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Evaluating the Diagnostic Accuracy of Artificial Intelligence in Periapical Radiographs

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Abstract

Background: Over the past few years, significant development has been made in the field of oral and dental diagnostics. A conservative treatment strategy with a favorable prognosis could be implemented by the clinician with an early diagnosis. It has been reported that examiners with greater expertise demonstrate higher diagnostic accuracy. AI may help clinicians by reducing workload.

Objectives: The purpose of this study was to evaluate the diagnostic accuracy of artificial intelligence in identifying common dental problems on periapical radiographs compared with experienced dentists.

Materials and Methods: **:** A total of 283 periapical radiographs were selected from the database of the University Dental Hospital. Two general dentists with more than 10 years of clinical experience manually assessed the periapical radiographs, which was ground truth. The same periapical radiographs were then uploaded into AI dental software.

Results: The obtained Cohen's Kappa values (0.61-0.8) indicated substantial agreement between the two investigators. Good agreement is noted in several parameters; F1 scores of apical radiolucency, obturation, and tooth detection were 0.7, 0.9, and 0.8, respectively. For Caries, the model had poor reliability with an accuracy of 61%.

Conclusion: AI demonstrated potential in detecting certain conditions on periapical radiographs but remains inconsistent, requiring further refinement before clinical integration.

Keywords: *Artificial intelligence, Radiography, Dental, Periapical, dental diagnosis*

Introduction

Over the past few years, significant development has been made in the field of oral and dental diagnostics. This rapid advancement has enabled clinicians to adopt more conservative treatment strategies leading to more favorable prognoses when the disease is identified early.[1,2] Among the most crucial tasks performed in a dentist's office is making an accurate diagnosis, which forms the foundation of effective treatment planning. Traditionally, this process is heavily dependent on clinical experience of the dentist, but even highly trained individuals are prone to cognitive fatigue and diagnostic variability. To deal with such limitations clinicians increasingly rely on adjunct methods to supplement their judgment and improve diagnostic precision.[1,3]

Clinical testing alongside radiographic analysis plays a critical role in achieving a comprehensive understating of the patient's condition. It has been well documented that clinical/visual assessment alone often fails to determine the extent of dental pathology especially in early phases of the disease. [4] Therefore, radiographs are indispensable for assessing and progression of the disease. However, despite their utility, the interpretations of radiographs are subjective to human errors. Greater expertise improves diagnostic accuracy; however, even experienced dentists may overlook subtle pathologies due to fatigue or distraction, with implications for patient outcomes. [3]

Periapical radiographs give a detailed view of the teeth and their surrounding structures. This is useful for detecting periapical disease, root or bone fractures, abnormalities in root canal anatomy, dental anomalies, and the health of the alveolar bone. Still, interpreting these images can be quite subjective. It often depends on the clinician's experience, mental fatigue, and even slight variations in the radiographic images. [5,6] These factors sometimes result in missed or inconsistent diagnoses, especially in the early stages of disease.[7]

Given these limitations in human interpretation, adjunctive approaches such as artificial intelligence are being explored to enhance diagnostic consistency. Automated diagnostic tools have been increasingly introduced in biomedical fields, including both medicine and dentistry. Among these advancements, the

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integration of artificial intelligence (AI) into daily diagnostic workflows in clinics stands out as especially promising. AI systems can learn from data, recognizing patterns, and supporting decision-making.[8] Over the past few years, AI has gained significant attention in healthcare because of its potential to reduce diagnostic errors and streamline clinical decision-making processes. Several studies suggest that AI-based systems can perform at par or even better than specialists in tasks that rely on image-based diagnosis, across specialties like radiology, pathology, and dermatology.[9]

In dentistry, AI is being explored for its potential to reduce the cognitive load on practitioners and enhance diagnostic precision. A variety of AI-powered tools are currently under development and evaluation, for example, in the detection of dental caries, periapical lesions, orthodontic planning, and even predicting outcomes of certain treatments. This broad utility suggests that AI could eventually become a regular part of clinical dental workflows.[10]

Machine learning (ML), a subset of AI, allows systems to detect patterns within data and make predictions without being given explicit programming instructions. A more advanced area within ML is deep learning, which uses multi-layered neural networks and has shown great success in analyzing complex datasets like dental radiographs.[11] Deep neural networks (DNNs) can extract relevant features from input images automatically and detect subtle patterns that might be missed by even experienced clinicians. When trained on large datasets, these models can evaluate new, unseen radiographs with fairly high confidence. This architecture is commonly referred to as "deep learning." With enough data and computing power, such neural networks (NNs) can learn the statistical patterns hidden in the data.[12]

Among various neural network types, convolutional neural networks (CNNs) are widely used in radiographic diagnostics. They are especially good at processing pixel-level information and identifying abnormalities in images. In dentistry, CNNs have shown promising results in detecting features such as apical radiolucencies, dental caries, and inadequate root canal obturations tasks usually carried out by dentists, though with some variability in accuracy. This opens the door for AI to serve as a helpful support tool, potentially minimizing diagnostic inconsistencies and improving patient outcomes.[13]

The objective of this study was to assess how accurately AI-based software can diagnose various dental conditions such as caries, apical radiolucencies, obturation errors, and tooth identification on periapical radiographs. By comparing the software's diagnostic output with evaluations made by two expert general dentists, we aim to understand how well AI performance aligns with clinical judgment and whether it could be used as a reliable adjunct in routine dental diagnostics.

Material and Methods

The study was conducted after obtaining ethical clearance from the Ethical Review Board of the University College of Dentistry (UCD), University of Lahore (Letter No: UCD/ERCA/24/867). A cross-sectional analytical study design was employed. Data were collected using a random sampling technique from the radiographic database of UCD. Out of an initial pool of 500 periapical radiographs, 283 were included based on diagnostic acceptability. All radiographs were acquired at UCD under standardized imaging protocols.

Periapical radiographs were captured using photostimulable phosphor (PSP) plates and scanned with a Soredex Digora® Optime scanner utilizing the paralleling technique to ensure geometric accuracy and minimize image distortion. Images were stored digitally at high resolution (300 dpi) and evaluated under uniform ambient lighting and consistent viewing conditions.

Inclusion criteria were based on diagnostic acceptability standards defined by the Faculty of General Dental Practice (FGDP UK) and Public Health England (PHE).[14] Radiographs of permanent teeth meeting diagnostic standards were included. Blurred, under- or over-exposed, cropped, distorted, or incomplete images were excluded. All radiographs were anonymized, and prior informed consent for data use had been obtained as part of UCD's clinical documentation policy.

Sample size was calculated assuming an expected Youden's index (p) of 0.87 for residual root detection on radiographs [15], with a desired precision (d) of 0.04 and a 95% confidence level ($Z = 1.96$), yielding a required sample size of 272 radiographs. However, 283 radiographs meeting the inclusion criteria were available and included in the analysis.

Two faculty members of UCD, each with more than 10 years of clinical experience, independently assessed the selected radiographs. Both evaluators analyzed the images manually at separate times and locations to minimize observer bias. The following diagnostic parameters were evaluated:

- Caries: Primary and secondary caries
- Apical radiolucency
- Obturation quality: Under- or over-obturation

Tooth detection

These expert evaluations served as the reference standard (ground truth) against which the AI-generated results were compared. The same 283 radiographs were uploaded into a commercially available dental AI diagnostic software (AI:Dental). Upon processing, the software automatically annotated the images using color-coded bounding boxes and circular markers (Figure 1), where:

- White box: Tooth detection
- Pink circle: Primary caries
- Blue circle: Secondary caries
- Red box: Apical radiolucency
- Yellow box: Under- or over-obturated tooth

All statistical analyses were performed using Python (Version 3.10). Inter-observer reliability between the two human evaluators was assessed using Cohen's Kappa coefficient [16], interpreted as follows:

- < 0.00 = Poor agreement
- 0.00–0.20 = Slight agreement
- 0.21–0.40 = Fair agreement
- 0.41–0.60 = Moderate agreement
- 0.61–0.80 = Substantial agreement
- 0.81–1.00 = Almost perfect agreement

The diagnostic performance of the AI model was evaluated against the human reference standard using F1-score, sensitivity, specificity, accuracy, and Youden's index. Additionally, Receiver Operating Characteristic (ROC) curves were plotted for each diagnostic category to visualize and compare the discriminative ability of the AI model relative to human evaluations. The Area Under the Curve (AUC) was calculated to quantify the model's overall diagnostic performance. A p-value < 0.05 was considered statistically significant.

Results

To establish a baseline for comparison, the agreement between the two human observers was first analyzed using Cohen's Kappa test and percentage agreement (Table 1). The results showed strong interobserver reliability for tooth detection, indicating near perfect

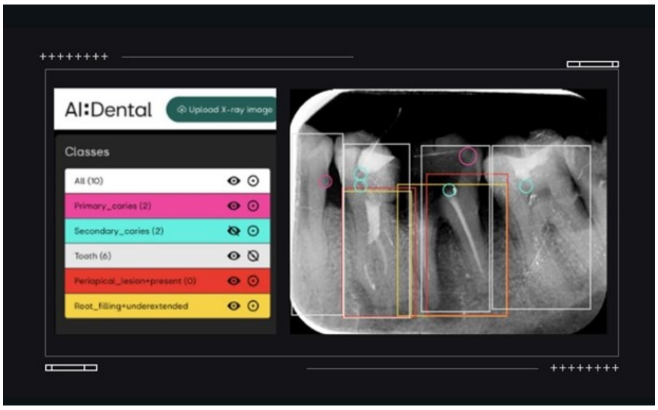

Figure 1: AI Interface Displaying Annotated Radiographic Outputs

consistency. Substantial agreement was also seen in caries and faulty obturation detection, while apical radiolucency showed a slightly lower but still acceptable agreement ($\kappa = 0.64$).

Next, F1 scores were calculated to compare the performance of AI system with the two human evaluators (Table 2). Observer 1 and 2 showed consistently high F1 scores, confirming strong internal agreement. In contratst, the AI system showed moderate performance in detecting apical radiolucency and poor performance in identifying caries suggesting reduced alignment with human evaluators. However, the AI performed well in detecting teeth and faulty obturation.

Statistical significance was assessed using one-way ANOVA and p values less than 0.05 were considered significant. The p values indicated a statistically significant difference for apical radiolucency, caries and tooth detection ($p<0.0001$) while the difference for faulty obturation was not significant ($p=0.31$) suggesting that AI performance for obturation detection

Table1: Inter-observer agreement between two human evaluators using Cohen's Kappa Test

Parameters	Kappa Score	Percentage Agreement
Apical Radiolucency	0.64	87.99
Caries	0.76	89.05
Faulty Obturation	0.69	96.11
Tooth Detection	0.97	99.65

Table2: F1 scores comparing observers and AI software

Parameters	Obs 1 vs Obs 2	Obs 1 vs AI	Obs 2 vs AI	p-value
Apical Radiolucency	0.875	0.696	0.763	<0.0001
Caries	0.889	0.53	0.622	<0.0001
Faulty Obturation	0.966	0.943	0.91	0.31
Tooth Detection	0.995	0.898	0.899	<0.0001

was comparable to human observers.

Finally, the diagnostic performance of AI software was evaluated using sensitivity, specificity and accuracy metrics (Table 3). The AI showed high sensitivity in detecting apical radiolucency (95.8%), faulty obturation (96.3%) and tooth detection (100%) indicating that it successfully identified most true positive cases. However, the very low specificity for apical radiolucency (11.8%) suggests a tendency towards overdiagnosis.

For caries detection, AI showed very low sensitivity (13.7%) but high specificity (95.2%) meaning it missed most true carious lesions but rarely produced false positives. These patterns were reflected in the overall accuracy scores which were highest for obturation and tooth detection while caries and apical radiolucency demonstrated comparatively lower accuracy.

The AI demonstrated excellent performance for tooth detection and apical radiolucency, reflected by high true positive rates (sensitivity = 100% and 95.8%, respectively). The estimated AUC values (≈ 0.91 for both) suggest strong discriminative ability. However, the low specificity for apical radiolucency (11.8%) indicates a tendency toward overdiagnosis, meaning

Table 3: Diagnostic performance of AI compared to human observers

Parameter	Sensitivity	Specificity	Accuracy
Apical Radiolucent	0.958	0.118	0.756
Caries	0.137	0.952	0.615
Obturation	0.963	0.533	0.940
Tooth Detection	1.000	0.819	0.820

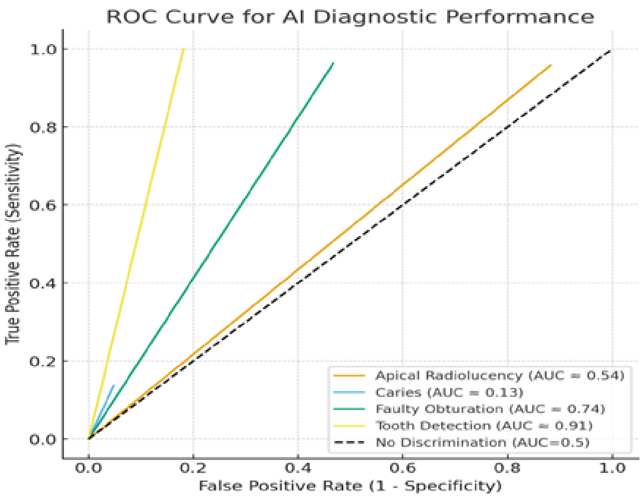

Figure No:1: Receiver Operating Characteristic (ROC) curve illustrating the diagnostic performance of the AI software for apical radiolucency, caries, faulty obturation, and tooth detection compared to human evaluators. The AI demonstrated excellent discriminative ability for tooth detection (AUC ≈ 0.91) and apical radiolucency (AUC ≈ 0.91), good performance for faulty obturation (AUC The ROC curve (Figure 2) illustrates the diagnostic performance of the AI software for detecting apical radiolucency, caries, faulty obturation, and tooth detection compared to human evaluators.

the AI often misclassified non-radiolucent areas as pathologic.

For faulty obturation, the AI achieved high sensitivity (96.3%) with moderate specificity (53.3%), corresponding to a good overall AUC of approximately 0.86. This indicates that the AI reliably detected obturation errors with relatively few false negatives, performing comparably to human evaluators, as also supported by the nonsignificant p-value ($p = 0.31$).

In contrast, the AI's performance for caries detection was poor, with very low sensitivity (13.7%) but high specificity (95.2%), resulting in an AUC of approximately 0.60. This pattern suggests that while the software rarely produced false positives, it failed to identify most true carious lesions, indicating underdiagnosis in this category.

Overall, the ROC curve emphasizes that the AI model's diagnostic capability is highly variable across different dental pathologies performing best for structural detection (teeth, obturation) and less reliably for disease-related features (caries, apical radiolucency ≈ 0.86), and poor performance for caries detection (AUC ≈ 0.60). The diagonal line represents the reference for no discrimination (AUC = 0.5).

Discussion

Artificial intelligence (AI) has become increasingly integrated into healthcare, with promising applications in dentistry for improving diagnostic accuracy, consistency, and speed. Radiographic interpretation, in particular, has been a focus of AI development due to its visual nature and the need for efficient, reproducible evaluation in routine dental care. This study contributes to the growing body of evidence by assessing the diagnostic capabilities of AI in detecting apical radiolucency, caries, obturation quality, and tooth identification on periapical radiographs.

A number of studies have shown that AI has the potential to support or even in some cases outperform clinicians in specific diagnostic tasks. For example, a study by Endres et al. tested a deep learning model on panoramic radiographs to detect periapical disease. Interestingly, the AI system outperformed more than half of the oral and maxillofacial surgeons who participated in their study. [17] Likewise, Ekert et al. evaluated a deep learning algorithm for identifying apical lesions and reported promising results in terms of sensitivity and specificity, using a large dataset of panoramic radiographic images. [18] However, panoramic datasets differ substantially from periapical datasets in terms of image scale, anatomic overlap, and contrast resolution. Panoramic radiographs capture the entire jaw but with more distortion and lower spatial detail, while periapical images offer higher resolution and less anatomical noise. This difference directly affects AI performance as models trained on panoramic data may rely on broader contextual cues rather than fine structural detail needed for periapical diagnosis .[19]

When comparing those earlier results to our findings, the AI tool we tested showed promise in some areas but still had noticeable limitations in others. Specifically, it performed fairly well in tasks where the radiographic signs were more clear and consistently visible like in identifying tooth numbers and evaluating the quality of root canal obturations. These observations are somewhat similar to what Do Hoan et al. reported, where their AI-based model achieved high accuracy in detecting periapical lesions using periapical radiographs. [20] Likewise, Orhan and colleagues successfully used the Diagnocat software to assess obturation quality and confirm tooth presence, further supporting the idea that AI may be more effective when applied to well-defined features. [21]

The comparison between panoramic and periapical models underscores an important methodological distinction: panoramic datasets introduce more variability from overlapping structures, motion artifacts, and exposure differences, while periapical images provide a controlled and localized field of view. Consequently, models trained on panoramic data may show inflated generalization that does not translate to periapical tasks. Future research should explicitly test how training data type influences diagnostic precision across modalities. [22,23]

Apical radiolucency remains a diagnostic challenge for both human evaluators and AI. Prior studies have suggested that AI can detect these lesions with reasonable success, but accuracy is often influenced by radiograph quality, image modality, and lesion size . [17,18] In our study, while AI showed potential in flagging many cases, it lacked precision in excluding healthy cases, which could lead to overdiagnosis. This aligns with the broader consensus that AI should currently be used as an adjunct rather than a replacement in clinical decision-making, especially for subtle or ambiguous findings

Caries detection posed the most significant limitation for the AI software. While some studies, such as one from India, reported diagnostic accuracies exceeding 90% [24] and others like Singh and Sehgal. [25] The variability may stem from differences in network architecture, dataset size, image modality and labelling standards. Furthermore, not all previous studies clearly defined caries types or severity, and in many cases, diagnosis lacked clinical or histological confirmation. These factors make direct comparisons difficult. It is also possible that caries features in periapical images are less distinct than in bitewing or panoramic radiographs limiting AI's ability to recognize early lesions.

Despite its limitations in caries detection, the AI demonstrated potential in evaluating obturation quality. This parameter benefits from well-defined, radiopaque boundaries that make AI interpretation more reliable. The model's performance is consistent with AI use in endodontic assessment. [21]In future clinical practice, such tools could serve as second readers, minimizing oversight in high-volume settings and assisting less experienced clinicians in identifying treatment errors.

Tooth detection was the most consistent and reliable task in our study, echoing findings from Muramatsu et al. and Tuzoff et al., who reported very high sensitivity in panoramic radiograph-based models. [26,27] While most published work uses panoramic views, our results confirm that AI can also effectively interpret periapical images for this purpose. This likely reflects the structural consistency of teeth across images where clear contrast boundaries support stable model recognition.

Overall, the observed variability in AI performance across diagnostic categories highlights the need for parameter-specific validation rather than general claims of diagnostic accuracy. Performance depends not only on radiographic features but also on the imaging modality dataset diversity and preprocessing quality. Image preprocessing, including contrast enhancement, noise reduction, and region-of-interest segmentation, has been shown to impact AI performance in other studies but was not applied here. Additionally, the AI software used was still in the preliminary evaluation phase and not validated on independent external datasets. Most of the well-performing models cited in literature were trained and tested on large, labeled datasets with clear gold standards, often including clinical or histological validation, which was not feasible in our setup.

There are several limitations to this study that should be acknowledged. The sample size was modest which limits the generalizability of the findings. Future research should aim for larger, more diverse datasets with standardized imaging protocols. Moreover, our study relied solely on radiographic interpretation without any clinical or histological correlation. This is particularly relevant for caries and apical pathology, where radiographs alone may not provide definitive diagnoses. The use of a single imaging system may have introduced device-specific bias, and image exposure settings were not normalized. Furthermore, while the AI tool was able to perform reasonably well in certain parameters, it was evaluated using a single dataset without a separate validation set, which restricts the robustness of the performance metrics.

Conclusion

AI demonstrated potential in certain diagnostic areas of dental radiology, particularly tooth detection and obturation assessment—its performance remains inconsistent for more complex evaluations like caries and apical pathologies. Continued research using larger datasets, multi-modal inputs, and clinical validation is critical for transitioning AI from experimental to practical use in dentistry.

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Author Contributions

1. **Adeel Haidar:** Conception and design of study, data collection
2. **Wajiha Alamgir:** Data analysis and interpretation
3. **Irsam Haider:** Literature review and drafting of manuscript
4. **Saqib Naeem Siddiqui:** Critical revision of manuscript
5. **Malik Adeel Anwar:** Supervision and final approval of version to be published
6. **Bakhtawar Khan:** Data acquisition and formatting
7. **Anfal Tariq:** Proofreading and reference management