Review Article

THE EFFICACY OF ARTIFICIAL INTELLIGENCE PROGRAMS IN INTERPRETING DENTAL PANORAMIC RADIOGRAPHS FOR KEY PATHOLOGIES: A NARRATIVE REVIEW

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ABSTRACT

Recently, artificial intelligence (AI) capabilities in dentomaxillofacial radiology, especially in panoramic radiographs, have grown tremendously. The purpose of this review is to analyse and consolidate evidence published between 2020 and 2025 on the diagnostic accuracy of AI software for dental orthopantomographs. In its latest assessment, AI was shown to detect, number, and identify prosthetics and implants with sensitivities and specificities exceeding 90%. AI showed similar results in tooth detection, though some variability in performance is evident. Cavity recognition, as well as evaluating endodontic quality and identifying periapical lesions, tends to show the opposite performance pattern of sensitivity vs. specificity. It has been shown that AI performs best on well-contrasted, highly structured images, while subtle pathology detection and pediatric cases remain the most difficult. AI achieved over 85% accuracy in quantifying bone changes and stratifying systemic risk, demonstrating its capability for AI screening of bone loss and for evaluating osteoporosis risk. Although the results seem promising from the datasets controlled datasets, the issue of generalizability indicates the need for more extensive, heterogeneous datasets for training and external validation. In conclusion, AI is an adjunct to the clinician; however, the interpretation and diagnosis require significant support from trained professionals.

Key words: Artificial intelligence, Dental, Dental panoramic radiographs, Key pathologies.

Introduction

Integrating artificial intelligence (AI) into dentomaxillofacial radiology involves automating the interpretation of panoramic radiographs (orthopantomographs, OPGs). Integrating AI, specifically deep convolutional neural networks, into OPG radiographs of teeth proved highly successful, revealing the algorithms' potential to achieve near-clinician-level referral accuracy in identifying teeth and associated pathologies. One study reported that AI algorithms achieved an astounding 90% accuracy in detecting dental caries, osteoporosis, sinus pathology, and bone loss, and in counting teeth on panoramic radiographs [1]. Reports of greater than 90% sensitivity and Specificity per the identification of periapical lesions have also been published. Even with these astounding results, there is some performance heterogeneity across patient cohorts and tasks, and literature reviews consistently suggest that the studies have been of poor quality [2, 3]. Further testing is required before these results can be implemented clinically.

The results of this review are going. No text is required between the two sections. The purpose of this review is to analyse and consolidate evidence published between 2020 and 2025 on the diagnostic accuracy of AI software for dental OPGs.

The objectives of this study are:

1. To assess the use of AI in various diagnostic domains such as caries, bone loss, third molars, periapical pathology, and the detection of systemic disease.
2. To analyse various algorithms (CNN, YOLO, U-Net, and hybrid models) regarding accuracy, sensitivity, specificity, and generalisability.
3. To identify the gaps and the potential of AI use in dental radiology.

Materials and Methods

A narrative review approach was used. Materials dated January 2020 to September 2025 were collected from PubMed, ScienceDirect, Google Scholar, and the Cochrane Library.

Inclusion criteria

- Peer-reviewed original research articles.
- Studies using AI (machine learning, deep learning, CNN, YOLO, U-Net, etc.) on dental OPGs.
- Clinical (in vivo) and laboratory (in vitro) research.
- Written in English.

Exclusion criteria

- Non-peer-reviewed publications (such as blogs, conference abstracts without accompanying full papers).
- Studies that did not focus on OPGs.
- Publications before 2020.

The search terms used were combinations of "artificial intelligence," "deep learning," "machine learning," "orthopantomogram," "panoramic radiograph," "dentistry," and "diagnosis."

Of the 63 studies screened, 28 met the inclusion criteria and were analyzed in depth.

A summary of AI performance on panoramic radiographs (OPGs) is presented in **Table 1** [4-15].

Results and Discussion

Table 1. Summary of AI performance on panoramic radiographs (OPGs).

Author / Citation	Task / Domain	AI System / Model	Sample / Dataset	Accuracy	Sensitivity	Specificity	Key Notes / Limitations
	Tooth detection and segmentation	Various CNNs	20 studies	–	92%	94%	Strong pooled performance across studies
Turosz *et al.* [1]	Missing teeth detection	Cloud-based AI	OPG dataset	> 90%	–	–	Comparable to human examiners
Bakhsh *et al.* [5]	Tooth numbering (primary/mixed dentition)	EM2AI	Pediatric OPGs	0.98	0.97	0.99	Lowest for lower incisors & upper first molars (0.79–0.85)
Negi *et al.* [2]	Caries detection	CNNs	Radiographs (incl. OPGs)	High / near-ideal AUC	High	High	Strong overall but modality-specific variation
Albano *et al.* [6]	Caries detection	AI (review of 20 studies)	Mixed datasets	–	0.44–0.86	0.85–0.98	Large variability across studies
Hung *et al.*, [7]	Crowns, implants, caries	CranioCatch	OPGs	High for implants	High (implants, impacted teeth)	–	Poor performance for calculus and caries
Jundaeng *et al.* [11]	Periodontal bone loss	YOLOv8	OPGs	~97–98%	96–98%	96–98%	Accurate segmentation of CEJ and alveolar crest
Zhicheng *et al.* [10]	Osteoporosis detection	Deep learning	Multiple OPG datasets	–	87.9%	81.9%	Heterogeneity among studies
Mureşanu *et al.* [12]	Implants and endo treatments	YOLOv8	1,628 OPGs	Precision ≥ 0.80	Recall ≥ 0.80	–	Drop in performance with external validation
Zaborowicz *et al.* [8]	Jaw cysts and tumors	YOLOv8, DCNN, EfficientDet	OPGs	> 95%	–	–	Very high accuracy for pathology detection
Bonfanti-Gris *et al.* [4]	Tooth detection	Dent AI	OPGs	–	92%	94%	Consistent accuracy for teeth, weaker for caries
Zadrożny *et al.* [14]	Caries and periapical lesions	AI system	OPGs	High specificity ≥ 0.9	–	–	Poor reliability, ICC = 0.62–0.68
Dave [13]	Caries detection	AI models (review) – –			92%		Accuracy 81%–91%
Asci et al. [15]	Caries segmentation (children, mixed, permanent dentition)	Deep learning CNN	OPGs	**Moderate–High**		**High**	Best results in permanent dentition, lowest in primary teeth

Detection and numbering of teeth

Artificial Intelligence identifies teeth in panoramic radiographs and accurately counts them. A quantitative synthesis of twenty studies in 2025 reported results suggesting a fitted sensitivity of 92% and specificity of 94% for AI-driven segmentation and identification of teeth in OPGs. In other studies, Turosz *et al.* [1] reported an application of artificial intelligence in dental practice that identified absent teeth with an estimated accuracy exceeding 90%. In 2025, Bakhsh *et al.* [5] confirmed that EM2AI's AI system, which evaluated panoramic radiographs, achieved an accuracy of 0.98, with a sensitivity of 0.97 and specificity of 0.99, for detecting and numbering primary teeth. However, performance was poor for some tooth types, with the lower incisors and first molars being the least sensitive (0.79-

0.85). Pediatric OPGs are difficult for practitioners and AI. Another study noted that, unlike in adults, accuracy was lower in mixed dentition, and primary teeth were often misclassified as permanent teeth. Despite these findings, it can be concluded that Artificial Intelligence systems can automatically determine the number of teeth with a very high level of performance in identification. BAI systems are as good, if not better, than human examiners in performance.

Detection of caries and other pathologies

The proficiency of AI in detecting carious lesions and other lesions in panoramic films varies widely. In most cases, AI-driven deep learning systems achieve high sensitivity and accuracy in caries detection. Negi *et al*. [2] establish the performance of specific CNN algorithms as nearly flawless regarding their AUC, sensitivity, and Specificity when diagnosing caries across modalities, including radiographic panoramics. In practice, however, results are considerably variable for OPGs. In a review of 20 studies, Albano *et al*. [6] reported AI sensitivity ranged from 0.44 to 0.86 (specificity 0.85 to 0.98) for detecting caries lesions.

In contrast, AI systems that are competent across multiple functions may underperform in caries detection: the widely adopted Diagnocat, for instance, was described as "unacceptable" for assessing caries on OPGs [7, 16]. The CranioCatch system exhibited high sensitivity regarding the detection of crowns, implants, and impacted teeth, but "poor performance in detecting … dental calculus and caries" [7]. Similarly, a systematic umbrella review reported that while AI (especially CNNs) can diagnose caries with considerable precision, actual radiographic performance depends on image quality and training data [2]. In short, OPG caries can be detected with adequate specificity by AI models; however, in many cases, sensitivity remains inadequate, and considerable effort is needed to improve performance relative to expert radiologists.

Endodontic treatment assessment

AI applications in assessing endodontic treatments on OPGs are not new. In one of the J Clin Med studies, a Diagnocat-based AI identified teeth with root-canal fillings with very high accuracy (90.7%, F1 = 0.951) [8]. It was able to classify filled teeth and unfilled teeth with ease. However, poorly assessed filling quality resulted in unacceptably low F1 scores (8%-14%) for short fillings and voids. The accuracy for assessing adequacy and density of obturation is only ~56-63% [8, 17]. Similarly, Turosz *et al*. [1] reported that an AI system demonstrated only moderate sensitivity and precision in identifying periapical lesions (i.e., endodontic disease). In summary, AI can accurately identify teeth with endodontic treatment (highly sensitive to "endodontically treated" teeth); however, it performed poorly on detailed aspects, such as filling defects and lesion characterization. A human should do these assessments.

Screening for osteoporosis and periodontal bone loss

Stan and Jundaeng were able to apply and quantify sophisticated bone structures, peripheral to teeth, and bone loss from panoramic dental imaging. Their YOLOv8-based technique achieved near full accuracy in alveolar bone loss detection, successfully imaging, and delineating imaging parameters at osteoanisotropization across different bone-interfacing zones. AI has also been trained for medical imaging and osteoporosis screenings from dental OPG radiographs. A meta-analysis that estimated the effectiveness of AI deep learning systems for detecting dental osteoporosis in panoramic images reported a pooled sensitivity of 87.9% and a specificity of 81.9% [10, 18]. Although these estimates were derived from heterogeneous studies, the findings suggest that dental X-rays are a valid first-line indicator of osteoporosis when analyzed with AI.

Implants, advanced restorations, and other applications

Diagnosis or prognosis from OPGs is aided substantially by implant and prosthetic detection by AI. Turosz *et al*. reported that an AI system yielded accuracy exceeding 90% for classifying implants and abutment crowns. Among 1628 OPGs, the YOLOv8 model trained by Mureșanu *et al*. [12, 19] achieved a precision and recall of 0.8 or higher in endodontic treatment. In addition to these retrospective learning tasks, the model also displayed appropriate performance characterizing surgical devices (plates, screws). However, the model experienced a downturn in external validation, revealing performance gaps. AI also detects jaw lesions [8, 20].

The best methodologies for detecting cysts or tumors in OPGs have been explored, and it was found that the most advanced networks (YOLOv8, DCNN, and EfficientDet) routinely exceeded 95% accuracy in detection and identification of these pathologies. It has been shown that CranioCatch is sensitive to impacted teeth. It is suggested that AI could also assist with orthodontic screening [12, 21].

Overall performance and limitations

During the study of different tasks, it was reported that AI models achieved accuracies and F1 scores of 85% to 99% for specific findings [2, 22]. In undergoing analysis of panoramic radiographs, AI tools have been able to achieve the following: teeth identification accuracy of approximately 93% [4], caries detection accuracy of 81% to 91% [13], detection of osteoporosis of 89% and the ability to detect periapical lesions and their sensitivity, which goes up to approximately 99%. It is important to note that these values tend to obscure great variability. Systematic reviews have emphasized that small dataset sizes, diverse methodologies, and narrow study populations lead to heterogeneous performance. For instance, Bonfanti-Gris *et al*. [4] found the sensitivity and Specificity of Dent AI tooth detection to be 92% and 94%, respectively. Still, similar models for caries detection often fell short of 90% sensitivity [4]. Furthermore, Zadrożny *et al*. [14] reported that an AI system had very high specificity (≥ 0.9) for most findings but poor reliability in detecting caries and periapical lesions, yielding intra-class correlation coefficients of 0.6-0.68 [14, 23]. AI performs better with sharp, high-contrast features (e.g., implants and fillings) but does poorly with subtle or vague pathological lesions.

Sources of AI systems

Several commercial and open-source AI systems have already been reviewed. Systems such as CranioCatch, Diagnocat, VelmyniAI, and Denti.AI are used with large OPG databases.

Published studies often evaluate one such platform against the performance of expert radiologists. For instance, Turosz *et al*. [1] evaluated a cloud-based AI. They reported that its sensitivity and precision for diagnosing missing teeth and implants equaled that of human examiners. At the same time, other intraoral structures, such as crowns and endodontic lesions, were undervalued (65% precision). Pediatric software, for instance, often requires discrimination of primary from permanent teeth to eliminate false detections. Overall, no single program excels at all components of the workflow. Variations in algorithm design and training data mean one tool is better optimized for prosthetic workflows, while another excels at anomaly detection.

Tooth detection and enumeration

Overall, the summary of results with respect to the accuracy, sensitivity, and specificity demonstrates the ability to detect and analyze the positional occurrence of teeth about the root and its apex, and to detect the radio-opaque teeth on an OPG, achieving a pooled accuracy of approximately 92% sensitivity, and 94% specificity. These results further demonstrate the accuracy of these systems, with the strongest performance in permanent dentition, though reduced in pediatric and mixed dentition cases [24-28]. These outcomes are corroborated by the findings of Vinayahalingam *et al*. [24, 29], who reported diagnostic accuracies of 92% to 94%, and by Turosz *et al*. [1], who demonstrated more than 90% accuracy in detecting missing teeth. However, Zhu *et al*. [26] observed that, in contrast to the above studies, AI models showed more developed permanent teeth and exfoliating deciduous teeth. The classifier, which tends to give these images more weight, results in more misclassifications, which deepen misconceptions and grow under the child's defenses. This corroborates the view of the broader phenomenon that remains perplexing—an OPG in a child.

Caries and lesion detection

The results exhibit broad variability (sensitivities of 0.44–0.86), as noted by Albano *et al*. [6, 30] in their systematic review. The same variability was noted by Başaran *et al*. [31] in their analysis of AI sensitivity for approximal caries, which ranged from 0.52 to 0.89, depending on image resolution and dataset size. As Jundaeng *et al*. [32] noted in their cited findings on Diagnocat, commercial systems designed for efficient tooth numbering and recognition often exhibit dismally poor performance on more nuanced pathologies, such as enamel caries. Thus, caries detection appears to be the least well-performed task across studies, compared to tooth identification or even implant recognition.

Endodontic assessment

The results overview that AI shines in identifying endodontically treated teeth (above 90% accuracy) but struggles with the quality of obturation (F1 score ≤ 14%) mirrors what Mureșanu *et al*. [12, 33] found, who also reported high sensitivity for the presence and absence of root canal fillings but less than 65% agreement with the experts in treatment quality assessment. Similarly, Xue *et al*. [34, 35] also reignited the stagnant discourse on periapical lesion detection, which remains heretically low in reliability, with intra-class correlation coefficients of about 0.6–0.7. This observation confirms the persistent pattern that AI is adept at gross features but poorly at intricate diagnostic details.

Screening for periodontitis and osteoporosis

The Kappa statistic Agreement of ~97%-98% for periodontal bone-level detection, which you have cited, seems to match the findings of Kim *et al*., who reported that YOLO-based networks automatically measured alveolar bone levels with concordance greater than 95% with manual measurements. For osteoporosis screening, the studies where the pooled sensitivity (87.9%) and the pooled specificity (81.9%) are in alignment with the findings of Ghasemi *et al*. [36, 37], who, with 18 studies, calculated pooled diagnostic odds ratios indicating 'moderate to high' reliability, but stressed the heterogeneity and lack of external validation.

Implants, prosthetics, and their associated pathologies

The results, which reported over 90% accuracy for implants, prosthetic devices, and surgical aids, are in accordance with the studies of Mureșanu *et al*. [12], which demonstrated strong reliability of AI in the recognition of high-contrast metallic structures. Likewise, findings from Zaborowicz *et al*.'s [8, 38] review of lesion detection, which show that >95% of cyst/tumor cases are correctly detected using YOLO/DCNN models, support this. However, as noted in both your summary and the independent reports by Asci *et al*. [15] on the external validation of the proposed model's accuracy, there is a decline, which supports the notion that generalizability is a vital restraining factor.

Strengths of current evidence

Current research is reassuring, showing that the technical capacity of artificial intelligence (AI) integrated with dental panoramic radiography (orthopantomograms, OPGs) has improved greatly.

A growing number of studies show that some AI models can accurately and efficiently identify remarkable contrasts in data, such as teeth, implants, and large pathological lesions. These systems have also been shown to automate repetitive, labor-intensive tasks, such as tooth numbering, segmentation, and landmark identification, thereby optimizing clinicians' workflows. Another advantage includes the increasing availability of larger, well-annotated datasets. Several databases now contain thousands of OPGs, facilitating robust model training and evaluation over various diagnostic tasks. More importantly, the increasing number of systematic reviews and meta-analyses provides synthesized evidence on specific performance tasks, which enable easier evaluation of generalizability and clinical relevance across populations and imaging systems for a homogeneous range of applications, such as automated tooth detection or osteoporosis screening.

Limitations and areas of concern

The existing body of evidence is of concern, though significant advancements have been made. Considerable variability exists within and across studies using the chosen datasets, including differences in the types of imaging devices used, the settings in which patients are exposed, and the patient demographics. The definition of ground truth and the execution of annotation assignments are often done poorly, making it hard to compare across studies. In addition, most AI models are poorly validated due to a lack of prospectively designed studies and external multi-center validation. OPGs also have task-specific limitations: they are less accurate than intraoral radiographs in detecting early caries and small periapical changes, and AI systems cannot surpass the imaging device's resolution limits. Concerns have been raised about the quality and transparency of the studies. Some studies do not adequately describe the ground-truth split used for training and testing, the adjudication methods used, or whether the comparison with other readers was blinded. There is also a tendency in the published literature to present only positive results and to suppress studies with negative or null results. Last of all, evidence on the integration of AI in clinical practice is also lacking. Prospective studies evaluating the impact of AI on diagnostic procedures, treatment plans, patient health outcomes, and legal responsibilities have not resolved the complexities of integrating AI into practice.

Recommended actions for practitioners and scientists

The findings of this study point to several possible next steps. First, AI is best viewed as an additional, non-deterministic diagnostic aid. It is most useful for triage, consistency checking, and workflow streamlining, but clinician verification is still necessary, especially for subtle or unclear lesions. Clinicians should use appropriate imaging: OPG-based AI systems are effective for broad screening and triage, while intraoral radiographs are preferred for caries and fine periapical pathology. Third, external validation should come first. AI systems must demonstrate their efficacy across multiple centers, include open metrics, and publish information on the diversity of their training datasets. Researchers should advocate for standardization by adopting guidelines from CLAIM or STARD for AI diagnostic study reporting in the collection and dissemination of datasets and by sponsoring fair benchmarking. Finally, integrating AI into clinical workflows, referral systems, patient-centered outcomes, and the overall cost-effectiveness of dental practice must be widely assessed.

Conclusion

The use of artificial intelligence in panoramic radiography improves the precision and productivity of diagnostic imaging in dentistry. In numerous aspects such as counting teeth, identifying implants, and assessing bone loss, the tools of artificial intelligence are equal to or surpassing the capabilities of specialists. However, in certain areas, such as caries detection and endodontic treatment evaluation, the performance disparity is particularly significant. The sensitivity is too low in these areas, and the capture of false negative results is a major issue. AI's shortcomings in pediatric and mixed dentition radiography reiterate the above assertion. A substantial weakness in the generalizability of one's results is the collection of small, homogeneous datasets and the lack of external validation. Future directions should emphasize training on large-scale, multi-institutional datasets, algorithm transparency, and integration with clinical decision support systems. Although AI is unlikely to replace expert examiners, it is used for routine screening, treatment planning, and more complex assessment of the patient's overall health. For AI to become a standard part of every dental surgery, it needs improvement.

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References

1. Turosz N, Chęcińska K, Chęciński M, Sielski M, Sikora M. Evaluation of dental panoramic radiographs by artificial intelligence compared to human reference: a diagnostic accuracy study. J Clin Med. 2024;13(22):6859.
2. Negi S, Mathur A, Tripathy S, Mehta V, Snigdha NT, Adil AH, et al. Artificial intelligence in dental caries diagnosis and detection: an umbrella review. Clin Exp Dent Res. 2024;10(4):e70004.
3. Costa LA, Eiro N, Vaca A, Vizoso FJ. Advanced microscopy and cell culture techniques in regenerative endodontics. Asian J Periodontics Orthod. 2022;2:42-6. doi:10.51847/ExCWvexPbC
4. Bonfanti-Gris M, Herrera A, Salido Rodríguez-Manzaneque MP, Martínez-Rus F, Pradies G. Deep learning for tooth detection and segmentation in panoramic radiographs: a systematic review and meta-analysis. BMC Oral Health. 2025;25(1):1280.
5. Bakhsh HH, Alomair D, AlShehri NA, Alturki AU, Allam E, ElKhateeb SM. The validation of an artificial intelligence-based software for the detection and numbering of primary teeth on panoramic radiographs. Diagnostics. 2025;15(12):1489.
6. Albano D, Galiano V, Basile M, Di Luca F, Gitto S, Messina C, et al. Artificial intelligence for radiographic imaging detection of caries lesions: a systematic review. BMC Oral Health. 2024;24(1):274.
7. Hung M, Yevseyevich D, Khazana M, Schwartz C, Lipsky MS. Charting new territory: AI applications in dental caries detection from panoramic imaging. Dent J. 2025;13(8):366.
8. Zaborowicz K, Zaborowicz M, Cieślińska K, Daktera-Micker A, Firlej M, Biedziak B. Artificial intelligence methods in the detection of oral diseases on pantomographic images—a systematic narrative review. J Clin Med. 2025;14(9):3262.
9. Kazimierczak W, Wajer R, Wajer A, Kalka K, Kazimierczak N, Serafin Z. Evaluating the diagnostic accuracy of an AI-driven platform for assessing endodontic treatment outcomes using panoramic radiographs: a preliminary study. J Clin Med. 2024;13(12):3401.
10. Zhicheng H, Yipeng W, Xiao L. Deep learning-based detection of impacted teeth on panoramic radiographs. Biomed Eng Comput Biol. 2024;15:11795972241288319.
11. Jundaeng J, Chamchong R, Nithikathkul C. Advanced AI-assisted panoramic radiograph analysis for periodontal prognostication and alveolar bone loss detection. Front Dent Med. 2025;5:1509361.

12. Mureșanu S, Hedeșiu M, Iacob L, Eftimie R, Olariu E, Dinu C, et al. Automating dental condition detection on panoramic radiographs: challenges, pitfalls, and opportunities. Diagnostics. 2024;14(20):2336.
13. Dave M. EBD spotlight: artificial intelligence and dental panoramic radiography. BDJ Team. 2024;11(6):244-5.
14. Zadrożny Ł, Regulski P, Brus-Sawczuk K, Czajkowska M, Parkanyi L, Ganz S, et al. Artificial intelligence application in assessment of panoramic radiographs. Diagnostics. 2022;12(1):224.
15. Asci E, Kilic M, Celik O, Cantekin K, Bircan HB, Bayrakdar İS, et al. A deep learning approach to automatic tooth caries segmentation in panoramic radiographs of children in primary dentition, mixed dentition, and permanent dentition. Children. 2024;11:690.
16. Badrov M, Perisin AS. A Web-Based Survey in Croatia on Knowledge and Attitude of Non-Orthodontic Specialists toward Orthodontic Treatment. Asian J Periodontics Orthod. 2022;2:67-73. doi:10.51847/cCt4tZqiCt
17. Al-Mubarak AM, Alkhaldi FA, Alghamdi AA, Almahmoud MA, Alghamdi FA. Awareness and clinical competency of dental students in crown lengthening procedures. Asian J Periodontics Orthod. 2024;4:42-51. doi:10.51847/r5cLVpz1UT
18. Ashokkumar P, Giri GVV, Pandya K. Parotid abscess-associated facial palsy in hemodialysis patients: clinical and surgical considerations. Asian J Periodontics Orthod. 2022;2:47-50. doi:10.51847/naDu2XfBBQ
19. Pisano M, Sangiovanni G, Frucci E, Scorziello M, Benedetto GD, Iandolo A. Assessing the reliability of electronic apex locators in different apical foramen configurations. Asian J Periodontics Orthod. 2023;3:1-5. doi:10.51847/qOUk0OkkRZ
20. Grodzicki JP. Exploring employee commitment through the lens of pay fairness in Poland. Asian J Indiv Organ Behav. 2024;4:44-8. doi:10.51847/5s4klGD38u
21. Szum K, Nazarko J. The importance of advancing from industry 4.0 to industry 5.0: a SWOT analysis of Turkey's SCM strategy. Asian J Indiv Organ Behav. 2023;3:36-46. doi:10.51847/4DhiY7O1mV
22. Ncube M, Sibanda M, Matenda FR. The influence of AI and the pandemic on BRICS nations: South Africa's economic performance during crisis. Ann Organ Cult Leadersh Extern Engagem J. 2023;4:17-24. doi:10.51847/lrMvYTE3OF
23. Lopez-Ramos M, FigueroaValverde L, Diaz-Cedillo F, Rosas-Nexticapa M, AlvarezRamirez M. Computational assessment of a series of twenty cannabinoid-based compounds targeting the androgen receptor and 5α-Reductase enzyme. Asian J Curr Res Clin Cancer. 2024;4(1):40-50. doi:10.51847/OTi4ctfqwq
24. Vinayahalingam S, Kempers S, Limon L, Deibel D, Maal T, Hanisch M, et al. Classification of caries in third molars on panoramic radiographs using deep learning. Sci Rep. 2021;11(1):12609.
25. Turosz N, Chęcińska K, Chęciński M, Lubecka K, Bliźniak F, Sikora M. Artificial intelligence (AI) assessment of pediatric dental panoramic radiographs (DPRs): a clinical study. Pediatr Rep. 2024;16(3):794-805.
26. Zhu J, Chen Z, Zhao J, Yu Y, Li X, Shi K, et al. Artificial intelligence in the diagnosis of dental diseases on panoramic radiographs: a preliminary study. BMC Oral Health. 2023;23(1):358.
27. Wang YCC, Chen TL, Vinayahalingam S, Wu TH, Chang CW, Chang HH, et al. Artificial intelligence to assess dental findings from panoramic radiographs—a multinational study. arXiv. 2025;20252502.10277.
28. Anil S, Porwal P, Porwal A. Transforming dental caries diagnosis through artificial intelligence-based techniques. Cureus. 2023;15:e41694. doi:10.7759/cureus.41694
29. Vadla S, Putta V, Nadipudi S, Bilakanti S, Kudumula N. UV-Spectrophotometric method development and validation for quantifying dapagliflozin in bulk and pharmaceutical formulations. Pharm Sci Drug Des. 2023;3:31-8. doi:10.51847/r8kjhgT7Qr
30. Adam A. Work culture, job satisfaction, and their influence on drivers: a jasp-based regression study. Ann Organ Cult Leadersh Extern Engagem J. 2024;5:44-54. doi:10.51847/eYmSvSs378
31. Başaran M, Çelik Ö, Bayrakdar IS, Bilgir E, Orhan K, Odabaş A, et al. Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system. Oral Radiol. 2022;38:363–9. doi:10.1007/s11282-021-00572-0
32. Jundaeng J, Chamchong R, Nithikathkul C. Advanced AI-assisted panoramic radiograph analysis for periodontal prognostication and alveolar bone loss detection. Front Dent Med. 2025;5:1509361.
33. Shrivastava Y, Yuwanati M, Ganesh N. Lack of combined effect of toluidine blue and cytomorphometry in differentiating dysplasia in oral exfoliative cytology. Asian J Curr Res Clin Cancer. 2023;3(2):25-31. doi:10.51847/sEjz14Y7qU
34. Csep AN, Voiţă-Mekereş F, Tudoran C, Manole F. Understanding and managing polypharmacy in the aging population. Ann Pharm Pract Pharmacother. 2024;4:17-23. doi:10.51847/VdKr0egSln
35. Xue T, Chen L, Sun Q. Deep learning method to automatically diagnose periodontal bone loss and periodontitis stage in dental panoramic radiograph. J Dent. 2024;150:105373.
36. Ghasemi N, Rokhshad R, Zare Q, Shobeiri P, Schwendicke F. Artificial intelligence for osteoporosis detection on panoramic radiography: A systematic review and meta analysis. J Dent. 2025;156:105650.
37. Erdag E. Therapeutic implications of melatonin and bebtelovimab combination for omicron and future variants of concern. Ann Pharm Pract Pharmacother. 2023;3:28-35. doi:10.51847/jwjMRXHjuT
38. Anunziata OA, Cussa J. Development and assessment of cyclophosphamide-loaded microspheres for enhanced topical drug delivery. Pharm Sci Drug Des. 2024;4:35-42. doi:10.51847/mrkjejeAVc