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Artificial intelligence in modern dentistry

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Abstract---Advancements in the domain of computer science have made artificial intelligence (AI) almost ubiquitous in everyday life.

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Dentistry is known to easily adapt to new technologies and hence can easily acclimatize to this nascent field. With AI spreading into dentistry, models are being used to ascertain almost every dental condition, ranging from the routine dental caries to the more complex conditions like oral cancer, maxillofacial cysts, alveolar bone loss, and even appraising the urgency for orthodontic extractions. Artificial intelligence, has untapped potential and shows promising prospects. Multiple studies have been evaluated to highlight the progress made till date and it has been seen that AI based automated systems are exceptional in a limited domain and perform on par to dental specialists on a variety of performance parameters. Better adaptation and utilization of technology will help in better and precise treatment outcomes, while also reducing the work burden of the clinician. Databases such as PubMed Central and Google Scholar were used to scout approximately 33 articles of recent origin using keywords such as artificial intelligence; artificial neural networks; convolutional neural networks; deep learning; and machine learning were used. This article discusses the various techniques being used to compile data and the applications of those techniques to issues pertaining to dentistry as well as certain challenges and limitations to widespread use of artificial intelligence to improve diagnostic quality and overcome treatment challenges.

***Keywords*---**oral diagnosis, panoramic radiography, oral cancer, alveolar bone loss.

Introduction

Everyday activities have been greatly influenced by the inclusion of Artificial Intelligence in existing technology. AI support in fields such as the surgical field, automated diagnosis and personalized medicine has enabled individuals to become aware of their predisposition to diseases, has helped diagnosis and treatment for a given individual.[1] John McCarthy explained it as the potential of machines to perform tasks that fall in the range of "intelligent" activities and is widely recognized as the founder of artificial intelligence.[2] Newer technologies were developed that do not just follow pre-programmed instructions, but adapt to changing inputs.[3]

Applications

Patient Management

Virtual dental assistants can perform various functions and tasks with great accuracy in the dental clinic, with minimal errors and less man power. It can help to arrange appointments, manage insurance as well as helping in diagnosis and planning treatment.[4, 5] "D-Assistant", an AI system designed by Dentem, was created that listens to commands and analyzes dental images and records. It can provide a boost to both dental practitioners and assistants, reducing errors and streamlining decision-making. D-Assistant can also schedule appointments, keep dental records and routine tasks reminder.[6, 7] In this time of pandemic, online consultations have secured a prominent role with virtual databases giving easy access to the medical and dental history of the patient making it easier to treat the patient.[8]

Oral Medicine and Maxillofacial Radiology

Szegedy et al. used a pre-trained CNN network to identify dental caries in posterior teeth. The diagnostic accuracy was 88.0% for molars and was 89.0% for premolars.[9] Jeyaraj et al.[10] used CNNs with hyper-spectral images as input for diagnosis and prognosis of oral cancer; achieving an accuracy of 91.4% in a 7-fold cross validation. Hatvani et al. presented a DL-based method for improving the resolution of dental CT images using two CNN architectures. Better detection of attributes like the size, shape, and curvature of the root canal were made possible using the CNN technique, which improved the CT images.[11] Clinical clues from a patient's complaint and history are important for diagnosing temporo-mandibular joint disorders (TMDs).[12] A natural language processing model was successful in differentiating TMD-mimicking conditions from genuine TMDs, according to the frequency of word usage in the patient's chief complaint and mouth-opening size.[12, 13] Multiple studies distinguished normal and osteoporotic subjects on panoramic radiographs based on relevant criteria that were both pertinent to high bone turnover rate, low skeletal BMD and a higher risk of osteoporotic fracture. Various performance parameters reached 95% and above demonstrating that these models might be used in clinical practice in the near future.[14] Lee et al. exhibited very promising results with AI models for the detection of osteoporosis using Deep CNN (DCNN) based diagnostic systems on panoramic radiographs.[15]

Oral and Maxillofacial Surgery

Extent of facial swelling has been predicted by Zhang et al. using ANN models to anticipate postoperative facial swelling due to extraction of impacted mandibular 3rd molars with 98% accuracy. This would greatly benefit clinicians for determining the prognosis of the treatment.[16] A recent study by Yilmaz et al. used handcrafted engineered features in CBCT to differentiate periapical cysts from keratocystic odontogenic tumors using SVMs with 94% accuracy.[17] Rana et al. used existing surgical navigation software to automatically section keratocysts and measure their volume. Detection of lesions is still a manual task and it remains a challenge to develop a fully automated model that can identify cysts and/or tumors.[18] CNN models were applied for image classification on CT images to identify lymph node metastasis and showed high performance factors in a study by Ariji et al.[19] An investigation by Hung et al. appraised the performance of AI models in diagnosing extra nodal extension of cervical lymph node metastasis on CT images. Both the studies showed a performance at or a level higher than professional radiologists.[20]

Exceedingly positive results were seen by Aubreville et al. with CNNs in diagnosing oral squamous cell carcinoma when used with confocal laser endomicroscopy images and is expected to aid in early diagnosis.[21] A novel study by Sunny et al. with ANN was used for early detection of Oral Cancer, using tele cytology (TC), which is digitization of the cytology slides. The model showed improved malignancy detection accuracy up to 93%, and a potentially malignant lesion detection of 73%.[22, 23] AI was employed by Shams et al. to predict the occurrence of malignancy and potential transformation of benign lesions into oral cancer using gene expression profile. Deep-learning models demonstrated 96.5% accuracy.[24]

AI software programs have assisted surgeons to plan surgeries with reduced operation time and simulated preservation of vital structures prior to the actual surgery with higher intra operative accuracy. A recent development is the Voxelman system for planning and training in paranasal surgery.[25] In terms of postoperative rehabilitation, an ML-based voice conversion technique by Fu et al. has been used to transform non-audible murmurs of source speakers into the normal speech of target speakers. By learning a set of bases that is representative of the entire set of voice and target dictionary, this technique adapted well to a limited amount of training data and acquired satisfactory short-time objective intelligibility scores.[26]

Oral Pathology

Computerized methods have rapidly evolved in digital pathology. A study by Chang et al. was done using artificial neural networks on oral cancer prognosis based on clinic-pathological and genomic markers, such as p53 and p63. With regard to other oral diseases, AI models might be very helpful for the reproducibility of the clinical and histo-pathologic diagnosis in selected lesions.[27] A new research employed by Poedjiastoeti and Suebnukarn used a CNN algorithm to distinguish two complex tumors which appear similar radiographically but differ clinically: ameloblastomas and keratocystic odontogenic tumors. The specificity and the accuracy of diagnosis by the algorithm were 81.8% and 83.3%, respectively, on par with those of clinical specialists. More significantly, efficiency was greatly improved with diagnostic time for specialists being 23.1 minutes while the CNN achieved similar results in 38 seconds.[28, 29]

Orthodontics

AI has been applied for gauging the maturity of cervical vertebrae stages. A mean accuracy of 77.02% was seen by Kök H. et al., using algorithms applied to cephalometric radiographs.[2, 30] With 3D scans and virtual models, it is easy to print aligners based on a customized treatment plan. This not only enables to deliver precise execution but also helps in monitoring the progress as well as reduces treatment time and appointment schedules.[31] An AI model was designed by Cheng et al. to automatically localize one key landmark on CBCT images; aimed to gradually replace cephalometric radiographs with CBCT images. But this model was limited in its performance of automatic localization. Therefore, the existing model/software is only recommended for a preliminary localization of the cephalometric landmarks, with a manual correction still being necessary.[32]

A decision-making AI model was constructed by Xie et al. to determine whether tooth extraction is needed for orthodontic treatment among 11-15 years old patients. The constructed ANN demonstrated 80% accuracy in the testing set.[33, 34] A recent study by Jung et al. demonstrated 92% accuracy using AI systems to decide on permanent tooth extraction, on lateral cephalometric radiographs. Both studies are suggestive that AI models were effective and accurate in predicting the need for extraction.[35] A ML algorithm was developed by Knoops et al. for automated diagnosis and planning in plastic and reconstructive surgery. Augmentation of automated image processing led to a binary outcome regarding referral to a specialist with 95.5% sensitivity and 95.2% specificity.[36] An ANN model by Choi et al. was applied to data obtained from measurement values of lateral cephalogram and reportedly the accuracy was found to be 96% for surgical treatment, and 91% for diagnosis of surgery type and extraction decision.[37] A compelling study was done by Patcas et al. to assess the extent of orthognathic treatments on facial attractiveness and age estimation using AI models. More than 0.5 million facial images with age labels were used to train CNN models for age estimation. For attractiveness prediction, more than 13000 face images and an excess of 17 million ratings for attractiveness were gathered from a dating site to feed into the CNN model. 66.4% of the patients improved with the treatment resulting in younger appearance of nearly 1 year.[38]

Prosthodontics

Virtual reality simulation (VRS) technology has been employed to simulate facial profiles post treatment. This enables dentists to efficiently design the treatment plan, provide better aesthetics, and also acts as a motivational tool for the patient.[39] Comprehensive assessment of facial and dental structures is essentially done through facial, dental and dento-gingival analysis using software. The advantages of virtual smile designing are patient involvement, treatment plan visualization and its prediction.[40] Bellus 3D Dental Pro Integration, an AI based software can make a 3D scan of the full face. This software can integrate the treatment plan with face configuration, providing a visualization of the final results in 3D. It provides automatic identification of the patient's teeth and simulates their removal, with the possibility of manually modifying the segmentation. A new tooth set can be chosen and superimposed with the model in the correct place.[41]

Tongue controlled devices have been developed which are non invasive, self-controlling, and have precise tongue computer interfaces that compensate the arm and hand functions, which are indicated as the upper most priorities for severely disabled individuals. These commands can then send a signal to control a computer, drive a wheelchair, or regulate the user's environment.[42, 43] A decision making model to assist dentists in deciding appropriate removable prosthetic options was developed. Such models aid in treatment planning of complex patient cases in prosthodontics and help further the development of tele-dentistry.[44, 45] In a retrospective clinical study by Lerner et al., monolithic zirconia crowns (MZC) cemented on customized hybrid abutments allowed the successful restoration of implants using a full digital protocol using AI models. During follow-up, few biological (1.9%) and prosthetic (5.7%) complications affected the implant-supported MZCs, leading to a three-year cumulative survival and success of 99.0 and 91.3%, respectively.[46]

Periodontics

Periodontal conditions provide the most common provocation for the early loss of teeth. A recent investigation by Jae-Hong Lee et al. used CNNs to identify periodontally compromised teeth with pre-labelled periapical radiographic datasets resulting in a similar diagnostic accuracy to those obtained by board-certified periodontists.[47, 48] A Deep CNN model by Aberin et al. showed that it could identify healthy images with a certainty of 98%. An accuracy of 75.5% was achieved on its overall performance, in correctly differentiating images of healthy and unhealthy teeth.[49] Machine learning techniques using different data types for detecting periodontal disease have been extensively explored in literature.[50] Using SVMs (Support Vector Machines) and clinical variables, an accuracy of 88.7% was achieved in a 10-fold cross-validation.[51] A biomarker comparison between gingivitis and periodontitis using salivary gene expression profiles, reached an accuracy of 78%.[52] Immunologic parameters, such as leukocytes, interleukins and IgG antibody titres were used in ANN models by Papantanopoulos and colleagues to distinguish between Aggressive Periodontitis (AgP) and Chronic Periodontitis (CP). It showed 90–98% accuracy. Better results were obtained when monocyte, eosinophil, neutrophil counts and CD4+/CD8+ T-cell ratio were taken as inputs.[53]

Pedodontics

AI has numerous applications which would change the face of behavioural paediatric practice in the future. The proportions of unerupted premolars and canines during mixed dentition phase can be predicted using ANNs. AI enabled pain control technology is the new, smarter way towards an injection free practice. Behaviour modification for paediatric patients can be better achieved through aids such as various 4D goggles and virtual reality based games.[54, 55] A CNN model for teeth detection and numbering using panoramic radiographs was reported by Tuzoff et al. This computer-aided diagnostic technique displayed an average sensitivity of 0.987 and precision of 0.9945. The performance was on par with specialists.[56] An ANN model was used to predict toothache using parameters such as daily tooth-brushing frequency, toothbrush replacement, manner of brushing, use of dental floss, frequency of oral prophylaxis and other epigenetic factors such as diet and exercise. It resulted in a predictive model which recognized oral hygiene, adequate eating habits and prevention of stress as the essential component in preventing toothaches.[57, 58]

Restorative Dentistry & Endodontics

ML models were utilized to select the most compatible variables to analyze and detect root caries in a study by Hung et al. The most relevant variable was seen to be the age of the individual out of several parameters used. Comparing different methods, it was seen that SVMs exhibited the best performance for the detection of root caries, with an accuracy of 97.1% and precision of 95.1%.[59] The working length was determined by Saghiri et al. using ANN models and it showed exceptional accuracy of 96%, being more precise than professional endodontists who demonstrated 76% accuracy.[60, 61] A study employed by Johari et al., showed an excellent accuracy of 96.6% for diagnosis of vertical root fractures using PNN on CBCT and periapical radiographs.[62] A high precision was demonstrated by Fukuda et al. for identifying vertical root fractures using CNNs on panoramic radiographs.[63] These assessments show that vertical root fractures can be effectively detected on CBCT and panoramic radiographs using AI based models.

A study by Ekert et al. described the application of CNN models for radiographic detection of periapical lesions. The model demonstrated quite satisfactory results, with high sensitivity and moderate specificity. It can assist dentists in diagnosing and detecting periapical lesions.[64] CNN models by Hiraiwa et al. were used to classify data to determine whether the distal root of the first mandibular molar has more than 1 canal. The images of the roots obtained from corresponding panoramic radiographs were processed by a DL algorithm with a relatively high accuracy of 86.9%.[65]

Community Health

AI in dentistry has made prevention and treatment techniques in the domain of public health as well as analytics of patient outcomes much easier. Machine-learning models were seen to be better than statistical models for predicting DMFT index in 12-year-old children.[66] They have been used to predict the DMFT score and determine independently the life-long mean index of carious teeth, extracted teeth and/or filled permanent teeth.[67] AI based oral health tracking mobile app “Denta Mitra” enables a person to monitor his/her dental status through an AI based scanner in the app. It measures and reminds users on oral hygiene periodically and helps the person to meet a nearby dentist, book appointments and virtually consult dentists.[54] Similarly, other mobile health (mHealth) alternatives are under development for the self-examination of different oral conditions using a smartphone and internet-of-things (IoT) approach.[68] Mask-RCNN network was used for a dental health IoT platform which was able to detect and classify seven different oral diseases, to reach a mean accuracy of 93.6%.[69] Preventive measures based on oral hygiene behaviour have also been reported; brushing and flossing behaviours were monitored using wrist-worn inertial sensors. Using sensor data, the authors were able to predict the start and end of the specific action. The model achieved 100% median recall with a false positive rate of one event for every 9 days of sensor wearing.[70]

Forensic Odontology

Excellent results have been seen in the domain of forensic odontology using AI models. Automated techniques based on CNNs were used by De Tobel et al. to estimate the age of a person by staging lower third molar development on panoramic radiographs. The system gave excellent results, comparable to trained examiners.[71] Gender was determined by Patil et al. using ANNs on panoramic radiographs, with promising results. This automates the process of identifying unknown gender or age with minimal errors.[72]

Hurdles and Challenges Ahead

Although AI techniques have shown outstanding results in a variety of fields, even surpassing results obtained by humans, they are still prone to errors and require large quantities of data to achieve the best performance.[73-77] Labelling of the dataset used in training and accuracy of annotations heavily influence quality of predictions. Clinic-labelled datasets may be inconsistent and can lead to diminutive results. Furthermore, health care professionals should possess insight regarding decisions and predictions made by an AI system, and the competence to defend them.[78-80] Moreover, data of medical and dental nature is not conveniently accessible, due to data protection concerns and organizational hurdles. Data on each patient is complex, multi-dimensional, and sensitive, with limited options for triangulating or validating them. Sampling often leads to selection bias, with either overly sick (e.g., hospital data), overly healthy (e.g., data from wearable devices), or overly affluent (e.g., data from those who can afford dental care) individuals being overrepresented. Models developed on such data will be inherently biased.[81, 82]

Systems must be adapted to protect patient confidentiality before successful integration of AI can be done in the healthcare sector.[83] Thus, before considering broader distribution, personal data will have to be anonymized.[84] AI programs require immense expenses due to their complexities and the software needs frequent upgrades. Likewise, the cost of repair is very high.[54]That being said, a study by Schwendicke et al. on the cost effectiveness of DL programs to detect proximal caries reported that detection of proximal caries on bitewings was cost effective regardless of a payer's willingness to pay. This cost effectiveness was achieved due to a higher sensitivity to detect early carious lesions, arresting them and thereby avoiding costly late re-treatments. Of note, this was only true if the treatment was non-restorative.[85]

Conclusion

AI is an adjunct tool to assist dentists with existing diagnostic and treatment techniques, all the while ensuring that humans have the last word regarding treatment and are able to make informed decisions. As various AI systems are developed and report encouraging preliminary results, successful assimilation of AI in the clinical space is the need of the hour.

References

1. Carrillo-Perez F, Pecho OE, Morales JC, Paravina RD, Della Bona A, Ghinea R et al. Applications of artificial intelligence in dentistry: A comprehensive review. J Esthet Restor Dent. 2022; 34(1):259-280.
2. Khanagar SB, Al-Ehaideb A, Maganur PC, Vishwanathaiah S, Patil S, Baeshen HA, et al. Developments, application, and performance of artificial intelligence in dentistry - A systematic review. J Dent Sci. 2021;16(1):508-522.
3. Tejaswi Katne, Alekhya Kanaparthi, Srikanth Gotoor, Srikar Muppirala, Ramaraju Devaraju, Ramlal Gantala. Artificial intelligence: demystifying dentistry – the future and beyond. International Journal of Contemporary Medicine Surgery and Radiology. 2019; 4(4):D6-D9.
4. Bindushree V, Sameen RJ, Vasudevan V, Shrihari TG, Devaraju D, Mathew NS. Artificial intelligence: In modern dentistry. J Dent Res Rev. 2020;7:27-31.
5. Zhu J, Wen D, Yu Y, Meudt HM, Nakhleh L. Bayesian inference of phylogenetic networks from bi- allelic genetic markers. PLoS Comput Biol. 2018; 14:e1005932.

6. Singh S, Singh J, Singh D and Chandra S. Artificial Intelligence in Dentistry: The Way Forward. Journal of Dental & Oro-facial Research. 2020; 16(1):9-14.
7. Philip Avery. AI- Powered innovations that are Transforming Dentistry. Available at: https://becominghuman.ai/ai-innovations-transforming-dentistry-aef03479664d.
8. Roy P, Vivekanand L, Singh GP. Artificial intelligence in dentistry and its future. GSC Advanced Research and Reviews. 2021; 07(01):082-6.
9. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the Inception Architecture for Computer Vision: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016:2818-26.
10. 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;145(4):829-837.
11. Hatvani J, Horváth A, Michetti J, et al. Deep learning-based super-resolution applied to dental computed tomography. IEEE Trans Radiat Plasma Med Sci. 2018; 3(2):120-8.
12. Shan T, Tay FR, Gu L. Application of Artificial Intelligence in Dentistry. J Dent Res. 2021;100(3):232-244.
13. Nam Y, Kim HG, Kho HS. Differential diagnosis of jaw pain using informatics technology. J Oral Rehabil. 2018; 45(8):581-8.
14. Hung K, Montalvao C, Tanaka R, Kawai T, Bornstein MM. The use and performance of artificial intelligence applications in dental and maxillofacial radiology: A systematic review. Dentomaxillofac Radiol. 2020; 49(1):20190107.
15. Lee JS, Adhikari S, Liu L, Jeong HG, Kim H, Yoon SJ. Osteoporosis detection in panoramic radiographs using a deep convolutional neural network-based computer-assisted diagnosis system: a preliminary study. Dentomaxillofac Radiol. 2019; 48(1):20170344.
16. Zhang W, Li J, Li ZB, Li Z. Predicting postoperative facial swelling following impacted mandibular third molars extraction by using artificial neural networks evaluation. Sci Rep. 2018;8(1):12281.
17. Yilmaz E, Kayikcioglu T, Kayipmaz S. Computer-aided diagnosis of periapical cyst and keratocystic odontogenic tumor on cone beam computed tomography. Comput Methods Programs Biomed. 2017; 146:91-100.
18. Rana M, Modrow D, Keuchel J, Chui C, Rana M, Wagner M et al. Development and evaluation of an automatic tumor segmentation tool: a comparison between automatic, semi-automatic and manual segmentation of mandibular odontogenic cysts and tumors. J Craniomaxillofac Surg. 2015; 43(3):355-9.
19. Ariji Y, Sugita Y, Nagao T, Nakayama A, Fukuda M, Kise Y et al. CT evaluation of extranodal extension of cervical lymph node metastases in patients with oral squamous cell carcinoma using deep learning classification. Oral Radiol. 2020;36(2):148-155.
20. Hung M, Voss MW, Rosales MN, Li W, Su W, Xu Jet al. Application of machine learning for diagnostic prediction of root caries. Gerodontology. 2019;36(4):395-404.
21. Aubreville M, Knipfer C, Oetter N, Jaremenko C, Rodner E, Denzler J et al. Automatic Classification of Cancerous Tissue in Laserendomicroscopy Images of the Oral Cavity using Deep Learning. Sci Rep. 2017;7(1):11979.

22. Khanagar SB, Naik S, Al Kheraif AA, Vishwanathaiah S, Maganur PC, Alhazmi Y, et al. Application and Performance of Artificial Intelligence Technology in Oral Cancer Diagnosis and Prediction of Prognosis: A Systematic Review. Diagnostics (Basel). 2021;11(6):1004.
23. Sunny S, Baby A, James BL, Balaji D, N V A, Rana MH et al. A smart tele-cytology point-of-care platform for oral cancer screening. PLoS One. 2019;14(11):e0224885.
24. Shams, W.K.; Htike, Z.Z. Oral Cancer Prediction Using Gene Expression Profiling and Machine Learning. Int. J. Appl. Eng. Res. 2017, 12, 4893–4898.
25. The Voxelman System. Accessed at: www.voxel-man.de/gallery
26. Fu SW, Li PC, Lai YH, Yang CC, Hsieh LC, Tsao Y. Joint Dictionary Learning-Based Non-Negative Matrix Factorization for Voice Conversion to Improve Speech Intelligibility After Oral Surgery. IEEE Trans Biomed Eng. 2017;64(11):2584-2594.
27. Chang SW, Abdul-Kareem S, Merican AF, Zain RB. Oral cancer prognosis based on clinic-pathologic and genomic markers using a hybrid of feature selection and machine learning methods. BMC Bioinformatics. 2013;14:170-84.
28. Nguyen TT, Larrivée N, Lee A, Bilaniuk O, Durand R. Use of Artificial Intelligence in Dentistry: Current Clinical Trends and Research Advances. J Can Dent Assoc. 2021;87:l7.
29. Poedjiastoeti W, Suebnukarn S. Application of Convolutional Neural Network in the Diagnosis of Jaw Tumors. Healthc Inform Res. 2018;24(3):236-241.
30. 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;20(1):41.
31. Deshmukh SV. Artificial intelligence in dentistry. J Int Clin Dent Res Organ. 2018;10:47-8.
32. Cheng E, Chen J, Yang J, Deng H, Wu Y, Megalooikonomou V et al. Automatic Dent-landmark detection in 3-D CBCT dental volumes. Annu Int Conf IEEE Eng Med Biol Soc. 2011;2011:6204-7.
33. Hung HC, Wang YC,Wang YC.Applications of Artificial Intelligence in Orthodontics," Taiwanese Journal of Orthodontics.2020;32(2):85-92.
34. Xie X, Wang L, Wang A. Artificial neural network modeling for deciding if extractions are necessary prior to orthodontic treatment. Angle Orthod. 2010;80(2):262-6.
35. Jung SK, Kim TW. New approach for the diagnosis of extractions with neural network machine learning. Am J Orthod Dentofacial Orthop. 2016;149(1):127-33.
36. Knoops PGM, Papaioannou A, Borghi A, Breakey RWF, Wilson AT, Jeelani O et al. A machine learning framework for automated diagnosis and computer-assisted planning in plastic and reconstructive surgery. Sci Rep. 2019;9(1):13597.
37. Choi HI, Jung SK, Baek SH, Lim WH, Ahn SJ, Yang IH et al. Artificial Intelligent Model With Neural Network Machine Learning for the Diagnosis of Orthognathic Surgery. J Craniofac Surg. 2019;30(7):1986-1989. Erratum in: J Craniofac Surg. 2020;31(4):1156.
38. Patcas R, Bernini DAJ, Volokitin A, Agustsson E, Rothe R, Timofte R. Applying artificial intelligence to assess the impact of orthognathic treatment

on facial attractiveness and estimated age. Int J Oral Maxillofac Surg. 2019;48(1):77-83.

39. Kikuchi H, Ikeda M, Araki K. Evaluation of a virtual reality simulation system for porcelain fused to metal crown preparation at Tokyo Medical and Dental University. J Dent Educ. 2013; 77(6):782-92.
40. Gali S. Digital Technology and Artificial Intelligence in Prosthodontics. Journal of Dental & Oro-facial Research. 2020;16(1):15-19
41. Tian S, Dai N, Zhang B, Yuan F, Yu Q, Cheng X. Automatic classification and segmentation of teeth on 3D dental model using hierarchical deep learning networks. IEEE Access. 2019; 7:84817-84828.
42. Shajahan P A, Raghavan R, Joe N. Application of artificial intelligence in prosthodontics. International Journal of Science & Healthcare Research.2021; 6(1): 57-60.
43. Chapelle O, Scholkopf B, Zien Eds. A. Semi-Supervised Learning (Chapelle, O. et al., Eds.; 2006) [Book reviews]. IEEE Trans Neural Netw. 2009; 20(3):542-542.
44. Bernauer SA, Zitzmann NU, Joda T. The Use and Performance of Artificial Intelligence in Prosthodontics: A Systematic Review. Sensors (Basel). 2021;21(19):6628.
45. Chen Q, Wu J, Li S, Lyu P, Wang Y, Li M. An ontology-driven, case-based clinical decision support model for removable partial denture design. Sci Rep. 2016;6:27855.
46. Lerner H, Mouhyi J, Admakin O, Mangano F. Artificial intelligence in fixed implant prosthodontics: a retrospective study of 106 implant-supported monolithic zirconia crowns inserted in the posterior jaws of 90 patients. BMC Oral Health. 2020;20(1):80.
47. Lavanya R., Hiremath S.K., Cheruku S, Bhargava S, Bhandari S. CNN in Periodontology: A Review. Journal of Dental & Oro-facial Research. 2020; 16(10:64-70.
48. Lee JH, Kim DH, Jeong SN, Choi SH. Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm. J Periodontal Implant Sci. 2018;48(2):114-123.
49. Aberin STA, Goma JCD. Detecting Periodontal Disease Using Convolutional Neural Networks," 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Baguio City, Philippines, 2018, pp. 1-6.
50. Chen WP, Chang SH, Tang CY, Liou ML, Tsai SJ, Lin YL. Composition Analysis and Feature Selection of the Oral Microbiota Associated with Periodontal Disease. Biomed Res Int. 2018;2018:3130607.
51. Farhadian M, Shokouhi P, Torkzaban P. A decision support system based on support vector machine for diagnosis of periodontal disease. BMC Res Notes. 2020;13(1):337.
52. Nagarajan R, Miller CS, Dawson D 3rd, Al-Sabbagh M, Ebersole JL. Patient-Specific Variations in Biomarkers across Gingivitis and Periodontitis. PLoS One. 2015;10(9):e0136792.
53. Papantonopoulos G, Takahashi K, Bountis T, Loos BG. Artificial neural networks for the diagnosis of aggressive periodontitis trained by immunologic parameters. PLoS One. 2014;9(3):e89757.

54. Rashmi J Kurup et al. Dentistry and Artificial Intelligence. Acta Scientific Dental Sciences. 2020; 4(10): 26-32.
55. Baliga MS. Artificial intelligence - The next frontier in pediatric dentistry. J Indian Soc Pedod Prev Dent. 2019;37(4):315.
56. Tuzoff DV, Tuzova LN, Bornstein MM, Krasnov AS, Kharchenko MA, Nikolenko SI, et al. Tooth detection and numbering in panoramic radiographs using convolutional neural networks. Dentomaxillofac Radiol. 2019;48(4):20180051.
57. B. Chandra Kanth, Chandradeep, Manepalli S.. Artificial intelligence and robotics: The enhanced paediatric dentist. International Journal of Advance Research, Ideas and Innovations in Technology. 2020;6(6):66-9.
58. Tandon D, Rajawat J. Present and future of artificial intelligence in dentistry. J Oral Biol Craniofac Res. 2020;10(4):391-396.
59. Hung M, Voss MW, Rosales MN, Li W, Su W, Xu J et al. Application of machine learning for diagnostic prediction of root caries. Gerodontology. 2019;36(4):395-404.
60. Boreak N. Effectiveness of Artificial Intelligence Applications Designed for Endodontic Diagnosis, Decision-making, and Prediction of Prognosis: A Systematic Review. J Contemp Dent Pract. 2020;21(8):926-934.
61. Saghiri MA, Asgar K, Boukani KK, Lotfi M, Aghili H, Delvarani A, Karamifar K et al. A new approach for locating the minor apical foramen using an artificial neural network. Int Endod J. 2012;45(3):257-65.
62. Johari M, Esmaeili F, Andalib A, Garjani S, Saberkari H. Detection of vertical root fractures in intact and endodontically treated premolar teeth by designing a probabilistic neural network: an ex vivo study. Dentomaxillofac Radiol. 2017;46(2):20160107.
63. 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;36(4):337-343.
64. Ekert T, Krois J, Meinhold L, Elhennawy K, Emara R, Golla T et al. Deep Learning for the Radiographic Detection of Apical Lesions. J Endod. 2019;45(7):917-922.e5.
65. 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. Dentomaxillofac Radiol. 2019;48(3):20180218.
66. Yang Yong-Hoon., et al. “Prediction of dental caries in 12-year-old children using machine-learning algorithms”. Journal of Korean Academy of Oral Health 44.1 (2020): 55-63.
67. Miladinović Milan., et al. “Artificial intelligence in clinical med¬icine and dentistry”. Vojnosanitetski Pregled 74.3 (2017): 267-272.
68. Liu L, Xu J, Huan Y, Zou Z, Yeh SC, Zheng LR. A Smart Dental Health-IoT Platform Based on Intelligent Hardware, Deep Learning, and Mobile Terminal. IEEE J Biomed Health Inform. 2020;24(3):898-906. doi: 10.1109/JBHI.2019.2919916. Epub 2019 Jun 7. PMID: 31180873.
69. He K, Gkioxari G, Dollár P, et al. Mask r-cnn. Paper presented at: Proceedings of the IEEE International Conference on Computer Vision; 2017. p. 2961–2969.
70. Akther S, Saleheen N, Samiei SA, Shetty V, Ertin E, Kumar S. mORAL: a mHealth model for inferring oral hygiene behaviors in the- wild using wrist

worn inertial sensors. Proc ACM Interact Mobile, Wearable Ubiquitous Techol. 2019; 3(1):1-25.

71. De Tobel J, Radesh P, Vandermeulen D, Thevissen PW. An automated technique to stage lower third molar development on panoramic radiographs for age estimation: a pilot study. J Forensic Odontostomatol. 2017;35(2):42-54.
72. Patil V, Vineetha R, Vatsa S, Shetty DK,Raju A,Naik N,et al. Artificial neural network for gender determination using mandibular morphometric parameters: a comparative retrospective study. Cogent Engineering. 2020;7:1723783.
73. Xiong W, Droppo J, Huang X, Seide F, Seltzer M, Stolcke A, Yu D, et al. Achieving human parity in conversational speech recognition. arXiv. 2016;0:1610-5256.
74. Saon G, Kurata G, Sercu T, et al. English conversational telephone speech recognition by humans and machines. arXiv. 2017; 0:1703-2136.
75. Silver D, Schrittwieser J, Simonyan K, Antonoglou I, Huang A, Guez A et al. Mastering the game of Go without human knowledge. Nature. 2017;550(7676):354-359.
76. Raumviboonsuk P, Krause J, Chotcomwongse P, Sayres R, Raman R, Widner K et al. Deep learning versus human graders for classifying diabetic retinopathy severity in a nationwide screening program. NPJ Digit Med. 2019;2:25.
77. Vinyals O, Babuschkin I, Czarnecki WM, Mathieu M, Dudzik A, Chung J et al. Grandmaster level in StarCraft II using multi-agent reinforcement learning. Nature. 2019; 575(7782):350-354.
78. Redman TC. If your data is bad, your machine learning tools are useless. Harv Bus Rev. 2018; 2 April. Available: https://hbr.org/2018/04/if-your-data-is-bad-your-machine-learning-tools-are-useless (accessed 2019 June 12).
79. Murphy KP. Machine learning: a probabilistic perspective. Cambridge, Mass.: MIT Press, 2012.
80. Software as medical device (SaMD). Maryland: United States Food & Drug Administration; 2018. Available: https://www.fda.gov/medical-devices/digital-health/software-medical-device-samd (accessed 2019 June 7).
81. Schwendicke F, Samek W, Krois J. Artificial Intelligence in Dentistry: Chances and Challenges. J Dent Res. 2020; 99(7):769-774.
82. Gianfrancesco MA, Tamang S, Yazdany J, Schmajuk G. Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. JAMA Intern Med. 2018; 178(11):1544-1547.
83. Char DS, Shah NH, Magnus D. Implementing Machine Learning in Health Care - Addressing Ethical Challenges. N Engl J Med. 2018; 378(11):981-983.
84. He J, Baxter SL, Xu J, Xu J, Zhou X, Zhang K. The practical implementation of artificial intelligence technologies in medicine. Nat Med. 2019; 25(1):30-36.
85. Schwendicke F, Rossi JG, Göstemeyer G, Elhennawy K, Cantu AG, Gaudin R et al. Cost-effectiveness of Artificial Intelligence for Proximal Caries Detection. J Dent Res. 2021; 100(4):369-76.