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Intelligent Systems for Precision Dental Diagnosis and Treatment Planning – A Review

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ABSTRACT

Machines have changed the course of mankind. Simple machines were the basis of human civilization. Today with humongous technological development, machines are intelligent enough to carry out very complex nerve-racking tasks. The ability of a machine to learn from algorithms changed eventually into, the machine learning by itself, which constitutes artificial intelligence. Literature has plausible evidence for the use of intelligent systems in medical field. Artificial intelligence has been used in the multiple denominations of dentistry. These machines are used in the precision diagnosis, interpretation of medical images, accumulation of data, classification and compilation of records, determination of treatment and construction of a personalized treatment plan. The article aims to review the current and potential applications of intelligent systems in dentistry. Artificial intelligence can help in timely diagnosis of complex dental diseases which would ultimately aid in rapid commencement of treatment. Research helps us understand the effectiveness and challenges in the use of this technology. The apt use of intelligent systems could transform the entire medical system for the better.

Keywords: Deep Learning, Artificial Intelligence, Convolutional Neural Networks, Dentistry

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Introduction

Conventional medicine has had a 'one size fits all' approach towards ailments. Precision medicine is a set of strategies that help in the customization of both the diagnosis and the treatment plan to the likes of an individual.[1,2] A shift from conventional traditional outlook towards diseases to a more contemporary personalized outlook is bound to happen in the very near future. Personalized medicine is possible, by applying, superior knowledge of the disease and the deeper nuances of the factors associated, along with the extensive exploitation and consolidation of limitless data, through massive data analyzing tools, with the help of artificial intelligence (AI).[3,4]

Intelligent systems are machines with the ability to have a deeper understanding of the data, which is often comparable to the zeniths of human understanding.[5]These systems were profoundly invested in, to seek their role in modern medicine. Two approaches of learning has been instituted, one follows the case history type questions asked by the system and subsequently correlating it to the various symptoms, on the basis of the available huge data base in a short span of time. The other involves the use of neural networks and deep learning often yielding credible results which are superior.[6] Intelligent systems in the medical and dental field are either virtual or physical.[7,8] Virtual intelligent systems are used in health record maintenance, medical education, disease diagnosis and treatment planning. Physical systems have been used in robotic procedures. The data accumulation is further enhanced with the use of image analyzing artificial intelligence where raw data in the form of images could be interpreted for accurate results.[9] Dental diseases are often associated with morphological alterations of the tissues, such as the teeth, periodontium, oral mucosa and bone. The changes, as a consequence of various disease processes can be studied/predicted by AI in a standardized accurate manner and a short time frame. The exorbitant rise in oral pathoses and the need for quick and reliable diagnosis warrants more use of AI to assist dental practitioners. Intelligent systems have been previously used in several aspects of the dental field, nevertheless, the objective of this review is to highlight and understand the current and potential applications of these systems in the various clinical ramifications of dentistry.

History of Intelligent Systems

AI has witnessed vast developments in the past 50 years.[10] However, the view that the human mind is a set of syllogism has been set forth in motion by ancient Greek philosophers like Aristotle.[11] A pivotal point in the development of AI is the Turing test of 1950.[12,13] This marked the ability of a machine to make decisions comparable to that of the human mind. The history of development includes two lag phases called AI winters.[10,13] These periods mark developmental hurdles that artificial intelligence had to confront. The timeline of artificial intelligence in medicine is chiefly influenced by the rapid digitalization of the medical literary data. The shortcoming of the early developed machines was lack of data for input. This was eventually overcome with the availability of voluminous, easily accessible data through online databases. Intelligent systems grew by leaps and bounds with the development of the Convoluted Neural Network (CNN). CNN constitutes a network of algorithms which help the machines learn in a layered pattern. Figure 1 shows the various milestones in the development of artificial intelligence.[14,15]

Principle of Intelligent *Machines*

Machine learning is the ability of a system, to undertake elaborate functions by virtue of complex algorithms in the absence of definitive commands.[16] In the medical fraternity, machine learning is of limited use and often turns obsolete. The algorithms have shown great potential in processing data that is explicitly standardized, which is extremely challenging when it to comes to the medical field. Deep learning is the use of a layered model abstraction, enabling the system to comprehend from various inputs like images or texts.[17]

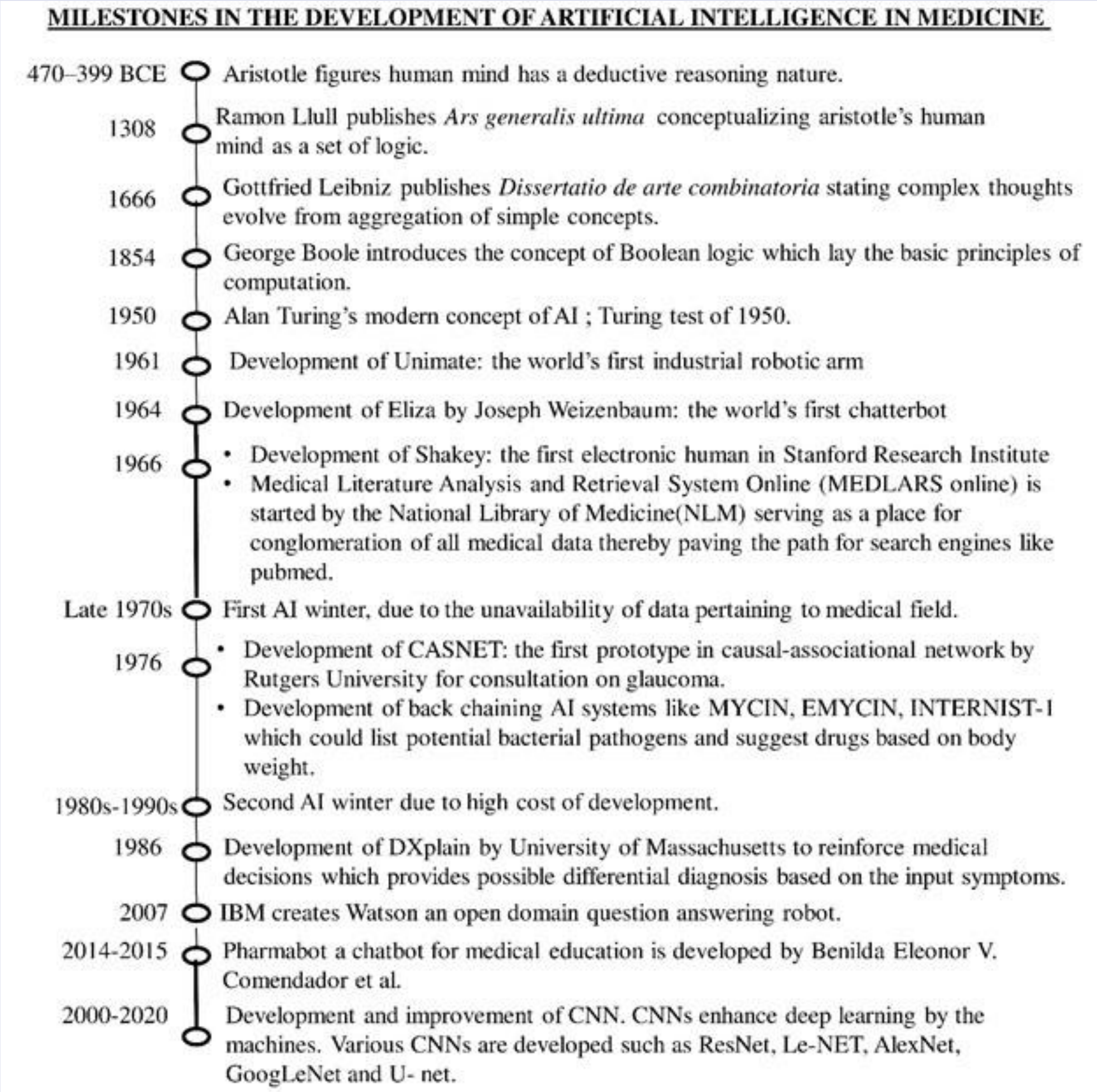

Figure 1. The various milestones in the development of artificial intelligence in medicine.

Deep learning is associated with two attributes; the multilayered non-linear processing of the data and the learning feature presentations in the layers.[18,19] The learning process could be supervised or unsupervised. This deep learning is facilitated by the use of artificial neural networks (ANNs). The inspiration for these neural networks is the cortical neural connections in the human brain. The neural networks were constructed in a similar pattern. Medical application of neural networks would not be possible without 'big data'.[20,21] Big data is the conglomeration of all relevant data. A few examples in the medical field include genomic sequences, medical imaging technology and micro-molecular structure of proteins. ANNs were reinstated with deeper and more hidden layers to improve efficiency. Though the increase in number of layers is desirable, in order to improve the efficiency of the system, it presents with the disadvantage of reducing the magnitude of the input variables required to arrive at a final prediction, which affects the result. To overcome this, layer wise pre-trained deep auto-encoder has been employed.[22,23] Image recognition, segmentation, video recognition is processed using CNN.[24,25] Tabular data is processed efficiently by the ANN. The significant layer in CNN includes the convolution layer and the pooling layer.[26] The image is scanned and each receptive field is checked by the convolution layer and the resultant input variables are pooled into the pooling layer.[27] Through this procedure the image can be analyzed. Through pattern recognition the resultant image is tagged with valuable information which guides the clinician to make decisions, aiding in precision diagnosis and advocating a personalized treatment plan.

Intelligent Systems in Dentistry

The role of intelligent systems in dentistry is based on the paradigm that any medical decision requires the physician to have adequate knowledge on the subject matter which can be reinforced by AI.[28] Data in the healthcare field is aggregated universally, and is available in heterogeneous clumps such as demographic data, socioeconomic data, medical history, clinical and investigational data all of which can be integrated and correlated by AI.[29] Artificial intelligence plays a role in research and interactive patient care. The ability of the patients to monitor their own heart rate, blood pressure or oral status through wearables, acts as a strong motivation factor. Continuous monitoring allows shortening of the lag between disease development and medical intervention. This immediate medical/dental attention could help reduce chronic illnesses which wreaks havoc and burdens the society.[30] Nevertheless without appropriate patient compliance the use of any monitoring device is futile.AI in the form of deep learning has been applied in various aspects of dentistry which will be discussed further. A summary of all the applications of artificial intelligence in dentistry has been included in Table 1. Several deep learning systems have been employed for this feat such as U-Net (CNN), MLPNN (Mutli layer perceptron neural network (ANN)), AlexNet (CNN), DetectNet (CNN), VGG16 (Visual geometry group also called Oxford Net with 16 layer depth(CNN)), ResNet50(Residual neural network(ANN)), Inception-v3 (CNN), EfficientNet-B0 (CNN), InceptionResNet-v2 (CNN), Xception (CNN), and MobileNet (CNN).[31,32]

Various studies have hypothesized the potential of AI to assist in the diagnosis of oral lesions. A deep learning network, EfficientNet-B0 has been trained to classify oral lesions into benign and malignant using real time clinical images. The system showed results with an increased accuracy of 85%.[31] Speight PM *et al.* (1995) have used ANNs to screen for the likelihood of the presence of premalignant lesions in the oral cavity among 2027 adults with a history of tobacco and alcohol abuse.[33] The results gained from the study proved the ANNs to have a comparable specificity and sensitivity to that of a dental expert.ResNet-101 and R-CNN (Region-based Convolutional Neural Networks) has been employed for the detection of oral lesions and the need for referral for such lesion with better accuracy of 87.07%.[31] According to McCartney S *et al.* (2014) the diagnosis of facial pain could be assisted by AI. This is achieved by collecting a questionnaire with various historical data. The inputs when processed through the neural networks are able to identify and differentiate the facial pain into nervus intermedius neuralgia (NIN), atypical facial pain (AFP), glossopharyngeal neuralgia (GPN) and temporomandibular joint disorder (TMJ) with a specificity of 99-100%.[34] Song A *et al.* (2018) used a CNN to detect the presence of facial nerve paralysis from 1049 clinical images of the patients.[35] The AI system was able to identify the presence of facial nerve paralysis with 97.5% accuracy which was up to neurologist standards. In a study by Men K *et al.*[36] (2019) rCNN (Residual CNN) deep learning architecture has been exploited to predict the development of xerostomia after radiation therapy in oral squamous cell carcinoma in 784 patients. The functioning of the salivary gland is checked using Tc-99m pertechnetate through scintigraphy. The manual interpretation of the scans were highly reproducible but on an average it took 15 mins per SPECT/CT scan, which was effectively interpreted in under 1 minute by deep learning architectures.[37] Temporomandibular joint pathology is often best visualized and diagnosed using magnetic resonance imaging(MRI). The ability to diagnose a disc perforation from an MRI, rests totally on the expertise of the radiologist and is deemed a challenging task by many. The deep learning architectures help in the diagnosis of disc perforation from MRI scans with high accuracy.[38]

Table 1. Applications of artificial intelligence (AI) in the various branches of dentistry

BRANCH OF DENTISTRY	APPLICATION OF ARTIFICIAL INTELLIGENCE
Oral Medicine	• Classification of malignant and benign lesion[31] • Correlation between tobacco, alcohol abuse and development of oral premalignant lesion[33] • Identification and classification of facial pain[34] • Detection of facial nerve paralysis[35] • Predicting xerostomia post radiotherapy[36] • Detection of TMJ disc perforation[38]
Oral Radiology	• Classification of dental radiographs[39] • Tooth identification from radiographs[40] • Diagnosis of Sjogren's syndrome[42,43]
Forensic Odontology	• Identification of age and gender by tooth morphology[32] • Identification of age from hand-wrist radiograph[45,46]
Oral Surgery	• Diagnosis of maxillary sinusitis[47] • Identification of supernumerary teeth[49] • Prediction of swelling following extraction of third molar[51]
Oral Cancer	• Early diagnosis of oral cancer[53] • Prediction of oral cancer survival rates[55]
Prosthodontics	• Identification of prosthesis and restorations[57] • Classification of implant systems based on radiographs[58]
Orthodontics	• To decide the need for extraction in the treatment plan[59,60] • Identification of various orthodontic problems such as overbite, crossbite,etc[61] • Identification of radiographic landmarks[63]
Endodontics	• Diagnosis of accessory root canal[64] • Identification of apical constriction[65] • Identification of early dental carious lesions[67]
Periodontics	• Prediction of oral malodour[68] • Development of smart tooth brush[69,70] • Prediction of periodontal bone loss[71]

Artificial intelligence has been employed in various aspect of oral radiology. The large pools of dental radiographs often gets accumulated in the clinical setting, which can be efficiently classified in a retrospective pattern.[39] AI was capable of classifying a huge number of the radiographs into periapical, bitewing, cephalogram and panoramic radiographs with utmost accuracy.The radiographs can be processed to label the teeth with the appropriate tooth numbering system.[40] This will help in the quick compilation of dental records. Sur J *et al.* have found a remarkably positive response to the use of AI in dental radiology in India.[41] With 69% of the participants looking forward for AI systems to aid in the radiological diagnosis. Literature review reveals employment of deep learning systems to diagnose Sjorgren's syndrome from CT scans and ultrasonography.[42,43] The research concluded with the deep learning systems diagnosing Sjorgren's syndrome as efficiently as an experienced radiologist.

Forensic odontology has identified various areas where the augmentations with intelligent systems prove effective. The scope into forensic odontology is based on the perpetuity of teeth against the pangs of time.[44] Avuçlu E *et al.* (2019) used 1315 dental x-ray images for the identification of age and gender based on the tooth morphology using a CNN called multilayer perceptron neural network (MLPNN).[32] This yielded a 100% accurate correct classification of the dental radiographic images which could be used in the identification of individuals. CT skull and hand-wrist radiographs have predicted the age of an individual with utmost accuracy.[45,46] Panoramic radiographs have been used to identify individuals, with much accuracy based on the presence of edentulous spaces, using deep learning systems such as VGG16, ResNet50, Inception-v3, InceptionResNet-v2, Xception, and MobileNet-v2 of which VGG16 has shown 100 % accuracy.

The intelligent systems show futuristic potential in oral surgery. A deep learning system, using panoramic images for diagnosis of maxillary sinusitis, revealed 87.5% diagnostic performance.[47] This was comparable to the experienced radiologist and significantly higher than the junior dental residents. The identification and classification of supernumerary teeth have been effortlessly produced by various deep learning systems such as AlexNet, DetectNet, VGG-16. These systems, using panoramic images, are able to identify the presence of supernumerary teeth and the number of teeth present. Kuwada C *et al.* (2020) tested 550 panoramic images for detection of supernumerary teeth in the maxillary incisor region, with 96% accuracy.[48] Diagnostic precision, AI reinforced treatment planning, custom manufacturing of surgical appliances and equipment, post-operative follow-up by superimposing pre and post operation images have all been applied for the betterment of orthognathic surgeries, in the form of deep learning.[49,50] The necessity for an orthoganthic surgery can be predicted by deep learning systems by means of cephalograms. Artificial neural networks were able to predict very accurately the occurrence of facial swelling following extraction of a third molar, based on the anatomy of the wisdom teeth and the surgical procedure done.[51] This helps the surgeon to follow a personalized treatment plan for the patient including an appropriate pain alleviation protocol.

Oral cancer has been regarded as one of the most common neoplasm in the world.[52] Oral cancer is best tackled when diagnosed early like most other cancers. AI can help in the early diagnosis of oral cancer by the use of hyperspectral images of the lesions driven to map the presence of oral squamous cell carcinoma.[53] Fu Q *et al.* used 1469 intraoral photographic images to detect oral cancer using a cascaded convolutional neural network which resulted in accuracy, sensitivity and specificity comparable to that of an oral cancer expert and significantly better than a medical student.[54] Cancer survival rates can be predicted using log-rank test and Cox proportional hazard which use cancer prognostic factors for their prediction.[55] However these models are found to be unsatisfactory and hence a deep learning survival rate prediction using DeepSurv has been employed. DeepSurv produced better more accurate prediction of the survival rates of oral cancer patients.Various multinomic data such as genetic, proteomic, radiologic, clinical, histopathologic and biochemical data related to oral cancer can be accumulated and congregated by AI.[56] With the conglomeration of all this data each cancer could be traced to its origin and each individual will receive a personalized treatment crafted for the specific cancer.

AI has played a role in the identification of prostheses and restorations in the dentition thereby assisting in the treatment planning process.[57] The AI system shows very high accuracy for identifying metallic restorations and moderate accuracy for tooth coloured restorations. AI has been trained and tested to identify and classify various implant systems from radiographs.[58] This could help in the identification of dental implant brand just from the radiograph, which is a tedious task even for an experienced radiologist. Such identification of the implant can be exploited for the identification and classification of fractured dental implants.

Literature review reveals that neural networks have been used for deciding the need of extraction as part of orthodontic treatment using data from various indices such as ‘IMPA (Incisor to Mandibular Plane Angle Index)’.[59, 60] These systems showed 100% accuracy in the training sets and showed 80% accuracy in the test set. Artificial intelligence has been employed to identify the various variables such as missing tooth, overbite, anterior openbite, posterior openbite, diastema, overjet thereby aiding in orthodontic treatment decision.[61] Choi HI *et al.* found that deep learning could help in making the choice between surgical or non-surgical management.[62] Radiographic landmarks in cephalograms, hand- wrist radiographs and cervical vertebrae are efficiently identified by artificial neural networks.[63] This has a two-fold use in orthodontics in that the growth and development of the individual and the level of bone maturity can be identified. Additionally it is also used to plot cephalometric landmarks to identify dental or skeletal malocclusion thereby assisting treatment planning.

In endodontics, artificial neural networks have been used in the diagnosis of accessory root canals from panoramic radiographs, which was counter checked using CBCT images.[64] This saves valuable time and ensures the success of endodontic therapy. Apical constriction can be identified very precisely by these neural networks thereby assisting in the effective cleaning and shaping of the root canals.[65]The detection of caries from dental radiographs is one of the most significant and straight forward application of neural networks in dentistry. This could be due to the fact that dental caries is the most common disease affecting man.[66] The ability for AI to effectively identify early lesions, lessens the burden of dental caries on humanity by leaps and bounds.[67] Various models of neural networks like GoogLeNet, Inception v3 CNN, MLPNN have been employed in research to evaluate the accuracy, sensitivity and specificity in the diagnosis of caries from radiographs.The results from all such studies reveal that a highly accurate, sensitive and specific diagnosis of dental caries can be yielded by AI.

Oral malodour has been predicted by neural networks by evaluating saliva samples for the presence of operation taxonomical units in the 16s RNA of the bacteria thereby differentiating the malodourous bacteria from healthy commensals.[68] This opens the potential to develop oral malodour screening, aiding in the diagnosis of halitosis. Artificial intelligence has been employed in the development and fine tuning of smart toothbrush which makes a colossal difference in the lives of the debilitated and bedridden patients.[69,70] This is made possible by continuous motion tracking systems, aiding in the development of a completely autonomous smart tooth brush. Krois J *et al.* using 1456 images of panoramic radiographs trained a 7 layer deep learning CNN which estimated periodontal bone loss with a mean accuracy of 81%.[71]

Challenges of AI in Dentistry

In comparison to other branches of medicine, dentistry is one of the most suitable areas where the applications of AI are limitless. Yet surprisingly, although the origin of AI was as early as 1950s, it is still being applied more only for the purpose of research.[72] The reasons behind this compromised growth could be, the discord among various dental clinical data sources and their incompatibility.[73]Secondly, this data could be biased and might not represent the whole population.[74]Data validation requires a huge number of experts, which is tedious to procure.[75] The results generated might not be directly applicable to patient needs.[76] In dentistry, like any other medical field, the responsibility of the physician channels alongside the need of the patient.[77]With the employment of huge data base, especially in case of a sensitive patient there is a need for an ironclad security to respect the individual's autonomy and privacy. This goes parallel with the need of adaptability of AI to the current effective legal, ethical and governing bodies.[30,78] Use of a federated AI might mitigate the said concern. The lack of standardization of AI especially in the dental field is yet another hurdle. Besides this, there will be a lacuna that is always felt in terms of the human touch comprising of empathy and care.[79] The practical applications of AI as a part of the normal life will see light of day only when these challenges are addressed today.

Conclusions

Artificial intelligence has the potential to make the diagnosis of complex dental diseases swifter and more precise which would ultimately aid in timely commencement of treatment. The ability to determine treatment routes, craft a personalized treatment plan and predict the outcome of the treatment given, could make the role of AI indispensable to health care.

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Conflicts of Interest Statement

The authors declare no conflict of interest.

References

1. Zhang S, Bamakan SMH, Qu Q, Li S. Learning for personalized medicine: a comprehensive review from a deep learning perspective. IEEE Rev Biomed Eng 2019; 12: 194-208.
2. Belard A, Buchman T, Forsberg J, Potter BK, Dente CJ, Kirk A, et al. Precision diagnosis: a view of the clinical decision support systems (CDSS) landscape through the lens of critical care. J Clin Monit Comput 2017; 31: 261–271.
3. Schork NJ. Artificial intelligence and personalized medicine. Cancer Treat Res 2019; 178: 265–283.
4. Russell S, Norvig P. Artificial intelligence. 3rd ed. Upper Saddle River, N.J.: Pearson Education: 2009: 480.
5. Amisha, Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Family Med Prim Care 2019; 8: 2328–2331.
6. Hamlet P, Tremblay J. Artificial intelligence in medicine. Metabolism 2017; 69S: S36–S40.
7. Imran N, Jawaid M. Artificial intelligence in medical education: Are we ready for it? Pak J Med Sci 2020; 36: 857-859.
8. Sandip P, Yvonne C, Chander D, Morey J, Juan FM, Michel K. Artificial intelligence and the future of surgical robotics. Ann Surg 2019; 270: 223-226.
9. Du G, Cao X, Liang J, Chen X, Zhan Y. Medical image segmentation based on U-net: a review. J Imaging SciTechnol 2020; 1: 64.
10. Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. GastrointestEndosc 2020; 92: 807–812.
11. Perlovsky LI. Neural mechanisms of the mind, Aristotle, Zadeh, and fMRI. IEEE Trans Neural Netw 2010; 21: 718-733.
12. Turing A. On computable numbers, with an application to the Entscheidungs problem. Proc London Math Soc 1936; 42: 230–265.
13. Park WJ, Park J-B. History and application of artificial neural networks in dentistry. Eur J Dent 2018; 12: 594–601.
14. Weizenbaum J. ELIZA-a computer program for the study of natural language communication between man and machine. Commun ACM. 1966; 9: 36–45.
15. Kulikowski CA. Beginnings of artificial intelligence in medicine (AIM): computational artifice assisting scientific inquiry and clinical art - with reflections on present AIM challenges. Yearb Med Inform 2019; 28: 249-256.
16. Goldhahn J, Rampton V, Spinas G. Could artificial intelligence make doctors obsolete? BMJ 2018; 363: k4563.
17. Yu D, Deng L. Deep learning and its applications to signal and information processing. IEEE Signal Process Mag 2011; 28: 145-154.
18. Hubel DH, Wiesel TN. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. J Physiol 1962; 160: 106–154.
19. Hubel DH, Wiesel TN. Receptive fields of single neurones in the cat's striate cortex. J Physiol 1959; 148: 574–591.
20. LeCun Y, Touresky D, Hinton G, Sejnowski T. A theoretical framework for back-propagation. Proc 1988 Connect Model Summer Sch 1988; 1: 21–28.
21. Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. Science 2006; 313: 504-507.
22. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015; 521: 436-444.
23. Hinton G, Deng L, Yu D, Dahl GE, Mohamed A, Jaitly N. Deep neural networks for acoustic modeling in speech recognition: the shared views of four research groups. Signal Process Mag IEEE 2012; 29: 82-97.
24. Lawrence S, Giles CL, Tsoi AC, Back AD. Face recognition: a convolutional neural-network approach. IEEE Trans Neural Netw Learn Syst 1997; 8: 98-113.
25. Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation. Proc IEEE ComputSocConfComput Vis Pattern Recognit 2015; 79: 3431–3440.
26. Lecun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proc IEEE 1998; 86: 2278–2324.
27. Cao C, Liu F, Tan H, Song D, Shu W, Li W, et al. Deep learning and its applications in biomedicine. Genomics Proteomics Bioinformatics 2018; 16: 17–32.
28. Naylor CD. On the prospects for a (deep) learning health care system. JAMA 2018; 320: 1099-1100.
29. Israni ST, Verghese A. Humanizing artificial intelligence. JAMA 2019; 321: 29-30.
30. Schwendicke F, Samek W, Krois J. Artificial intelligence in dentistry: chances and challenges. J Dent Res 2020; 99: 769–774.
31. Jubair F, Al-karadsheh O, Malamos D, Al Mahdi S, Saad Y, Hassona Y. A novel lightweight deep convolutional neural network for early detection of oral cancer. Oral Dis 2021; 00: 1-8.
32. Avuçlu E, Başçiftçi F. Novel approaches to determine age and gender from dental X-ray images by using multiplayer perceptron neural networks and image processing techniques. Chaos Solitons Fractals 2019; 120: 127-138.
33. Speight PM, Elliott AE, Jullien JA, Downer MC, Zakzrewska JM. The use of artificial intelligence to identify people at risk of oral cancer and precancer. Br Dent J 1995; 179: 382-387.

34. McCartney S, Weltin M, Burchiel KJ. Use of an artificial neural network for diagnosis of facial pain syndromes: an update. Stereotact Funct Neurosurg 2014; 92: 44-52.
35. Song A, Wu Z, Ding X, Hu Q, Di X. Neurologist standard classification of facial nerve paralysis with deep neural networks. Future Internet 2018; 10: 111.
36. Men K, Geng H, Zhong H, Fan Y, Lin A, Xiao Y. A deep learning model for predicting xerostomia due to radiation therapy for head and neck squamous cell carcinoma in the rtog 0522 clinical trial. Int J RadiatOncolBiol Phys 2019; 105: 440-447.
37. Park J, Lee JS, Oh D, Ryoo HG, Han JH, Lee WW. Quantitative salivary gland SPECT/CT using deep convolutional neural networks. Sci Rep 2021; 11: 1–10.
38. Kim JY, Kim D, Jeon KJ, Kim H, Huh JK. Using deep learning to predict temporomandibular joint disc perforation based on magnetic resonance imaging. Sci Rep 2021; 11: 6680.
39. Cejudo JE, Chaurasia A, Feldberg B, Krois J, Schwendicke F. Classification of dental radiographs using deep learning. J Clin Med 2021; 10: 1496.
40. 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. DentomaxillofacRadiol 2019; 48: 20180051.
41. Sur J, Bose S, Khan F, Dewangan D, Sawriya E, Roul A. Knowledge, attitudes, and perceptions regarding the future of artificial intelligence in oral radiology in India: A survey. Imaging Sci Dent 2020; 50: 193–198.
42. Kise Y, Ikeda H, Fujii T, Fukuda M, Ariji Y, Fujita H, et al. Preliminary study on the application of deep learning system to diagnosis of Sjögren's syndrome on CT images. DentomaxillofacRadiol 2019; 48: 20190019.
43. Kise Y, Shimizu M, Ikeda H, Fujii T, Kuwada C, Nishiyama M, et al. Usefulness of a deep learning system for diagnosing Sjögren's syndrome using ultrasonography images. DentomaxillofacRadiol 2020; 49: 20190348.
44. Dalitz GD. Age determination of adult human remains by teeth examination. J Forensic SciSoc 1962; 3: 11-21.
45. Bewes J, Low A, Morphett A, Pate FD, Henneberg M. Artificial intelligence for sex determination of skeletal remains: application of a deep learning artificial neural network to human skulls. J Forensic Leg Med 2019; 62: 40-43.
46. Gross GW, Boone JM, Bishop DM. Pediatric skeletal age: determination with neural networks. Radiology 1995; 195: 689-695.
47. 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; 35: 301–307.
48. Kuwada C, Ariji Y, Fukuda M, Kise Y, Fujita H, Katsumata A, et al. Deep learning systems for detecting and classifying the presence of impacted supernumerary teeth in the maxillary incisor region on panoramic radiographs. Oral Surg Oral Med Oral Pathol Oral Radiol 2020; 130: 464-469.
49. Bouletreau P, Makaremi M, Ibrahim B, Louvrier A, Sigaux N. Artificial intelligence: applications in orthognathic surgery. J Stomatol Oral Maxillofac Surg 2019; 120: 347-354.
50. Shin WS, Yeom HG, Lee GH, Yun JP, Jeong SH, Lee JH, et al. Deep learning based prediction of necessity for orthognathic surgery of skeletal malocclusion using cephalogram in Korean individuals. BMC Oral Health 2021; 21: 130.
51. 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: 122-181.
52. Miranda-Filho A, Bray F. Global patterns and trends in cancers of the lip, tongue and mouth. Oral Oncol 2020; 102: 104551.
53. Halicek M, Lu G, Little JV, Wang X, Patel M, Griffith CC, et al. Deep convolutional neural networks for classifying head and neck cancer using hyperspectral imaging. J Biomed Opt 2017; 22: 60503.
54. Fu Q, Chen Y, Li Z, Jing Q, Hu C, Liu H, et al. A deep learning algorithm for detection of oral cavity squamous cell carcinoma from photographic images: A retrospective study. EClinicalMedicine 2020; 27: 100558.
55. Kim DW, Lee S, Kwon S, Nam W, Cha IH, Kim HJ. Deep learning-based survival prediction of oral cancer patients. Sci Rep 2019; 9: 6994.
56. Wang X, Li BB. Deep learning in head and neck tumor multiomics diagnosis and analysis: review of the literature. Front Genet 2021; 12: 624820.
57. Takahashi T, Nozaki K, Gonda T, Mameno T, Ikebe K. Deep learning-based detection of dental prostheses and restorations. Sci Rep 2021; 11: 1960.
58. Sukegawa S, Yoshii K, Hara T, Yamashita K, Nakano K, Yamamoto N, et al. Deep neural networks for dental implant system classification. Biomolecules 2020; 10: 984.
59. Xie X, Wang L, Wang A. Artificial neural network modeling for deciding if extractions are necessary prior to orthodontic treatment. Angle Orthod 2010; 80: 262-266.
60. Jung SK, Kim TW. New approach for the diagnosis of extractions with neural network machine learning. Am J OrthodDentofacialOrthop 2016; 149: 127-133.
61. Thanathornwong B. Bayesian-based decision support system for assessing the needs for orthodontic treatment. Healthc Inform Res 2018; 24: 22-28.
62. Choi HI, Jung SK, Baek SH. Artificial intelligent model with neural network machine learning for the diagnosis of orthognathic surgery. J Craniofac Surg 2019; 30: 1986-1989.
63. 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. ProgOrthod 2019; 20: 41.
64. 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. DentomaxillofacRadiol 2019; 48: 20180218.
65. Saghiri MA, Asgar K, Boukani KK. A new approach for locating the minor apical foramen using an artificial neural network. IntEndod J 2012; 45: 257–265.
66. Benjamin RM. Oral health: the silent epidemic. Public Health Rep 2010; 125: 158–159.
67. Geetha V, Aprameya KS, Hinduja DM. Dental caries diagnosis in digital radiographs using back-propagation neural network. Health InfSciSyst 2020; 8: 8.
68. Nakano Y, Suzuki N, Kuwata F. Predicting oral malodour based on the microbiota in saliva samples using a deep learning approach. BMC Oral Health 2018; 18: 128.
69. Ganss C, Klein P, Giese-Kraft K, Meyners M. Validation of motion tracking as tool for observational toothbrushing studies. PLoS One 2020; 15: e0244678
70. Scquizzato T, Gazzato A. Adopting a smart toothbrush with artificial intelligence may improve oral care in patients admitted to the intensive care unit. Crit Care 2019; 23: 223.
71. 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; 9: 8495.

72. Schwendicke F, Golla T, Dreher M, Krois J. Convolutional neural networks for dental image diagnostics: A scoping review. J Dent 2019; 91: 103-226.
73. Gianfrancesco MA, Tamang S, Yazdany J, Schmajuk G. Potential biases in machine learning algorithms using electronic health record data. JAMA Intern Med 2018; 178: 1544–1547.
74. Walsh T. Fuzzy gold standards: Approaches to handling an imperfect reference standard. J Dent 2018; 74: S47-S49.
75. Collins GS, Reitsma JB, Altman DG, Moons KG. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement. BMC Medicine 2015; 13: 1.
76. Maddox TM, Rumsfeld JS, Payne PRO. Questions for Artificial Intelligence in Health Care. JAMA 2019; 321: 31-32.
77. Sattler F, Wiedemann S, Muller KR, Samek W. Robust and communication-efficient federated learning from non-i.i.d. data. IEEE Trans Neural Netw Learn Syst 2020; 31: 3400-3413.
78. El Naqa I, Ruan D, Valdes G, Dekker A, McNutt T, Ge Y, et al. Machine learning and modeling: Data, validation, communication challenges. Med Phys 2018; 45: e834-e840.
79. Khanna S. Artificial intelligence: contemporary applications and future compass. Int Dent J 2010; 60: 269-272.