend becomes apparent. The precision value of the YOLOv8 model was found to be higher at 90.0% compared to 81.9% for the Cascade Mask R-CNN model. In other words, 90% of the regions flagged as lesions by YOLOv8 actually corresponded to true lesions, whereas this rate was approximately 82% for Cascade Mask R-CNN. This result indicates that YOLOv8 achieved higher specificity by generating fewer false positives (FP), but at the expense of sensitivity. Indeed, the specificity values were calculated as 99.6% for YOLOv8 and 98.9% for Cascade Mask R-CNN; both models correctly classified nearly all healthy regions as non-lesion areas. Both models produced almost no false alarms in healthy regions.

When examining the F1-scores, Cascade Mask R-CNN achieved a markedly higher value of 0.79 compared to 0.671 for YOLOv8. This finding suggests that the overall performance of the Cascade Mask R-CNN model was superior to that of YOLOv8.

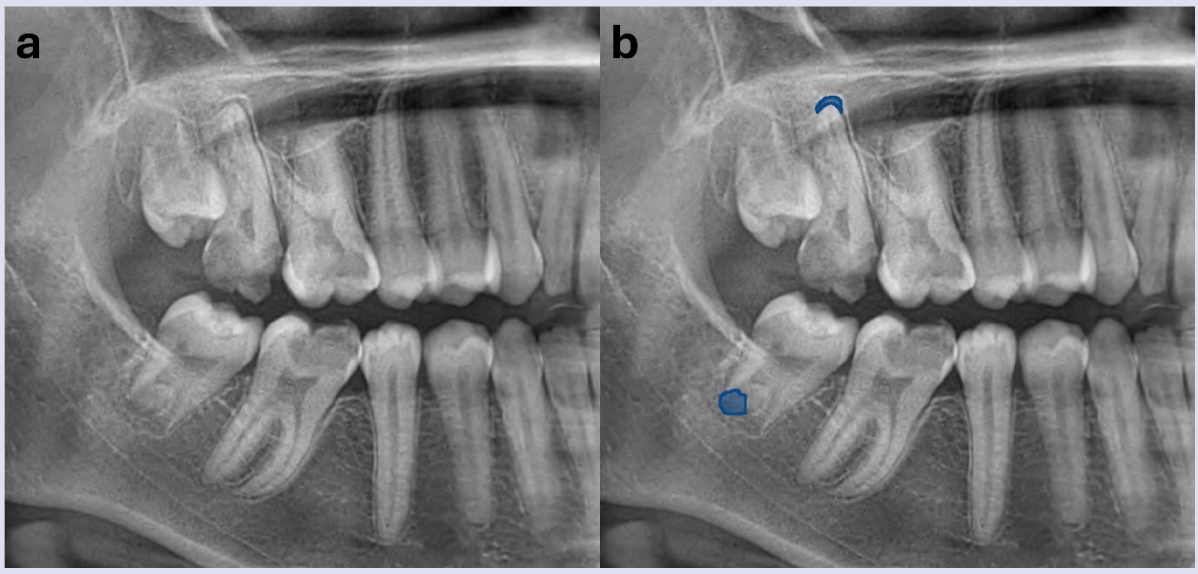


Figure 2. a. The right side of a patient's panoramic radiograph from the test dataset. b. The detections made by the trained Cascade Mask R-CNN model. The detection on tooth #17 is correct (true positive, TP), whereas the apical papilla observed at the developing root apex of tooth number 47 was mistakenly identified as an apical lesion (FP). Additionally, the YOLOv8 model did not make any detections for either of these structures, which corresponds to a false negative (FN) for tooth #17 and a true negative (TN) for tooth #47.

Discussion

Our hypothesis that image processing artificial intelligence models can be utilized for the diagnosis of apical lesions was rejected. There is no universally accepted minimum performance threshold that a diagnostic tool must achieve. However, the World Health Organization (WHO) has stated that rapid diagnostic tests for SARS-CoV-2 should achieve a minimum sensitivity of 80% and a specificity of 97%. These values were adopted as benchmark thresholds in our study. While both models met the minimum specificity criterion (99.6% for YOLOv8 and 98.9% for Cascade Mask R-CNN), they failed to achieve sufficient sensitivity (53.5% for YOLOv8 and 76.2% for Cascade Mask R-CNN).

In this study, two different deep learning models were comprehensively evaluated for the automatic detection of periapical lesions from panoramic dental radiographs. The results demonstrated that the Cascade Mask R-CNN model exhibited substantially higher sensitivity compared to the YOLOv8 model within the examined dataset. In the Cascade Mask R-CNN architecture, multiple detectors are arranged sequentially; candidate regions identified at the initial stage are further refined in subsequent stages, and a segmentation mask is eventually generated for each lesion area. Cascade Mask R-CNN has the potential to reduce false negatives due to its cascaded structure, particularly improving the detection of small or ambiguous objects. Through this multi-stage detection strategy, the model achieved greater success in capturing small and indistinct lesion foci. On the other hand, the

YOLOv8 model tended to produce fewer false positives, resulting in higher specificity, but at the cost of missing a significant number of lesions. This outcome indicates that as a one-stage model, YOLOv8 preferentially flags lesions with high confidence scores while failing to detect borderline lesions. In contrast, Cascade Mask R-CNN re-evaluates candidate regions in its second and third stages, thereby capturing more true lesions. However, this gain in sensitivity comes at the expense of a slight increase in false positives, with some healthy areas mistakenly labeled as lesions.

Artificial intelligence (AI)-based detection of apical lesions holds significant potential; however, the findings of our study suggest that AI methods may not yet achieve the level of success claimed by previous research. Bayrakdar et al. utilized a U-Net-based deep learning model to perform periapical lesion segmentation on a dataset comprising 470 panoramic radiographs. In that study, the model was trained using images obtained from a single hospital and a single panoramic radiography device. The reported sensitivity, precision, and F1 score of the model were 92%, 84%, and 0.880, respectively.[10] A more comprehensive study on deep learning-based lesion detection in panoramic radiographs was reported by Çelik et al. and unlike our approach based on segmentation, their study adopted an object detection methodology. The object detection approach does not provide exact boundaries of the objects—in this case, periapical lesions—but instead indicates their location within bounding boxes on the image. Their study included 357 panoramic images and 454 lesions, and compared the performance of ten different deep learning models with various architectures, including RetinaNet, Faster R-CNN, YOLOv3, and Cascade R-CNN. According to their results, sensitivity values ranged between 74% and 91%, while precision values ranged between 82% and 93% across all models. The best-performing model, Adaptive Training Sample Selection (ATSS), achieved approximately 90% sensitivity and an F1 score of 0.895 [11]. Several studies have also evaluated commercial artificial intelligence (AI) systems for periapical lesion detection in panoramic radiographs. For example, in one study assessing the commercial AI software Diagnocat, the system reportedly achieved a sensitivity of 92.3%, a specificity of 97.87%, and an F1 score of 0.92.[12] However, another study reported a relatively low sensitivity of 39% despite a high specificity of 98.1%.[13] These substantial discrepancies between studies may be explained by differences in interpretation among researchers regarding the definition and identification of apical lesions.

When discussing the clinical applicability of AI-based diagnostic systems, it is essential to consider both the strengths and weaknesses of the models. Among the models evaluated in this study, Cascade Mask R-CNN appears to be more advantageous for clinical use compared to YOLOv8, primarily due to its higher sensitivity and superior ability to detect more lesions. Missing a potential lesion (false negative) is highly undesirable in clinical practice, as an undetected periapical lesion could result in an untreated underlying infection, potentially leading to more serious complications. In this regard, Cascade Mask R-CNN, by detecting approximately three-quarters of lesions, ensures that at least one lesion is identified in the majority of cases. However, a sensitivity of 76% is still not ideal for clinical practice; models intended for reliable clinical use are generally expected to achieve much higher sensitivity levels, typically exceeding 90%. The YOLOv8 model's sensitivity of only 53% appears clinically inadequate. On the other hand, the high specificity and precision values observed for YOLOv8 indicate that most of the positive alerts generated by the model correspond to true lesions. In a clinical scenario, a lesion flagged by YOLOv8 would have a high probability of representing an actual lesion (low false positive rate). This could provide confidence, particularly for less experienced clinicians, when identifying existing lesions. Nevertheless, the main concern lies in the lesions that are missed by the model. Therefore, using YOLOv8 or similar models as standalone screening tools carries the risk of overlooking existing pathologies. Although the false positive rate of Cascade Mask R-CNN is slightly higher (approximately 1.1% compared to 0.4% for YOLOv8), this rate remains quite low and is generally tolerable in most clinical settings. Even if an average of one or two false alarms occur per panoramic radiograph, a skilled clinician could review and verify these alerts in a short time. Consequently, a model such as Cascade Mask R-CNN, which offers relatively high sensitivity, could effectively serve as an auxiliary decision support system. It may draw attention to a lesion that a clinician has overlooked or provide a second opinion when the clinician is uncertain about a diagnosis.

One of the relative strengths of this study is the use of panoramic radiographs obtained from different populations and various radiographic devices, encompassing both permanent and mixed dentitions. This approach allowed the test dataset to better reflect the clinical diversity encountered in real-world settings. Additionally, the trained models can serve as a foundation for future studies through transfer learning, enabling the development of more effective models. The primary limitation of this study is that the annotation of periapical lesions by the researchers was based solely on panoramic radiographs, without confirmation through clinical examination findings or additional imaging modalities such as CBCT. This introduces a potential margin of error regarding the definitive diagnosis of lesions. Future studies may aim to enhance the accuracy and generalizability of AI models by utilizing larger datasets and incorporating annotations validated through comprehensive clinical diagnostic methods.

Conclusions

Although AI-assisted systems hold promise as supportive tools in clinical endodontic diagnostics, they are not yet flawless. These models may help draw attention to lesions that could otherwise be overlooked on panoramic radiographs or provide a second opinion in

cases of diagnostic uncertainty. Nevertheless, given the lesions missed by the models, it is evident that the final diagnostic decision and responsibility must continue to rest with the clinician.

Acknowledgements

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Conflicts of Interest Statement

There is no conflict of interest.

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