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RESHAPING DENTISTRY WITH ARTIFICIAL INTELLIGENCE: A REVIEW

Sharanya V. Rao[a]* and Ashwini Savia Colaco[b]

[a,b]Department of Conservative Dentistry and Endodontics, A. J. Institute of Dental Sciences, Mangaluru, D.K., Karnataka-575004, India.

***Corresponding Author: Dr. Sharanya V. Rao**

Department of Conservative Dentistry and Endodontics, A. J. Institute of Dental Sciences, Mangaluru, D.K., Karnataka-575004, India.

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ABSTRACT

In recent years, Artificial Intelligence (AI) has gained significant traction worldwide. This is primarily due to its capacity to enhance diagnostic precision and streamline treatment planning processes and provide better patient outcomes. AI-based approaches in dentistry have been pivotal in leveraging various models through Machine Learning (ML) and Deep Learning (DL) to enhance predictive analytics and personalized patient care strategies. This review article highlights the subsets such as Machine Learning (ML), Deep Learning (DL) and other tools. It provides an overview of the advantages and its application in different disciplines of dentistry. Despite the transformative potential of AI in dentistry some challenges do persist. Hence further research aiming to refine AI algorithms and application should be encouraged. An interdisciplinary collaboration between health care professionals, researchers, and technology developers will benefit patients worldwide. Technological advancements with dental expertise can certainly promote better standard of oral healthcare globally.

KEYWORDS: Artificial intelligence; Dentistry; Deep learning; Machine learning.

1. INTRODUCTION

The term "artificial intelligence" (AI) was first coined in the 1950s, marking the beginning of an era where computational systems could simulate human intelligence to tackle complex tasks.[1] Initially conceptualized to emulate human thinking processes, AI has evolved into a transformative force across diverse industries, including healthcare and dentistry, by enhancing the capabilities of machines to perform tasks that traditionally require human cognition and decision-making.[2]

AI technology has implicitly penetrated into all aspects of life.[3] While AI adoption in dentistry initially lagged behind, in recent years a surge of interest has fuelled research and its application in dental practice. AI technologies have made significant strides across the various disciplines of dentistry. These advancements encompass diverse applications such as disease diagnosis, localization, classification, estimation, and overall assessment of dental conditions.[4][5][6]

2. Machine Learning, Deep Learning and other tools

AI, particularly through its subset Machine Learning (ML), has ushered in a new era in dentistry. It has revolutionized diagnostic accuracy, treatment planning, and risk assessment processes.[7] ML algorithms empower dental professionals to leverage vast datasets for predictive analytics and personalized patient care strategies. Deep Learning (DL) is a specialized branch of ML. It has enhanced these capabilities further by utilization of multi-layered neural networks such as Convolutional Neural Networks (CNNs) which excel in tasks requiring complex image analysis in dentistry.[1]

In dentistry, accurate data interpretation and diagnosis are crucial. Due to the complexity and time constraints in medical decision-making, intelligent tools are essential for assisting clinicians in making precise decisions. Tools such as Clinical Decision Support Systems (CDSS). Artificial Neural Networks (ANNs) have been employed for diagnosis, classification, and assessment.

3. Advantages of AI

The integration of AI technologies in dental practices has yielded substantial benefits. They are

- Operational efficiency
- Automation of administrative tasks,
- Workflow management
- Optimising informed decisions
- Improved disease detection accuracy.
- Synthesizing of patient data
- Providing accurate treatment outcomes
- AI-driven clinical decision support systems (CDSS) equipped with digital tools like computers and X-ray machines have been a big boon in health care.[8]

4. Overview of the applications of AI in dentistry

4.1 AI in Endodontics

Endodontics is a specialized branch of dentistry focused on diseases of the dental pulp and surrounding tissues. AI technologies have emerged as powerful tools to aid in the precise diagnosis and effective management of endodontic conditions. Ghaedi et al. introduced a circular Hough transform-based segmentation method for intraoral occlusal surface images, achieving an impressive 86.3% accuracy in caries detection and scoring.[9]

Berdouses et al. proposed a random forest-based machine learning algorithm for colored image analysis, outperforming pediatric dentists with an accuracy exceeding 80% in lesion detection.[10] DL models have also demonstrated robust performance in endodontics, such as Pauwels et al.'s transfer learning-based Convolutional Neural Network (CNN) for periapical lesion detection from intraoral radiographs, surpassing radiologists in diagnostic accuracy.[11]

Fukuda et al. utilized DetectNet for vertical root fracture detection in panoramic radiographs, showing enhanced detection capabilities compared to human observers.[12] Orhan et al. applied the U-Net model to 3D CBCT images for diagnosing periapical lesions with a reliability of 92.8%.[13] Ekert et al. developed a seven-layer feed-forward network for apical lesion diagnosis using panoramic radiographs, achieving an Area Under the Curve (AUC) of 85% compared to experienced dentists.[14]

Bayraktar and Aryan employed a YOLO(You Only Look Once)-based interproximal caries detection method on bitewing radiographs, achieving an accuracy of 94.59%, surpassing the performance of dental professionals.[15] Hiraiwa et al. evaluated AlexNet for classifying distal roots, demonstrating a detection performance of 87.4% in distinguishing between single and multi-rooted teeth, outperforming dental radiologists.[16]

Casalegno et al. presented a symmetric autoencoder for detecting occlusal and proximal caries lesions using near-infrared transillumination images, achieving high throughput compared to clinical assessments.[17] Kositbowornchai et al. implemented a probabilistic neural network as a Clinical Decision Support System (CDSS) for diagnosing vertical root fractures on intraoral digital radiographs, achieving an impressive accuracy of 95.7%.[18]

4.2 AI in Restorative Dentistry

AI technologies have demonstrated significant utility across multiple facets of restorative dentistry, encompassing the diagnosis of caries, prediction of restoration failure and personalized treatment planning. Researchers have leveraged AI algorithms to analyze diverse datasets including clinical cases, panoramic radiographs, oral photographs, and 3D dental model images to enhance clinical decision-making and patient care. AI-based technologies have emerged as promising tools to automate disease diagnosis, prognostication, and decision-making, thereby supporting dental clinicians in delivering accurate and timely interventions.

Javed et al. presented a feed forward ANN for identifying occlusal dentinal caries lesions, introducing an iOS application for precise caries prediction based on clinical cases.[19] Recently, Geetha et al. proposed a back propagation neural network for tooth decay detection, achieving an accuracy of 97.1% with a false positive rate of 2.8% using intraoral radiographs, thus highlighting the efficacy of ANNs compared to traditional methods.[20]

4.3 AI in Prosthodontics

Lee et al. introduced a machine learning approach based on decision trees to predict tooth outcomes for effective treatment planning, achieving an accuracy of 84.1% in clinical settings.[21] Abdalla-Aslan et al. proposed a cubic Support Vector Machine (SVM) algorithm for detecting and classifying dental restorations from panoramic radiographs, aiming to improve patient health outcomes.[22]

Lee and Jeong utilized a fine-tuned deep Convolutional Neural Network (CNN) to diagnose and classify dental implants based on panoramic radiographs, achieving an impressive Area Under the Curve (AUC) of 97.1%, comparable to assessments by periodontists.[23] Takahashi et al. employed a deep CNN pre-trained with ImageNet weights to accurately diagnose partially edentulous arches from oral photographs, achieving high accuracies of 99.5% and 99.7% for maxillary and mandibular arches respectively, particularly in designing removable partial dentures.[24] Xu et al. proposed a hierarchical CNN framework for precise segmentation of upper and lower teeth boundaries from 3D dental model images, ensuring accurate treatment planning and restoration design.[25] In terms of treatment planning and prognosis, Artificial Neural Networks (ANNs) have proven effective. Cui et al. developed a triple classification algorithm using extreme gradient boosting (XGBoost) with electronic health records, achieving superior accuracy above 90% compared to prosthodontists in predicting tooth extraction therapy outcomes.[26]

4.4 AI in Orthodontics

Orthodontic treatments are inherently complex and time-consuming, necessitating efficient solutions for effective patient management. AI has been pivotal in various facets of orthodontic care, leveraging machine learning (ML) techniques to analyze complex datasets derived from dental images and patient records, thereby enhancing diagnostic accuracy.

Chen et al. developed a machine learning algorithm integrating multisource data to assess maxillary structures using Cone Beam Computed Tomography

(CBCT) images, achieving notable performance with a Dice ratio of 0.80 in evaluating structural variations during unilateral canine impaction.[27] In another study, Nino-Sandoval employed a Support Vector Machine (SVM)-based algorithm to classify sagittal skeletal patterns using cephalograms, demonstrating an accuracy of 74.5%.[28] Yu et al. investigated Support Vector Regression (SVR) to evaluate facial attractiveness from orthodontic photographs, achieving an accuracy of 71.8%.[29]

ML techniques have also revolutionized treatment planning in orthodontics. Riri et al. proposed a tree-based classification method for identifying facial and dental molds from intraoral and extraoral images, achieving an impressive accuracy of 94.28%.[30] Suhail et al. implemented a random forest ensemble method for automating extraction decisions based on patient health records, achieving an accuracy of 94.4%.[31]

DL techniques have been instrumental in landmark detection, crucial for orthodontic assessments. Song et al. utilized a ResNet-50 model pre-trained via transfer learning to detect cephalometric landmarks, outperforming experienced clinicians with superior success rates.[32] Similarly, Kim et al. employed a two-stage Deep Neural Network (DNN) incorporating a stacked hourglass network for landmark detection on cephalograms, achieving substantial success rates across different datasets.[33] Gilmour et al. introduced a pretrained ResNet-50 model with foveated pyramid attention, achieving robust landmark detection performance.

AI-based CDSS(Clinical Decision Support System) utilizing Artificial Neural Networks (ANNs) have been pivotal in aiding clinical decision-making in orthodontics. Amasya et al. proposed an ANN to classify cervical vertebra maturation stages and vertebral morphology from cephalograms, demonstrating high accuracy (86.93%) in staging assessments.[34] Similarly Kok et al. developed an ANN-based network for consistent classification of cervical vertebrae stages from hand-wrist radiographs, showcasing stability and reliability compared to traditional assessments.[35]

4.5 AI in Periodontics

In the domain of periodontology, artificial intelligence (AI) has been extensively utilized to advance various applications, including the detection of periodontal bone loss, the diagnosis of gingival inflammation, and the assessment of connective tissues and periodontal caries. To address diagnostic errors, several machine learning techniques have been proposed.

Li et al. developed a plaque segmentation method using a convolutional neural network (CNN) with oral endoscopic images, achieving an accuracy of 86.42%, which is superior to traditional diagnostic methods.[36] Additionally, Li and colleagues evaluated an extreme machine learning approach combining contrast-limited adaptive histogram equalization and gray-level covariance matrix for gingivitis detection using digital photographs, achieving an accuracy of 74% with a limited dataset.[37]

In the context of alveolar bone loss localization, Lin et al. employed level segmentation methods utilizing support vector machines (SVM), k-nearest neighbors (KNN), and Bayesian classifiers, demonstrating high effectiveness in classification.[5]

Deep learning (DL) methods have gained prominence in recent years. Lee et al. proposed a VGG (Visual Geometry Group)-based neural network for diagnosing periodontal bone loss using 1,740 periapical radiographs, achieving an accuracy of 99% and an area under the curve (AUC) of 98%, outperforming the diagnostic performance of three dentists. Krois et al. evaluated a deep feed-forward CNN with panoramic radiographs, exhibiting diagnostic performance comparable to that of three human examiners.[4] Kim et al. and Lee et al. explored the use of transfer learning to improve bone loss and odontogenic cyst lesion detection using panoramic radiographs, demonstrating superior performance in tooth numbering compared to dental clinicians.[38][39]

Moran et al. utilized a ResNet model to classify regions based on periodontal bone destruction, achieving an accuracy of 82% with 467 periapical radiographs. Khan et al. introduced a U-Net-based disease segmentation method for detecting bone lesions and their shapes, surpassing the performance of three expert evaluators.[38] Zheng et al. developed an anatomically constrained dense U-Net method for bone lesion identification using cone beam computed tomography (CBCT) images, accurately detecting the shape of bone lesions.[6]

Duong et al. proposed a U-Net-based network for alveolar bone delineation using high-frequency ultrasound images, outperforming three expert evaluations. Nguyen et al. used ResNet34 as an encoder within a U-Net framework to assess 1,100 intraoral images for alveolar bone segmentation, achieving a dice coefficient of 85.3%.[40] Li et al. employed Mask R-CNN with a novel calibration method for periodontitis detection using panoramic radiographs, achieving an accuracy of 82%

Papantonopoulos et al. evaluated a multilayer perceptron ANN for bone loss assessment using medical health records, achieving an accuracy of 98.1% for periodontitis classification.[41] Additionally, Shankarapillai et al. proposed a multilayer feed-forward propagation network for effective periodontitis risk prediction using 230 textual subjects.[42]

4.6 AI in Oral Maxillofacial Surgery and Oral Pathology

In the field of oral pathology artificial intelligence (AI) is used for disease diagnosis and prognosis. Orhan et al. developed a machine learning algorithm combining k-nearest neighbors (KNN) and random forest methodologies to diagnose temporomandibular disorders (TMD) using magnetic resonance imaging (MRI). Their model achieved an accuracy of 77% for identifying condylar changes and 74% for detecting disc displacement.[43]

Similarly, Hung et al. introduced a three-step convolutional neural network (CNN) incorporating V-Net and support vector regression (SVR) for identifying maxillary sinusitis using cone beam computed tomography (CBCT) images. This model achieved an area under the curve (AUC) of 92% for mucosal thickening and 84% for mucous retention cyst detection.[44]

Kuwana et al. applied DetectNet to panoramic radiographs for detecting maxillary sinus lesions, achieving accuracy rates of 90% to 91% for maxillary sinusitis and 97% to 100% for maxillary sinus cysts.[45] Additionally, Choi et al. utilized a deep CNN, specifically ResNet, to diagnose temporomandibular joint (TMJ) osteoarthritis, achieving an accuracy of 78%.[46] Kim et al. assessed the performance of a CNN on water's view radiographs for identifying maxillary sinusitis and reported significantly higher diagnostic performance.[47]

Murata et al. evaluated the deep learning model AlexNet for diagnosing maxillary sinusitis using panoramic radiographs, showing diagnostic performance similar to that of radiologists and superior to that of resident dentists.[48] Jeyaraj et al. proposed a partitioned CNN based on GoogleNet and InceptionV3 for diagnosing oral cancer using hyperspectral images, achieving accuracies of 91.4% for benign tissue and 94.5% for malignant tissue.[49]

Clinical decision support systems (CDSS) have also been employed in oral pathology. Iwasaki et al. developed a Bayesian belief network (BNN) utilizing MRI to diagnose TMJ disorders, achieving an accuracy of 99%. This model is capable of evaluating the progression of TMD with respect to bone changes, disc displacement, and bony space alterations.[50] Furthermore, Bas et al. proposed a backpropagation artificial neural network (ANN) for identifying clinical symptoms of TMJ disorders. This model has demonstrated utility in diagnosing preliminary subtypes of TMJ disorders and supporting clinical decision-making processes.[51]

4.7 AI in Paediatric Dentistry

Accurate diagnosis is crucial in dentistry to determine optimal treatment procedures, especially in pediatric dentistry where swift and precise diagnoses enhance patient cooperation and treatment success rates. Dentists commonly rely on periapical and panoramic radiographs (PRs) for diagnostic purposes.

Recently, AI-based systems have been developed to augment dental diagnoses, aiming to reduce oversight of dental issues and enhance radiological accuracy. Kılıç et al. assessed the efficacy of a deep learning (DL) method in automatically detecting and numbering primary teeth using 421 PRs from pediatric patients aged 5 to 7. Similarly, Kaya et al.[52][53] employed the YOLOv4 deep convolutional B neural network (CNN) algorithm to detect permanent tooth germs in 4518 PRs of pediatric patients aged 5 to 12, aiming to streamline workflows and minimize human errors in diagnosis.

Calıskan et al. utilized CNN algorithms to detect and classify impacted primary molars in PR images of 74 pediatric patients aged 5 to 12, reporting high accuracy rates.[54]Ahn et al. explored four different DL methods with a dataset of 1100 images (including 550 mesiodens cases) to detect mesiodens in PRs from patients in primary and mixed dentition stages, finding that ResNet-101 and Inception-ResNet-V2 models exhibited superior performance.[55] Their study suggests that AI-supported PR analysis aids clinicians in early mesiodens detection, potentially reducing future dental complications. Ha et al. developed a CNN model based on YOLOv3 to detect mesiodens in PRs across various dentition stages, utilizing 612 PRs for model training.[56] Their AI model demonstrated promising performance, indicating clinical viability for mesiodens detection in dental practice.

These studies underscore the potential of AI technologies to enhance diagnostic accuracy and streamline workflows in pediatric dentistry, offering significant benefits in early detection and treatment planning for dental conditions.

5. Challenges in using AI

Artificial intelligence application in dentistry encounters several substantial challenges despite its promising prospects. The challenges faced are.

- Data Standardization and Quality: Effective utilization of AI in dentistry demands standardized protocols for data collection and stringent quality assurance measures. Variability in data acquisition methods, image quality, and annotation standards poses obstacles to developing reliable AI models.
- Interpretability of AI Models: AI algorithms, particularly deep learning models, often lack transparency in their decision-making processes, complicating their acceptance among dental professionals who require clear insights into AI-generated diagnoses and treatment recommendations.
- Integration into Clinical Workflows: Seamless integration of AI tools into existing clinical workflows is essential for practical adoption in dental practices. This necessitates user-friendly

interfaces, real-time processing capabilities and compatibility with current software systems without disrupting established workflows.

- Ethical and Legal Considerations: Ethical issues such as patient privacy, consent for data utilization, and liability associated with AI-generated diagnoses are critical concerns. Adherence to regulatory frameworksand addressing biases in AI algorithms are imperative for ethical deployment in clinical settings.
- Cost and Accessibility: The financial implications of implementing AI technologies, including hardware, software, and training costs, may limit access for smaller dental practices. Ensuring affordability and equitable access to AI solutions is pivotal for widespread adoption and equitable patient care.
- Validation and Clinical Application: Rigorous validation of AI models across diverse patient populations and healthcare settings is essential. Clinical trials and robust real-world studies are necessary to establish the accuracy, reliability, and safety of AI-driven diagnostic tools, facilitating regulatory approval and professional endorsement.

Addressing these challenges demands collaborative efforts among dental.

6. CONCLUSION

AI represents a paradigm shift in dentistry, empowering practitioners with sophisticated tools and insights that augment clinical decision-making capabilities and streamline healthcare workflows. As AI technologies continue to evolve and integrate seamlessly into dental practice, they promise to elevate standards of care, improve patient outcomes, and pave the way for personalized, data-driven approaches to oral health management. Through ongoing innovation and collaboration, AI's transformative impact on dentistry is poised to shape a promising future.

REFERENCE

1. Schwendicke F, Samek W, Krois J. Artificial Intelligence in Dentistry: Chances and Challenges. J Dent Res, 2020 Jul; 99(7): 769–74.
2. Dindorf C, Bartaguiz E, Gassmann F, Fröhlich M. Conceptual Structure and Current Trends in Artificial Intelligence, Machine Learning, and Deep Learning Research in Sports: A Bibliometric Review. IJERPH, 2022 Dec 22; 20(1): 173.
3. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. Nat Med, 2022 Jan; 28(1): 31–8.
4. Krois J, Ekert T, Meinhold L, Golla T, Kharbot B, Wittemeier A, et al. Deep Learning for the Radiographic Detection of Periodontal Bone Loss. Sci Rep, 2019 Jun 11; 9(1): 8495.
5. Lin PL, Huang PW, Huang PY, Hsu HC. Alveolar bone-loss area localization in periodontitis radiographs based on threshold segmentation with a hybrid feature fused of intensity and the H-value of fractional Brownian motion model. Computer Methods and Programs in Biomedicine, 2015 Oct; 121(3): 117–26.
6. Zheng Z, Yan H, Setzer FC, Shi KJ, Mupparapu M, Li J. Anatomically Constrained Deep Learning for Automating Dental CBCT Segmentation and Lesion Detection. IEEE Trans Automat Sci Eng, 2021 Apr; 18(2): 603–14.
7. Carleo G, Cirac I, Cranmer K, Daudet L, Schuld M, Tishby N, et al. Machine learning and the physical sciences. Rev Mod Phys, 2019 Dec 6; 91(4): 045002.
8. Bohr A, Memarzadeh K, editors. Artificial intelligence in healthcare. London San Diego, CA Cambridge, MA Oxford: Academic Press, 2020; 355 p.
9. Ghaedi L, Gottlieb R, Sarrett DC, Ismail A, Belle A, Najarian K, et al. An automated dental caries detection and scoring system for optical images of tooth occlusal surface. In: 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society [Internet]. Chicago, IL: IEEE; 2014 [cited 2024 Jul 24]. p. 1925–8. Available from: http: //ieeexplore.ieee.org/document/6943988/
10. Berdouses ED, Koutsouri GD, Tripoliti EE, Matsopoulos GK, Oulis CJ, Fotiadis DI. A computer-aided automated methodology for the detection and classification of occlusal caries from photographic color images. Computers in Biology and Medicine, 2015 Jul; 62: 119–35.
11. Pauwels R, Brasil DM, Yamasaki MC, Jacobs R, Bosmans H, Freitas DQ, et al. Artificial intelligence for detection of periapical lesions on intraoral radiographs: Comparison between convolutional neural networks and human observers. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 2021 May; 131(5): 610–6.
12. Fukuda M, Inamoto K, Shibata N, Ariji Y, Yanashita Y, Kutsuna S, et al. Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiol, 2020 Oct; 36(4): 337–43.
13. Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endodontic J., 2020 May; 53(5): 680–9.
14. Ekert T, Krois J, Meinhold L, Elhennawy K, Emara R, Golla T, et al. Deep Learning for the Radiographic Detection of Apical Lesions. Journal of Endodontics, 2019 Jul; 45(7): 917-922.e5.
15. Bayraktar Y, Ayan E. Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. Clin Oral Invest, 2022 Jan; 26(1): 623–32.
16. Hiraiwa T, Ariji Y, Fukuda M, Kise Y, Nakata K, Katsumata A, et al. A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on

panoramic radiography. Dentomaxillofacial Radiology, 2019 Mar; 48(3): 20180218.
17. Casalegno F, Newton T, Daher R, Abdelaziz M, Lodi-Rizzini A, Schürmann F, et al. Caries Detection with Near-Infrared Transillumination Using Deep Learning. J Dent Res., 2019 Oct; 98(11): 1227–33.
18. Kositbowornchai S, Plermkamon S, Tangkosol T. Performance of an artificial neural network for vertical root fracture detection: an ex vivo study. Dental Traumatology, 2013 Apr; 29(2): 151–5.
19. Javed S, Zakirulla M, Baig RU, Asif SM, Meer AB. Development of artificial neural network model for prediction of post-streptococcus mutans in dental caries. Computer Methods and Programs in Biomedicine, 2020 Apr; 186: 105198.
20. Geetha V, Aprameya KS, Hinduja DM. Dental caries diagnosis in digital radiographs using back-propagation neural network. Health Inf Sci Syst., 2020 Dec; 8(1): 8.
21. Lee SJ, Chung D, Asano A, Sasaki D, Maeno M, Ishida Y, et al. Diagnosis of Tooth Prognosis Using Artificial Intelligence. Diagnostics, 2022 Jun 9; 12(6): 1422.
22. Abdalla-Aslan R, Yeshua T, Kabla D, Leichter I, Nadler C. An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 2020 Nov; 130(5): 593–602.
23. Lee JH, Jeong SN. Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs: A pilot study. Medicine, 2020 Jun 26; 99(26): e20787.
24. Takahashi T, Nozaki K, Gonda T, Ikebe K. A system for designing removable partial dentures using artificial intelligence. Part 1. Classification of partially edentulous arches using a convolutional neural network. J Prosthodont Res, 2021; 65(1): 115–8.
25. Xu X, Liu C, Zheng Y. 3D Tooth Segmentation and Labeling Using Deep Convolutional Neural Networks. IEEE Trans Visual Comput Graphics, 2019 Jul 1; 25(7): 2336–48.
26. Cui Q, Chen Q, Liu P, Liu D, Wen Z. Clinical decision support model for tooth extraction therapy derived from electronic dental records. The Journal of Prosthetic Dentistry, 2021 Jul; 126(1): 83–90.
27. Chen S, Wang L, Li G, Wu TH, Diachina S, Tejera B, et al. Machine Learning in Orthodontics: Introducing a 3d Auto-segmentation and Auto-landmark Finder of Cbct Images To Assess Maxillary Constriction in Unilateral Impacted Canine patients. The Angle Orthodontist, 2020 Jan 14; 90(1): 77–84.
28. Niño-Sandoval TC, Guevara Perez SV, González FA, Jaque RA, Infante-Contreras C. An automatic method for skeletal patterns classification using craniomaxillary variables on a Colombian population. Forensic Science International, 2016 Apr; 261: 159.e1-159.e6.
29. Yu X, Liu B, Pei Y, Xu T. Evaluation of facial attractiveness for patients with malocclusion: A machine-learning technique employing Procrustes. The Angle Orthodontist, 2014 May 1; 84(3): 410–6.
30. Riri H, Ed-Dhahraouy M, Elmoutaouakkil A, Beni-Hssane A, Bourzgui F. Extracted features based multi-class classification of orthodontic images. IJECE, 2020 Aug 1; 10(4): 3558.
31. Suhail Y, Upadhyay M, Chhibber A, Kshitiz. Machine Learning for the Diagnosis of Orthodontic Extractions: A Computational Analysis Using Ensemble Learning. Bioengineering, 2020 Jun 12; 7(2): 55.
32. Song Y, Qiao X, Iwamoto Y, Chen Y wei. Automatic Cephalometric Landmark Detection on X-ray Images Using a Deep-Learning Method. Applied Sciences, 2020 Apr 7; 10(7): 2547.
33. Kim H, Shim E, Park J, Kim YJ, Lee U, Kim Y. Web-based fully automated cephalometric analysis by deep learning. Computer Methods and Programs in Biomedicine, 2020 Oct; 194: 105513.
34. Amasya H, Yildirim D, Aydogan T, Kemaloglu N, Orhan K. Cervical vertebral maturation assessment on lateral cephalometric radiographs using artificial intelligence: comparison of machine learning classifier models. Dentomaxillofacial Radiology, 2020 Jul; 49(5): 20190441.
35. Kök H, Acilar AM, İzgi MS. Usage and comparison of artificial intelligence algorithms for determination of growth and development by cervical vertebrae stages in orthodontics. Prog Orthod, 2019 Dec; 20(1): 41.
36. Li S, Guo Y, Pang Z, Song W, Hao A, Xia B, et al. Automatic Dental Plaque Segmentation Based on Local-to-Global Features Fused Self-Attention Network. IEEE J Biomed Health Inform, 2022 May; 26(5): 2240–51.
37. Li W, Chen Y, Sun W, Brown M, Zhang X, Wang S, et al. Expression of Concern: A gingivitis identification method based on contrast-limited adaptive histogram equalization, gray-level co-occurrence matrix, and extreme learning machine. Int J Imaging Syst Tech, 2019 Mar; 29(1): 77–82.
38. Khan HA, Haider MA, Ansari HA, Ishaq H, Kiyani A, Sohail K, et al. Automated feature detection in dental periapical radiographs by using deep learning. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 2021 Jun; 131(6): 711–20.
39. Kim J, Lee HS, Song IS, Jung KH. DeNTNet: Deep Neural Transfer Network for the detection of periodontal bone loss using panoramic dental radiographs. Sci Rep, 2019 Nov 26; 9(1): 17615.
40. Nguyen KCT, Duong DQ, Almeida FT, Major PW, Kaipatur NR, Pham TT, et al. Alveolar Bone Segmentation in Intraoral Ultrasonographs with

Machine Learning. J Dent Res, 2020 Aug; 99(9): 1054–61.
41. Papantonopoulos G, Takahashi K, Bountis T, Loos BG. Artificial Neural Networks for the Diagnosis of Aggressive Periodontitis Trained by Immunologic Parameters. Al-Ahmad A, editor. PLoS ONE, 2014 Mar 6; 9(3): e89757.
42. Shankarapillai, R.; Mathur, L.K.; Nair, M.A.; George, R. Periodontitis risk assessment using two artificial neural network algorithms—A comparative study. Int. J. Dental Clin, 2012; 4: 17–21.
43. Orhan K, Driesen L, Shujaat S, Jacobs R, Chai X. Development and Validation of a Magnetic Resonance Imaging-Based Machine Learning Model for TMJ Pathologies. Faot F, editor. BioMed Research International, 2021 Jul 5; 2021: 1–11.
44. Hung KF, Ai QYH, King AD, Bornstein MM, Wong LM, Leung YY. Automatic detection and segmentation of morphological changes of the maxillary sinus mucosa on cone-beam computed tomography images using a three-dimensional convolutional neural network. Clin Oral Invest, 2022 May; 26(5): 3987–98.
45. Kuwana R, Ariji Y, Fukuda M, Kise Y, Nozawa M, Kuwada C, et al. Performance of deep learning object detection technology in the detection and diagnosis of maxillary sinus lesions on panoramic radiographs. Dentomaxillofacial Radiology, 2020 Jul 15; 20200171.
46. Choi E, Kim D, Lee JY, Park HK. Artificial intelligence in detecting temporomandibular joint osteoarthritis on orthopantomogram. Sci Rep, 2021 May 13; 11(1): 10246.
47. Kim Y, Lee KJ, Sunwoo L, Choi D, Nam CM, Cho J, et al. Deep Learning in Diagnosis of Maxillary Sinusitis Using Conventional Radiography. Invest Radiol, 2019 Jan; 54(1): 7–15.
48. Murata M, Ariji Y, Ohashi Y, Kawai T, Fukuda M, Funakoshi T, et al. Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. Oral Radiol, 2019 Sep; 35(3): 301–7.
49. Jeyaraj PR, Samuel Nadar ER. Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm. J Cancer Res Clin Oncol, 2019 Apr; 145(4): 829–37.
50. Iwasaki H. Bayesian belief network analysis applied to determine the progression of temporomandibular disorders using MRI. Dentomaxillofacial Radiology, 2015 Apr; 44(4): 20140279.
51. Bas B, Ozgonenel O, Ozden B, Bekcioglu B, Bulut E, Kurt M. Use of Artificial Neural Network in Differentiation of Subgroups of Temporomandibular Internal Derangements: A Preliminary Study. Journal of Oral and Maxillofacial Surgery, 2012 Jan; 70(1): 51–9.
52. Kılıc MC, Bayrakdar IS, Çelik Ö, Bilgir E, Orhan K, Aydın OB, et al. Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs. Dentomaxillofacial Radiology, 2021 Sep 1; 50(6): 20200172.
53. Kaya E, Gunec HG, Aydin KC, Urkmez ES, Duranay R, Ates HF. A deep learning approach to permanent tooth germ detection on pediatric panoramic radiographs. Imaging Sci Dent, 2022; 52(3): 275.
54. A pilot study of a deep learning approach to submerged primary tooth classification and detection. International Journal of Computerized Dentistry, 2021 Feb 26; 24(1): 1–9.
55. Ahn Y, Hwang JJ, Jung YH, Jeong T, Shin J. Automated Mesiodens Classification System Using Deep Learning on Panoramic Radiographs of Children. Diagnostics, 2021 Aug 15; 11(8): 1477.
56. Ha EG, Jeon KJ, Kim YH, Kim JY, Han SS. Automatic detection of mesiodens on panoramic radiographs using artificial intelligence. Sci Rep, 2021 Nov 29; 11(1): 23061.