The effect of a deep-learning tool on dentists' performances in detecting apical radiolucencies on periapical radiographs

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- LT and DT are affiliated with Denti.Ai and a potential conflict of interest exists.

Background:

Artificial intelligence (AI) has emerged as a critical technology in oral health imaging, providing significant opportunities to enhance accuracy, efficiency, and reduce human error.

AI is the capacity of computer systems to execute tasks that are typically carried out using human intelligence.

Conventional machine learning and deep learning are both subsets of AI.

Machine learning is limited compared to deep learning, as it necessitates engineering and domain expertise to develop a feature extractor.

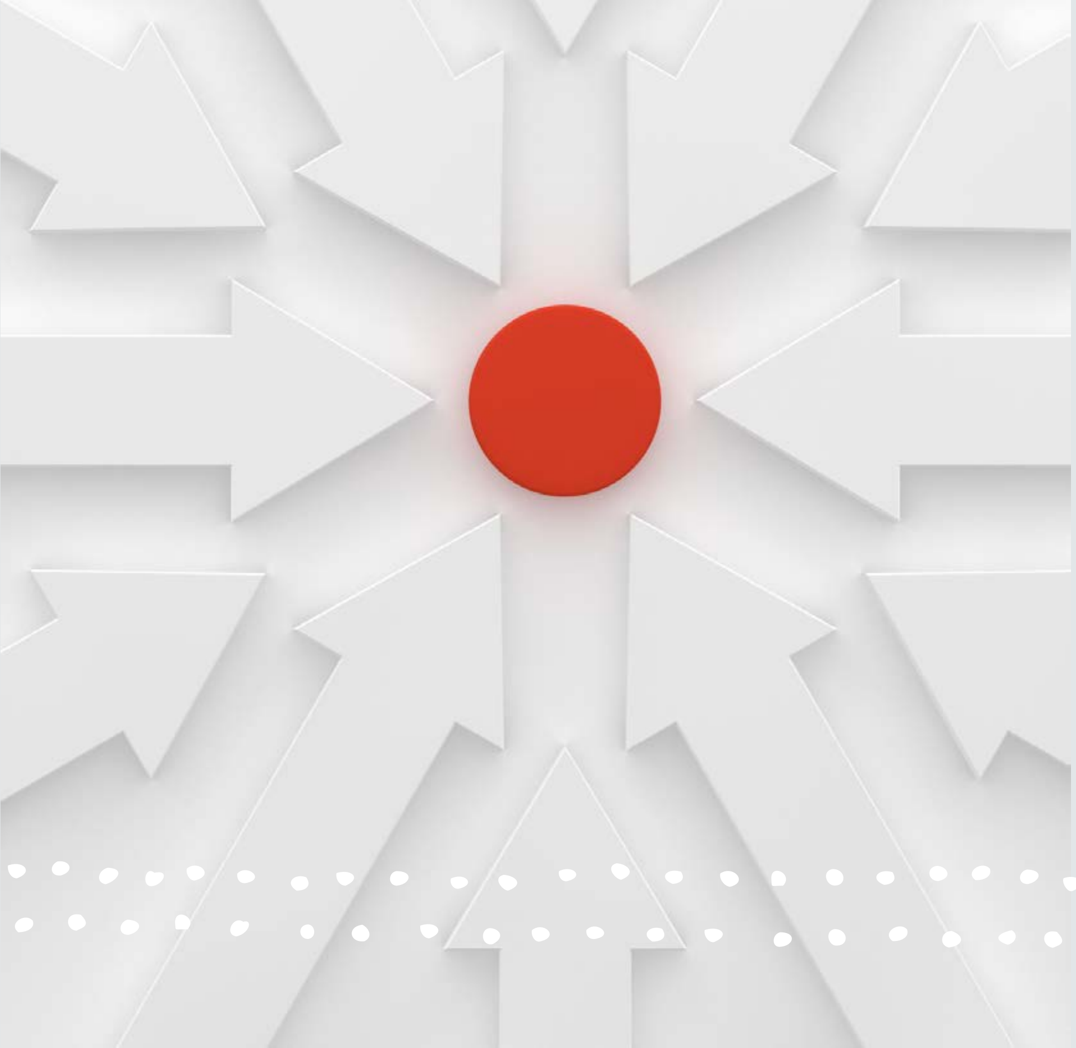
Deep learning's key characteristic is that the layers of features are not designed by engineers but are instead extracted automatically from the input data. In DL, a convolutional neural network (CNN) is a class of artificial neural network most applied to analyze visual imagery.

Applications of AI in Oral Radiology:

- Tooth detection and numbering
- Bone loss and periodontal disease detection
- Endodontics (ex: periapical lesions, MB canal detection, vertical root fractures..etc.)
- Orthodontic and orthopedic imaging applications (ex: landmark detection, determining growth and development by cervical vertebrae stages)
- Restorative and cariology applications (ex: caries detection)
- Identification and classification of dentomaxillofacial pathologies (ex: cysts and tumors)

..and many other ongoing research projects!.

Aims:



1- Primary aim:

To evaluate the effectiveness of a commercially available deep-learning (DL) software, namely DENTI.AI, in supporting dentists with the **identification of apical radiolucencies on periapical radiographs.**

2- Secondary aims:

Assess the efficacy of DL in subsets categorized based on the **size of the lesion** and the **treatment status of the tooth**.

Methods:

Part 1: Case Selection and Ground Truth

IRB (#19-1430)

CBCT referral log

Endodontic referrals between “08/2014-03/2019”
n=367 cbcts

Reports written by board certified radiologists.

Key terms: “apical rarefying osteitis” or “apical radiolucent lesions” or “apical widening of the PDL space”.

CBCT Exclusion Criteria

- Widest dimension < 2 mm
- Patients under18 years
- Primary teeth

Once a case was considered eligible to be included in the sample, the patients' records were searched for a corresponding, same-site IO periapical radiograph.

Periapical Radiograph inclusion Criteria

- Periapical radiograph is diagnostically acceptable
- PA is acquired <6months from CBCT

Methods: Cont'd

We collected **184 positive** intraoral radiographs after applying appropriate inclusion and exclusion criteria. These radiographs were split into two subsets:

1- A model-tuning subset of **54 images**

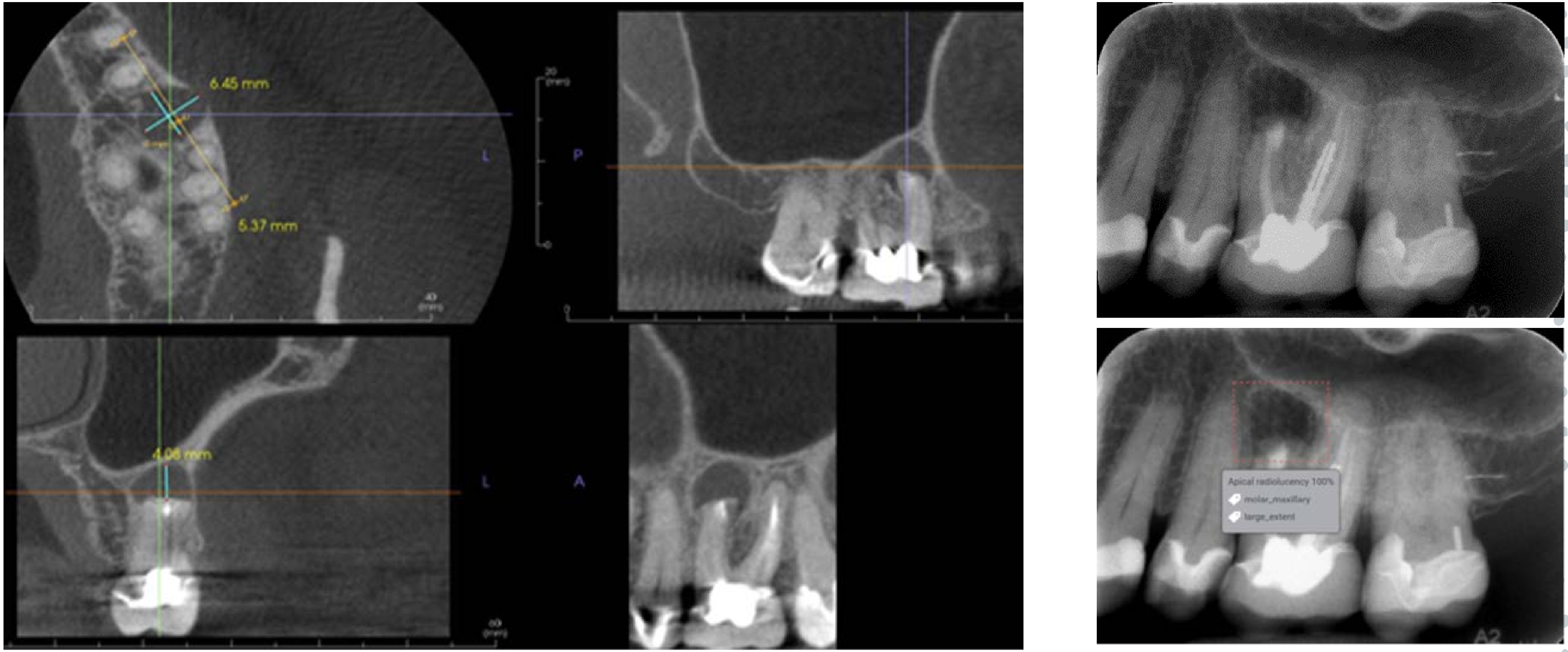
2- A testing subset of **130 images**

Additionally, **132** periapical radiographs with sound apical periodontium were collected and utilized as control radiographs. From the control and testing subsets, a final **testing subset of 68 images** was randomly selected utilizing a random number generator.

Cases	Number of periapical radiographs	Number of teeth	Number of lesions
Positive cases	38	152	56
Control cases	30	116	0
Total cases	68	268	56
56 lesions extent and treatment status			
Extent		**Number of lesions**	
Small (2–5 mm)		31	
Large (>5 mm)		25	
Treatment status		**Number of lesions**	
Endodontically treated		31	
Not endodontically treated		25	

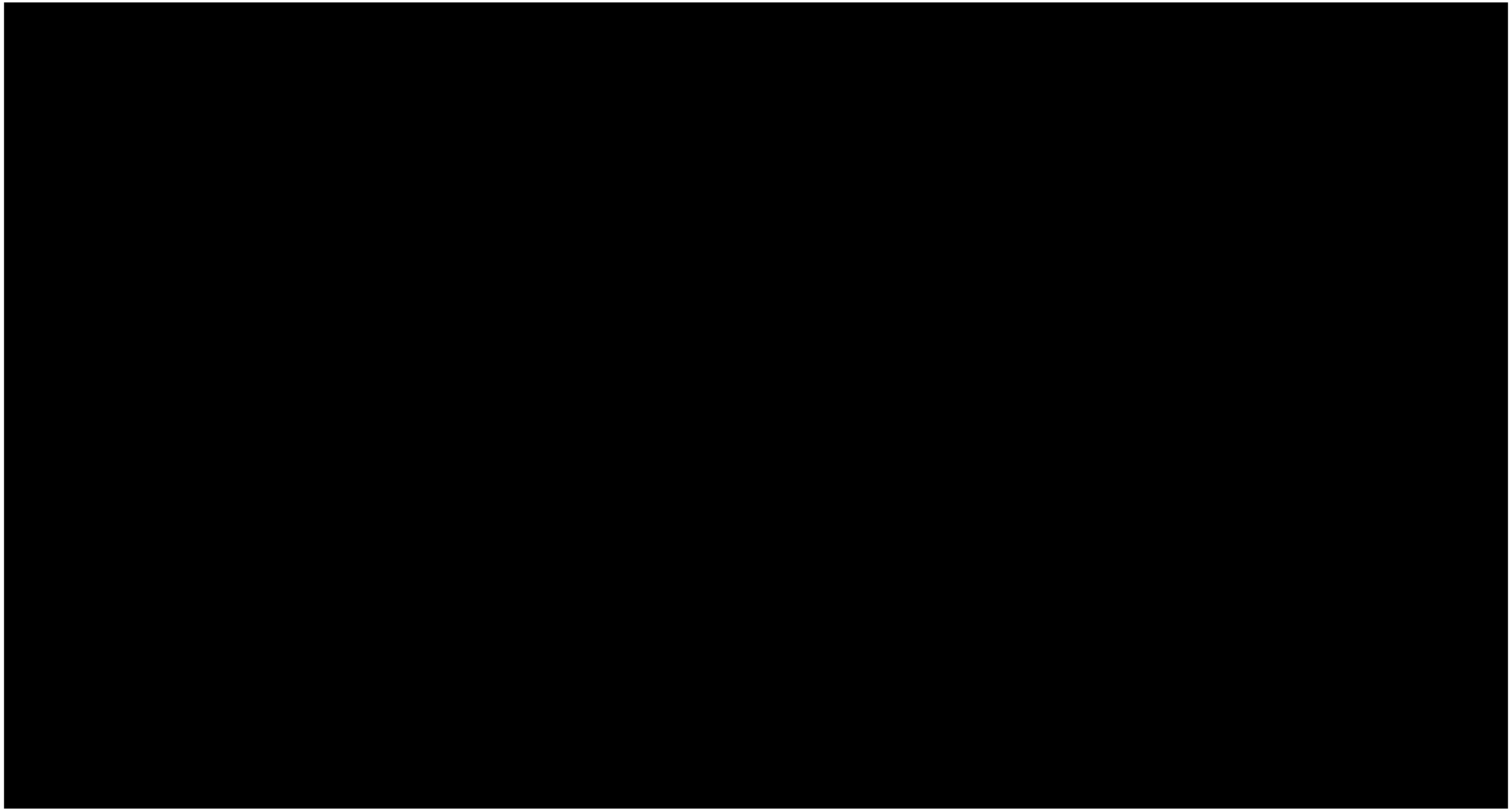
CBCT as Ground Truth :

Prior to the execution of our study, no research had been conducted on periapical radiolucencies using CBCT as a reference standard. Earlier studies relied on consensus panels, which is deemed to be less reliable compared to the CBCT reference standard.



- Left image: detection and verification of apical radiolucency presence and measurements on CBCT (Right upper image) Same-site IO radiograph - acquired within a 6 months period (Right-down) CBCT-guided ground-truth annotations of the IO radiograph by addition of location and extent tags.

Example of Ground Truth Annotation Process:



Reader Study Execution:

Eight dentists performed a cross-over reading scenario.

They analyzed the same testing subset collection of 68 images under two conditions; without and with the aid of AI predictions.

Washout period of more than one month.

They were requested to include confidence score tags in order to indicate their level of confidence in their decision. A confidence rating scale ranging from 1 to 5 was utilized for this purpose.

Statistical Analysis and Results:

- Primary endpoint: Alternative Free-Response Receiver Operating Characteristic (AFROC) AUC metric was evaluated for comparing the performance of the readers for the two reading scenarios.

- Secondary endpoint analysis included the following metrics: sensitivity (by case) specificity (by case), and sensitivity (by lesion).

Statistical Analysis and Results:

Primary and Secondary Endpoints (68 images, 56 lesions, eight readers)								
	AFROC	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.892	0.833	0.951	**0.071**	0.022	0.119	**0.005**	**8.6%**
Read 1	0.822	0.749	0.894					
	Sensitivity by Case	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.931	0.884	0.978	**−0.007**	−0.043	0.030	0.712	−0.7%
Read 1	0.938	0.904	0.971					
	Specificity by Case	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.733	0.644	0.822	**0.138**	0.048	0.277	**0.005**	**23.1%**
Read 1	0.596	0.506	0.685					
	Sensitivity by Lesion	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.888	0.831	0.946	**0.067**	0.017	0.117	**0.010**	**8.2%**
Read 1	0.821	0.759	0.884					

Localization of lesion accuracy (AFROC-AUC), specificity and sensitivity (by lesion) detection demonstrated improvements in the AI-aided session in comparison with the unaided reading session.

Statistical Analysis and Results:

Subgroup Statistics (eight readers)								
Small Extent (31 lesions)								
	Sensitivity by Lesion	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.859	0.808	0.910	**0.109**	0.058	0.160	<**0.001**	**14.5%**
Read 1	0.750	0.684	0.816					
Large Extent (25 lesions)								
	Sensitivity by Lesion	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.925	0.876	0.974	**0.015**	−0.021	0.051	0.409	1.6%
Read 1	0.910	0.866	0.954					
Endodontically treated (31 lesions)								
	Sensitivity by Lesion	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.956	0.933	0.978	**0.125**	0.069	0.181	<**0.001**	**15%**
Read 1	0.831	0.762	0.899					
Non-endodontically treated (25 lesions)								
	Sensitivity by Lesion	CI Lower	CI Upper	Read 2 – Read 1	CI Lower	CI Upper	*P*-Value	%
Read 2 (Aided by AI)	0.805	0.726	0.884	**−0.005**	−0.053	0.043	0.827	−0.6%
Read 1	0.810	0.754	0.866					

Subgroup performance analysis revealed an increase in sensitivity for small radiolucencies and in radiolucencies located apical to endodontically treated teeth.

Conclusions:

- The study shows that the DENTI.AI system has the potential to assist dentists in localizing and detecting apical lesions on intraoral images.
- However, conducting further research with a more diverse and extensive range of cases and readers would provide stronger evidence regarding the impact of this DL tool.

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