ORIGINAL ARTICLE

International Journal of Dental Materials (ISSN: 2582-2209 (Online))
DOI: http://dx.doi.org/10.37983/IJDM.2025.7202

Use of Artificial Intelligence for Caries Detection on Dental Radiographs

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Article History
Received: 6th June 2025
Accepted: 29th June 2025
Published: 14th July 2025

Abstract

Background: Dental caries, being among the most frequent oral issues, calls for careful attention. Early checks help. Without them, things can slowly get worse, sometimes before anyone even notices. Standard ways of evaluating these cases still depend heavily on clinical skill, which isn't always consistent. Mistakes in reading the signs aren't rare. Now, with advancements in Artificial Intelligence, the field is shifting. It's not just about detection anymore. AI enters the scene with promise bringing shifts in how diagnosis happens, care is planned, and cases are followed. Even the utilization of the time gets changed in clinics.

Aim: To spot interproximal caries in periapical x-rays using artificial intelligence (AI). Also, to compare the efficacy of AI findings against the readings done by radiologists.

Materials and Methods: A dataset of 400 periapical images was selected, representing 900 posterior teeth with suspected interproximal caries. A convolutional neural network (CNN) was trained using labelled periapical images for caries detection.

Results: The statistical analysis confirmed that the AI-model achieves statistically significant and clinically excellent performance in interproximal caries detection (McNemar's test (χ^2 = 4.447, p-value=0.035)), and with near-perfect Cohen's Kappa = 0.916. Model accuracy stood at 95.8%, with statistical comparison to radiologists showing no significant difference (p=0.089) and particularly notable results in advanced caries cases. The accuracy of the AI model was 95.8 percent and matched with the radiologists' findings, with a p-value of 0.089. The results were especially strong in dealing with advanced caries cases. The AUC curve reached 0.957, and with a sensitivity of 97.4 percent.

Conclusion: AI showed solid accuracy and dependable results in finding dental caries on periapical images. Its performance closely reflected as that of experienced dental professionals'.

Keywords: Artificial intelligence, AI, Bitewing radiograph, Dental caries, Interproximal caries, Periapical radiograph, Teeth.

Cite this article as: Jasim HH. Use of Artificial Intelligence for Caries Detection on Dental Radiographs. **Int J Dent Mater. 2025;7(2):37-46.**

1. Introduction

Dental caries, a chronic condition, results in progressive damage to hard dental tissues. Acids are involved, released as bacteria break down carbohydrates from a food source [1]. Based on guidelines from the American Dental Association, dental caries falls into categories reflecting how far lesions have progressed: normal, initial, moderate, or extensive [2]. A condition influenced by many factors, including the mix of microbes present, how saliva flows and what it contains, levels of fluoride exposure, consumption of sugars in the diet, and the habits practiced to keep oral hygiene in check [3]. Reversible conditions characterise the early stages of this disease; however, when left unattended, damage to the tooth can become permanent. Therefore, timely diagnosis, continuous monitoring, along immediate treatment plays crucial roles in preventing additional harm to dental surfaces [4]. Early identification of carious activity often allows intervention before significant progression occurs. Active lesions, at this stage, may become inactive through conservative methods such as topical fluoride, sealing of pits and fissures, and sometimes the application of preventive resin restorations, generally used to manage lesions in early development [5,6].

In clinical routines, visual–tactile checks and radiographic tools often serve as go-to techniques for spotting dental caries. Still, these older diagnostic practices bring limitations [7-9]. In recent times, quite a few new tools have appeared aiming to spot carious lesions. Electrical conductance tests, fiber-optic transillumination, quantitative light-induced fluorescence for short (laser fluorescence) systems, and optical coherence tomography. These methods are still not everywhere in clinics yet. But often, they show details that older, traditional ways can miss or blur over [10]. In many cases, though not all, what happens is that the diagnostic tests, despite their purpose, tend to fall short in specificity, which, more often than expected, might end up increasing the likelihood of calling something caries when it actually isn't a false-positive, in effect [11]. In addition, due to typically elevated setup expenses, many such devices remain impractical options for regular use in clinical settings [12,13]. Sensitivity in these methods often falls short, mainly because of overlapping structures, and contrast inconsistencies in exposure as well. As a result, detection fails in over half of carious lesions, which tend to go unnoticed [14].

Radiographic imaging, particularly bitewing type, often becomes necessary, considered by many as the gold standard in identifying demineralised proximal lesions not visible in regular clinical settings [15]. Bitewing radiographs are still widely used and remain part of the routine clinical dental evaluations. Not because they're perfect, but because, in practice, they work well enough most of the time. Still, reading caries from radiographs isn't always consistent. In fact, with the same image, two people might not agree at all. Some might see decay while others don't. These shifts in interpretation arise from several overlapping elements: technique issues during the X-ray itself, changes in contrast, minor magnification effects, and even how sharp or fuzzy the final image looks [16-18]. Therefore, it is advisable to develop an automatic detection method that assists in diagnosis and treatment evaluation stages on radiographic images by assisting artificial intelligence (AI).

Artificial intelligence, or AI, means the ability to imitate how humans think. These days, AI systems have been created and are being used quite a bit in many areas — medicine and dentistry included [19]. AI algorithms can help spot diseases, often cutting down on extra tests or treatments that might not be needed [20]. Machine learning (ML), part of artificial intelligence, focuses on building algorithms by using training data. Instead of being explicitly programmed for every task, these algorithms can get better on their own, adjusting and improving with experience. Over time, as more data comes in, the system—or computer—starts to pick up skills independently, refining how it performs without needing direct human guidance [21].

Deep learning (DL) algorithms stand out as the most widely used nowadays. Early neural networks were often quite simple, built with fewer layers, and usually called "shallow" learning models; these were among the first algorithms developed. In contrast, DL neural networks involve architectures with many large layers stacked together. When it comes to handling large and complex images, convolutional neural networks (CNNs) tend to be the preferred choice. [22]. Convolutional Neural Networks (CNNs), often applied in deep learning tasks, have been developed with a focus on handling image-related data. Convolutional layers, when used, tend to pull out certain features from images automatically. This makes them especially useful for interpreting dental radiographs [23]. CNNs find a lot of use in detecting caries, mostly because they can spot and classify carious lesions with good accuracy, even in subtle spots where traditional methods sometimes fall short. [24]. Networks like these tend to work well at spotting local patterns and distinctive features within images. They do so by stacking several convolutional layers, mixed with pooling steps. This combination helps in telling apart carious lesions from non-carious tissues [25,26]. "Deep Convolutional Neural Networks (DCNNs)" — think of them as more complex CNNs — work by stacking layers, convolution and pooling, to catch tricky image patterns. In dental imaging, they're used on things like bitewing and panoramic radiographs, aiming to spot dental caries. The results often show pretty solid accuracy and reliability. Because of this, lots of researchers seem to favour these models [27,28]. This study aimed to detect interproximal caries in periapical x-rays using artificial intelligence (AI) model, and compared its performance against the readings done by radiologists.

2. Materials and methods

A total of 400 periapical images were randomly collected from a dental imaging archive. The patients involved were adults and the data gathered over the period from October 2024 to May 2025. These images were used for different diagnostic reasons. A total of 1200 posterior teeth (including premolars and molars) were examined on periapical images, and only 900 posterior teeth showed evidence suggesting interproximal caries. Images of poor quality or containing artefacts that could interfere with caries detection were excluded from the study. The radiologists then observed each image and sorted it into one of three categories. Class I meant normal teeth involving healthy enamel and dentin. Class II pointed to early or incipient caries involving enamel demineralization, and Class III showed advanced caries involving dentin involvement or cavitation. To ensure fairness and free of bias, the radiologists analyzed the periapical images independently, without being aware of the others findings. All images were captured using the Planmeca ProX Intraoral X-ray Unit equipped with Planmeca ProSensor, Size 2 (Planmeca 2016, Helsinki, Finland), operating at 60 kVp and 8 mA.

Analysis with Deep Convolutional Neural Network used ResNet-50 architecture [29]. The work was done with Fiji software, version 2.14.0, using DeepImageJ tools [30,31]. Hardware included a 12th Gen Intel Core i7 12700. Paired with it, there was an NVIDIA GeForce RTX 3070. Memory-wise, it held 32 GB of DDR4 RAM. The speed sat around 3200 MHz.

2.1 Periapical image processing

Before starting the analysis, all periapical X-ray images went through a standardisation routine. This step, pretty crucial, aimed at keeping input quality consistent, which in turn supported diagnostic reliability. Images were resized to the size 224 by 224 pixels, as it tends to suit many deep learning setups. After this step, each image shifts into 8-bit greyscale to make things smoother while using FIJI, and even during feeding into DeepImageJ routines. The resizing process was uniform, making sure spatial resolution stayed steady across every sample. Next came histogram normalization. Contrast improved noticeably, making enamel, dentin, and carious lesions pop out clearly. Noise reduction was the next, using a median filter set to a 2-pixel radius. Most structural details stayed intact, but background artefacts softened quite a bit. After that, edge enhancement was done. An unsharp mask helped sharpen the interproximal boundaries. Finally, images got saved as TIFF format files, keeping quality lossless and metadata untouched. This last step played a crucial role, making sure deep learning inference with ResNet-50 worked optimally.

2.2 Analysis of periapical images by AI model

Interproximal caries detection was performed by merging the Fiji platform with a pretrained ResNet-50 deep learning model, using the Deep ImageJ plugin. About 400 high-resolution periapical radiographs involving 900 posterior teeth were loaded into Fiji, where standardised preprocessing took place: histogram normalisation and contrast enhancement aimed at better grey-level differentiation. The ResNet-50 model, trained earlier on annotated dental datasets, found its way into Fiji via Deep ImageJ. This setup made it possible to run local inference on every single image. Pixel intensities were examined carefully, especially focusing on grey-value thresholds.

These thresholds ended up grouped into three categories: Class I representing normal tooth involving healthy enamel and dentin (more radiopaque-grey values ranging from 160-255). Class II pointing to early or incipient caries involving enamel demineralization (less radiolucent-grey values, ranging from 100-159), and Class III indicating advanced caries involving dentin involvement or cavitation (more radiolucent-grey values, ranging from 0-99). This sorting helped in determining the condition of the tissue.

As illustrated in Figure 1, each periapical image went through separate processing. Predictions were layered right onto the original images, showing up as segmented probability maps. This way, detection ran fully automated, happening in real-time. The outputs stayed pretty consistent across different cases. Then, the results were compared with the with the findings of the expert radiologists' readings to check accuracy and agreement.

2.3 Statistical analysis

- McNamar's test was applied for paired proportions, AI against radiologist, across caries and normal classifications. Simple difference, just outcome flips counted, subtle but telling shifts.

- A Z-test was employed, and it aimed at the metrics, sensitivity, specificity, accuracy, all stacked against some benchmark, say the radiologist baseline. No assumptions of similarity left unchecked.
- Cohen's Kappa (κ) was used for inter-rater alignment beyond pure chance, handled the trickier tiers: Normal, Early, and Advanced. Captured the broader agreement picture. Not just a match or mismatch.
- Confidence intervals, Wilson-style, was used to wrap sensitivity and specificity with uncertainty margins—tight, sometimes wide, always grounding the estimates.
- The Receiver Operating Characteristic- Area Under the Curve (ROC-AUC) were used to understand the receiver curves stretching from false positives to true positives, measuring how well the model splits carious from healthy. Discrimination ability, laid out in curve space.
- DeLong's test was used to compare the Area Under the ROC Curve (AUC) of two diagnostic models (Radiologist vs. AI model) to determine if their performance differences are statistically significant.

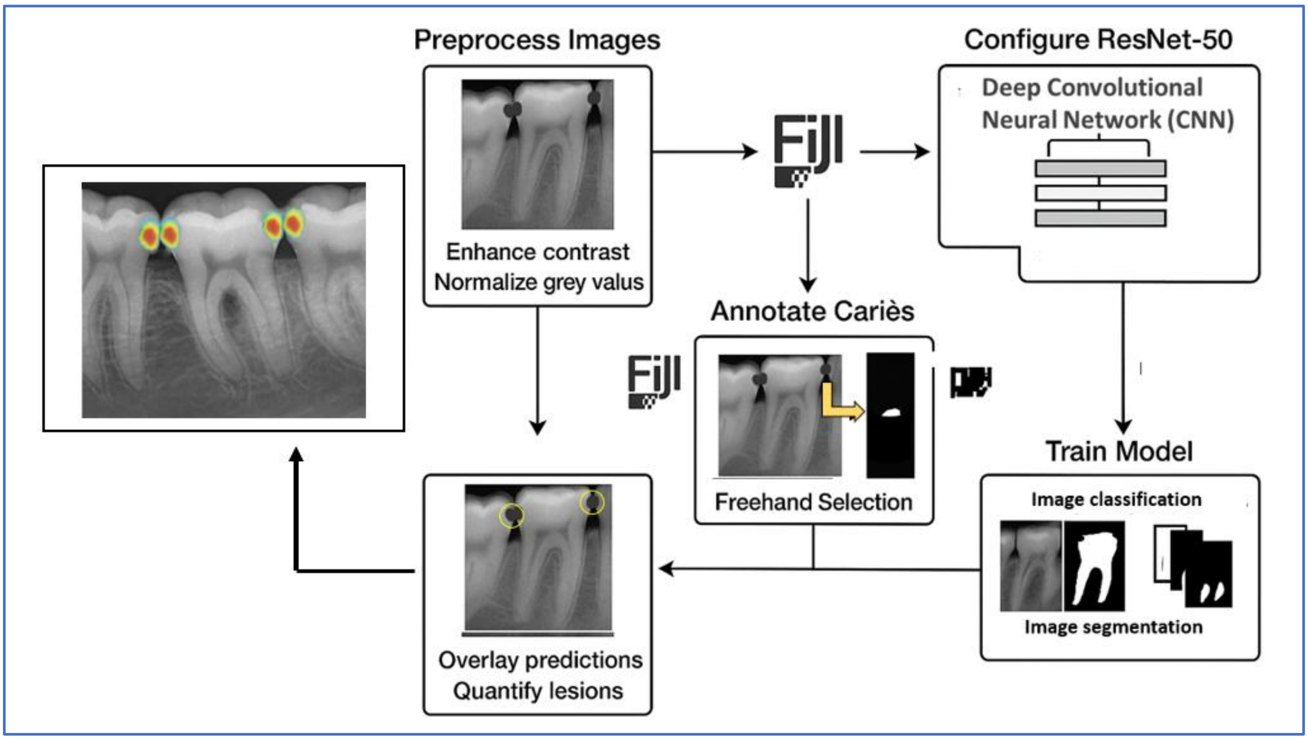

Figure 1. Diagram showing the steps in processing 400 periapical images through a Fiji-powered ResNet model for interproximal caries detection.

3. Results

A total of 400 periapical images representing 900 posterior teeth were analyzed for interproximal caries detection by an AI model. The reference standard for interproximal caries detection was determined by consensus of three experienced dental radiologists (Fleiss' Kappa value=0.977), indicating excellent consistency among the three Dental Radiologists in diagnosing the periapical images (Figures 2 and 3). The statistical analysis confirmed that the AI model achieves statistically significant and clinically excellent performance in interproximal caries detection (McNemar's test ($\chi^2 = 4.447$, p-value = 0.035)), and with near-perfect Cohen's Kappa = 0.916 (95% confidence intervals: 0.890-0.942).

The comparative evaluation of interproximal caries detection on periapical images between Radiologists' consensus readings and an AI model across 900 teeth revealed close agreement with slight variations. In cases of Class I (Normal teeth), the AI model demonstrated caries detection rates (31.8%, n=286) compared to Radiologists' consensus readings (33.3%, n=300). In cases of Class II (Early caries), the AI model demonstrated marginally higher detection rates (14.0%, n=126) compared to Radiologists' consensus readings (15.3%, n=138). For Class III (Advanced caries), the AI model showed better caries detection

(52.2%, n=470) compared to Radiologists' consensus readings (51.3%, n=462). Placed next to the Radiologists' consensus reads, the AI system showed a sensitivity of 97.4%. The confidence interval ranges from 96.0 to 98.8%. The Z value reached 5.23, with a p-value less than 0.001. The specificity was 94.1% and the confidence interval, 95% level, was in the range of between 91.9% and 96.3 %. The Z was 2.84, p-value equaling 0.0023. This value, though a bit lower, still sits comfortably within a strong performance range. Accuracy showed 95.8%, yet this number didn't show a significant difference compared to the radiologists (95% CI: 94.3–97.0%; Z = 5.23, p-value = 0.089). The overlap seen here is quite notable.

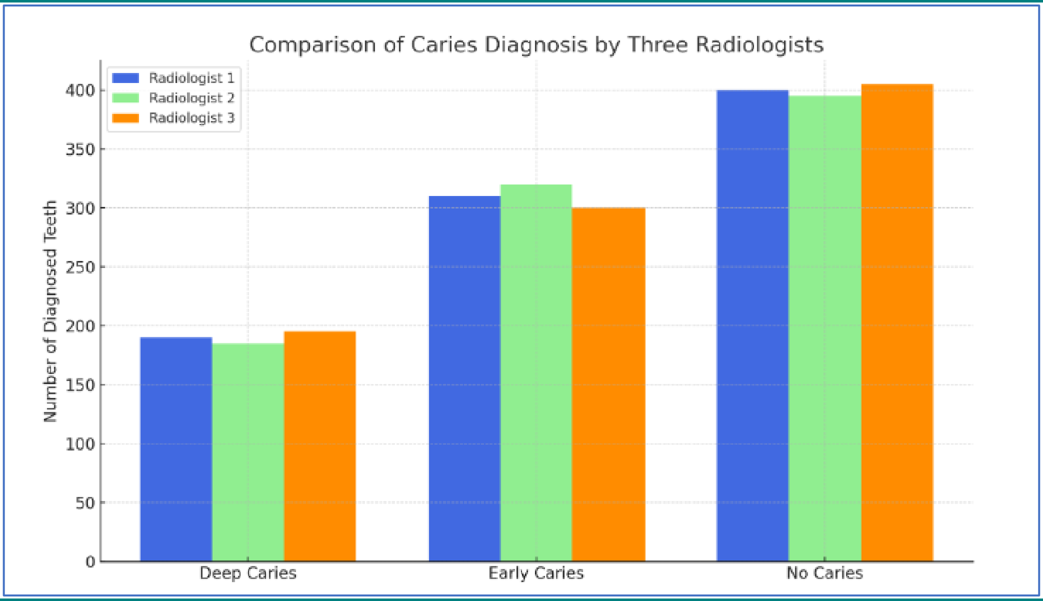

Figure 2. A bar graph compares caries diagnosis by three radiologists across 900 posterior teeth. Fleiss' Kappa value=0.977) indicated excellent consistency among the three dental Radiologists in diagnosing the periapical images.

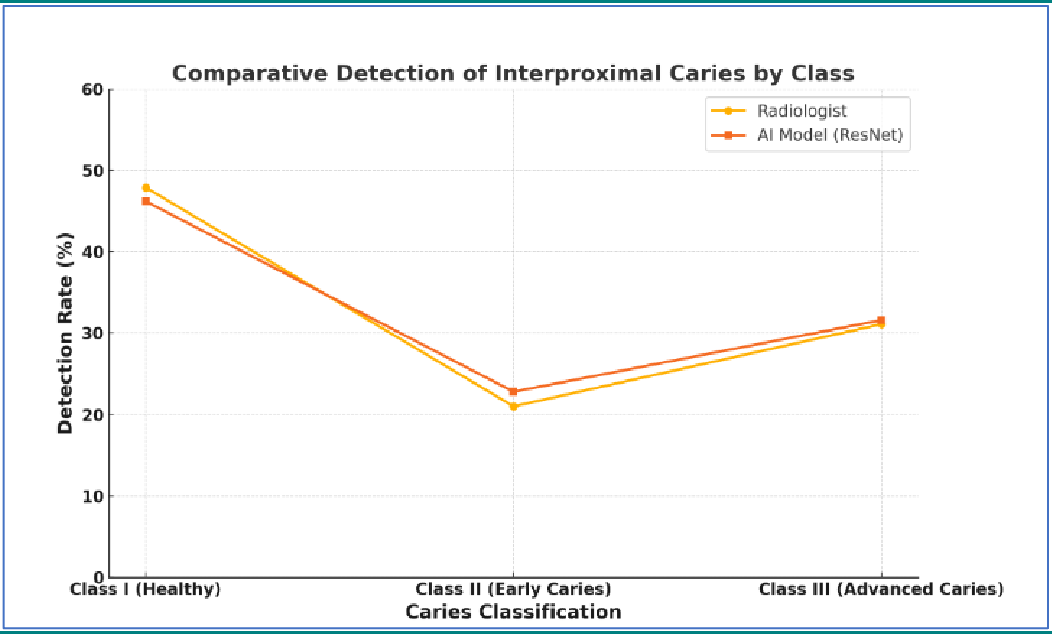

Figure 3. A line graph comparing detection rates of interproximal caries by class (I to III) between radiologists and the AI model. It shows close alignment between the two, with slight variations favouring the AI in early and advanced caries detection.

Results, while precise, still allow some room for interpretation, especially given the narrow confidence intervals and the variability often seen in clinical settings. These numbers point to a strong alignment, particularly in sensitivity, but the overall, it suggests more of a subtle equivalence than clear superiority. Statistical analysis revealed an F1-score of 95.9%. That's just slightly closer to those near-perfect numbers radiologists tend to get. The score kind of balances precision, 94.5%

and recall, at 97.4%. This mix points toward a fairly solid harmony overall. It works to reduce false positives and false negatives effectively. Such a balance is important, especially when applying the method in real-world settings where accuracy matters most. The findings showed near-perfect detection for advanced caries in the AI model (AUC = 0.957), aligning with high sensitivity (97.4%), while early caries detection was weaker (AUC = 0.892), but the findings indicated no statistically significant difference in AUC between the two models. (DeLong's test: Z = 1.62, p-value = 0.105) and the agreement with Radiologists' consensus readings remained high, 95.8% overall, Cohen's κ = 0.916 (0.890–0.942) (Figure 4).

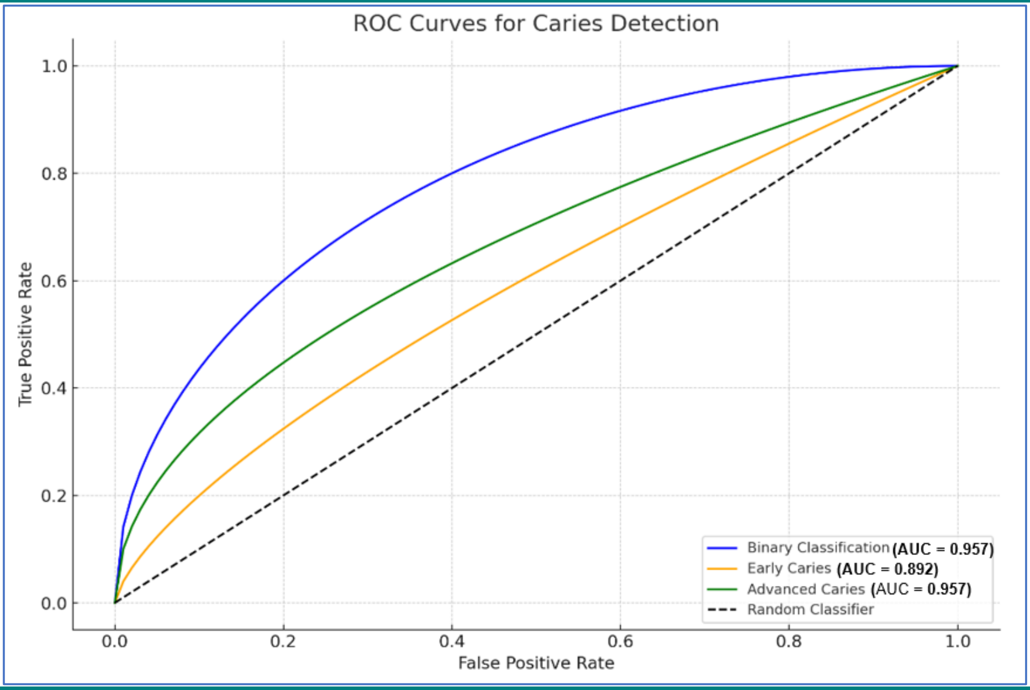

Figure 4. ROC curves demonstrating AI performance in detecting interproximal caries from periapical radiographs.

4. Discussion

AI-powered caries detection mirrors the subtle, sometimes complex decision-making seen in everyday dental practice. Helps shave off minutes from exams, lightens the load on dental teams. Patients feel the difference less poking around, fewer steps that don't add much. Accuracy sharpens through algorithm-based image reads, spotting early enamel or dentin wear fast, and doing it the same way every time. At the same time, it offers a fuller view of oral health, not replacing expertise but sitting just behind it, supporting it quietly.

AI offers real promise in supporting both diagnosis and treatment planning across dental care [32–34]. In recent work, deep learning models proved remarkably effective at picking up intricate patterns hidden in massive image collections, leading to many useful dental applications [32,35–39]. Among these, deep learning applied to dental radiographs stands out as efficient, sharp in accuracy, and practical for spotting oral diseases. Through the use of convolutional neural networks, systems for identifying such conditions can be built with notable effectiveness [40].

"Convolutional neural networks (CNNs)", a form of deep learning rooted in artificial intelligence, serve image classification and object detection tasks across visual data [41–43]. CNNs show capability in spotting dental caries and interpreting dental imagery to locate affected areas [28]. Trained networks highlight early indicators of caries within images, supporting earlier diagnostic steps [44–48].

From a health economics standpoint and in making treatment choices, these matters—dental caries therapies differ depending on where and how deep the lesion is. Options like remineralisation, cavity fillings, root canals, or extractions shift accordingly [28,49-51]. Lately, growing interest surrounds the use of deep learning, particularly convolutional neural networks (CNNs), in handling medical images across a range of formats. Results, so far, quite promising. Adoption of deep learning in disease diagnosis continues to rise steadily. Fast and accurate identification, often observed. Clinical results, in many cases, show noticeable improvement [52]. Back in 2015, interest sparked in applying deep convolutional networks within the field of dentistry. Since then, several deep learning approaches—each exploring the identification of dental caries or detecting lesions in dental X-ray scans—have emerged and been examined [28,53,54].

The AI model showed very high accuracy and clinical reliability in the current study. Agreement with Radiologist consensus was almost perfect Cohen's κ coming out to 0.916. Overall accuracy was 95.8%, which was statistically on par with Radiologists ($p = 0.089$). Particularly impressive was advanced caries detection, AUC of 0.957 and a sensitivity of 97.4%. In other words, the AI nailed true advanced cases, barely missing any.

Early caries detection was a bit different. The AI's rate was 14.0%, slightly under Radiologists' 15.3%, but this difference didn't pass statistical significance (DeLong's test, $p = 0.105$). The performance was weaker here, AUC 0.892, which hints that subtle lesions still manage to trick the model sometimes. Yet, overall, it stayed fairly reliable. The interesting fact is that McNemar's test ($p = 0.035$) showed a slight tendency for the AI to overcall early caries. False positives showed up more than usual, actually. That was kind of expected. It fits with a cautious setup, after all. The Realism seems to be where this AI leans. It doesn't gloss over the fine stuff. There's a bit of a tilt maybe even an instinct—to catch rather than miss. Most of the time, that cautious bend helps. Specificity comes out strong, touching close to 94.1 percent. As for the F1-score, it settles around 95.9, and was fairly balanced. Precision hovers right about 94.5. Recall climbs higher still, nearly at 97.4. The system doesn't chase everything, nor does it let things slide. Not flawless, but solid. Research has spent time on this and caries detection by AI is getting plenty of attention.

Numerous studies have shed light on AI's involvement in spotting dental caries. For example, Cantu et al. showed a CNN model outperforming dental practitioners with anywhere from 3 to 14 years of experience when diagnosing early carious lesions [51]. In a similar vein, Devito et al., shared promising results using an "Artificial Neural Network (ANN)" aimed at detecting interproximal caries on bitewing radiographs [55]. Hung et al. also looked into AI for root caries prediction, finding notably strong performance [56]. On another front, Ekert et al. verified that CNNs can effectively pick out apical lesions (ALs) on dental panoramic images [57]. The AI-driven ML model by Hung et al. for diagnosing dental root caries, showed impressive accuracy (97.1%), precision (95.1%), and sensitivity (99.6%) [56]. Likewise, Pang et al. created an AI-based machine learning model that predicts dental caries risk by analysing environmental and genetic factors, though some limits arise due to the dataset's diversity [58].

Lee et al. [59] developed an AI-driven convolutional neural network (CNN) aimed at detecting early caries, using bitewing radiographic images. Their study applied the UNet deep CNN architecture, which clearly improved clinician sensitivity when identifying small to moderate caries lesions.

On the flip side, the model had a higher false positive rate, mostly with overlapping proximal surface lesions, showing the algorithm still needs some fine-tuning. Then, Chen et al. [60] tried a Faster R-CNN deep learning model targeting proximal caries. After a lot of training, it hit an accuracy of 0.87, close to dental students who scored 0.82. This AI also showed sensitivity at 0.72 and specificity at 0.93, while students' sensitivity stayed below 0.40, highlighting the model's edge in diagnostic sensitivity.

Although statistically significant p-values do point to real differences, interpretation needs grounding in context; they're more about the AI playing it safe, not so much about clinical issues. The model, in actual use, shows impressive diagnostic ability. Cuts radiologist workload a lot. Patient safety stays intact, thanks to human review when cases aren't clear-cut. Still, keeping an eye on false positives over time, plus recalibrating thresholds now and then, helps maintain accuracy, especially as the model runs into new imaging types and populations. Caries detection in dentition with complex shapes, such as molar teeth, remains tricky for such models. Take one study with a CNN model—performance was better with premolars, but molars, because of their complicated form, were tougher to handle. Another drawback is that current automated caries detection research tends to look just at images. Important stuff like patient history or clinical exam results, which dentists usually consider, often gets left out.

5. Conclusion

AI shows strong accuracy and reliability when it comes to spotting dental caries on periapical images. In many cases, performance reaches levels seen in experienced dental experts. Sensitivity rates often go beyond 95 percent. Specificity stays over 90 percent as well. As a result, fewer cases slip through, both missed and misidentified. That matters, especially when dealing with early-stage caries. These initial spots often show up as faint shadows on radiographs. Barely there, hard to be sure, not always easy to read and hard to make sense of, sometimes. In situations like these, artificial intelligence enters the scene. Not as a replacement. Just as a helping hand, steady and present. Acts more like a second set of eyes. A kind of steady guide. Helps even out the inconsistencies that can surface when clinicians differ in experience or simply in how they see things. Especially helpful for training new people or in spots where specialists don't come around much. Adding AI into everyday dental work seems to speed things along. It can point out urgent cases right away and take care of documenting results without wasting time.

Ethical approval: This study was conducted under the ethical standards of the Ethics Committee for Scientific Research at the College of Dentistry, University of Wasit, Ref. No. 22024 in 1/10/2024.

Informed consent: The informed consent was obtained from all individual participants included in the study.

Conflicts of interest: Authors declared no conflicts of interest.

Financial support: None.

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