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Artificial Intelligence in Dentistry: What We Need To Know?

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Abstract

Although dated back to 1950, artificial Intelligence (AI) has not become a practical tool until two decades ago. In fact, AI is the capacity of machines to do tasks that normally require human intelligence. AI applications have been started to provide convenience to people's lives due to the rapid development of big data computational power, as well as AI algorithm. Furthermore, AI has been used in every dental specialties. Most of the applications of AI in dentistry are in diagnosis based on X-ray or visual images, whereas other functions are not as operative as image-based functions mainly due to data availability issues, data uniformity and computing power for processing 3D data. AI machine learning (ML) patterns assimilate from human expertise whereas Evidence-based dentistry (EBD) is the high standard for the decision-making of dentists. Thus, ML can be used as a new precious implement to aid dental executives in manifold phases of work. It is a necessity that institutions integrate AI into their theoretical and practical training programs without forgetting the continuous training of former dentists.

Keywords: Artificial Intelligence (AI); Machine learning (ML); Deep learning (DP); Dentistry; Diagnostic

Introduction

Artificial Intelligence (AI) is developing fast in all sectors. It may assimilate human expertise and do tasks that required human intelligence. It can be defined by the theory and development of computer systems capable of executing tasks that need human understanding, such as seeing perception, talk identification, resolution, and translation [1]. Also, it a machine's ability to express its own intelligence by solving problems based on data. Machine learning (ML) uses algorithms to anticipate outcomes from a set of data. The aim is to facilitate it for machines without human contribution to study from data and fix problems (Figure 1) [2]. Artificial intelligence has been employed in every domain such as industry, medicine, dentistry, research, portable display, hospital monitoring, automatic and non-Human assistants. AI may be often used as a practical implement helping dentists to minimize their work time. In addition of diagnosing utilizing data feed directly, AI is able to acquire a knowledge from several information origins to make a diagnostic further on human capabilities.

Classifications of AI

AI may be sorted as weak AI and strong AI. Weak AI, utilizes an application skilled to fix unique or precise functions. Now, the most utilized AI is weak AI. For example, of AI in strengthening studying we can cite AlphaGo, and talk operating we have Google translation, and Amazon chat robot [3]. Strong AI calls attention to the competence and cleverness of AI equalling that of humans. It possesses its proper understanding and behaviour whose supplessness is comparable to humans [4]. Therefore, till then no strong AI applications are available. In Addition, ML is classified as supervised, semi-supervised and unsupervised learning. Supervised learning utilizes labelled inputs for learning to supervise the algorithm. The algorithm studies from the labelled input, releases and recognizes the shared characteristics of the labelled input to take auguries about unlabelled input [5].

At variance, unsupervised learning, performs automatically to discover the different characteristics of unlabelled data [6]. Semi-supervised learning reposes in mid of supervised and no-supervised learning, which employs a little size of labelled input jointly with a big size of unlabelled data during training [7]. Lately, a novel process named weakly supervised learning has been progressively common in the AI domain to reduce labelling expenses. Especially, the item division function solely utilizes picture-level marks as an alternative of item limit or position details for studying [8].

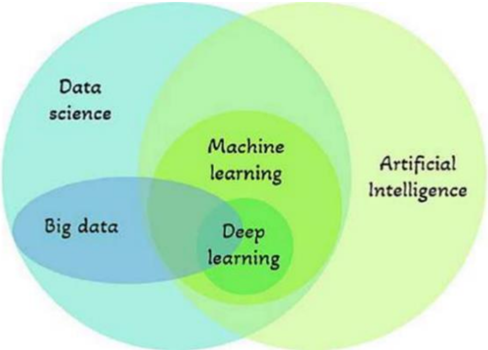

Figure 1: *Key elements of artificial intelligence systems. (2).*

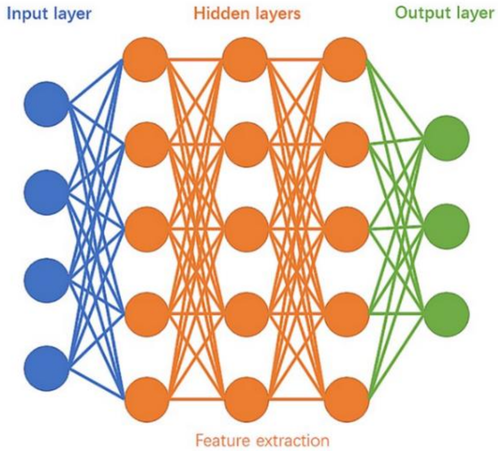

Figure 2: *Schematic diagram of deep learning (9).*

Deep learning (DP) is now a significant experimentation zone and constitutes a part of ML. It may use the two supervised and unsupervised learning. DP represents an artificial "neural network" composed of a base of three nodal layers—input, manifold "hidden", and output layers. Every layer is made of several interconnected nodes (synthetic neurons) while every node is characterized by weight and biased threshold from m crucial factors, provided by its proper linear regression model. The weight is assigned when there is an input of the node. Similar to a decision tree model, the neural network as a feedforward network is defined from the process of passing data from one layer to the next (Figure 2) [9]. A deep neural connection may bring characteristics from the input, without human intervention. Neural networks (NN) are the mainstays of deep learning algorithms. In fact, there are different variants of NN, the most important sorts of neural networks are artificial neural networks (ANN), convolutional neural networks (CNN) and generative adversarial networks (GAN).

Artificial Neural Networks (ANN)

ANN is composed of a set of neurons and layers, a group of three layers corresponds to an elemental pattern for deep learning. Only forward direction is allowed to inputs. Input neurons bring out characteristics of input data from the input layer and dispatch data to hidden layers, and the data traverse all the hidden layers consecutively. At the end, the output layers expose and summarize the results. From previous layers, all the hidden layers in ANN may weigh the data and perform adjustments to send data to the next layer. Each hidden layer acts as an input and output layer, allowing the ANN to understand more complex features [10].

Convolutional Neural Networks (CNN)

CNN is a sort of deep learning pattern mostly utilized for picture identification and production. The presence in CNN of convolution layers, the pooling layer and the fully connected layer in the hidden layers is the principal difference between CNN and ANN. Utilizing convolution kernels, characteristic maps of input data were produced by convolution layers. The input picture is bended by the kernels. Because of the weight sharing convolution, the intricacy of pictures is decreased. The pooling layer is mostly continued by every set of convolution layers, which decreases the size of characteristic maps for more characteristic taking out. The fully connected layer is utilized succeeding the convolution layer and pooling layer. The fully connected layer links to every activated neurons in the previous layer and converts the 2D characteristic maps into 1D. 1D characteristic maps are then coupled with nodes of groups for categorization [11,12]. Finally, image recognition is showing greater leverage and preciseness in CNN compared to ANN due to the use of the functional hidden layers.

Generative Adversarial Networks (GAN)

GAN is a sort of deep learning algorithm conceived by Good fellow from the input data, this unsupervised learning method automatically discover and generates new data with alike characteristics or models in comparison with the input data [13]. 2 neural networks: a generator and a discriminator. The principal aim for the generator is to produce input which doesn't allow to the discriminator to identify if the input is produced by the generator or from the initial input data. The essential goal for the discriminator is to differentiate between the output produced by the generator and the initial input data as much as possible. The two GAN networks ameliorate themselves and supplement each other. Furthermore, GAN has been spread fast after its creation. They are mostly used picture-to-picture movement and creating credible pictures of items, environments, and individuals [14,15]. A new 3D-GAN structure was created founded on a conventional GAN connection [16]. It generates 3D items from a specified 3D spot by joining new discoveries in GAN and dimensional convolutional networks. Different from a traditional GAN network, it is competent to create items in 3D automatically or from 2D images. It provides a larger spectrum of feasible utilizations in 3D input operating juxtaposed with its 2D shape.

AI in Dentistry

AI in operative dentistry

Dentists identify dental decays by ocular and manual investigation or by X-ray assessment but detecting early-stage lesions is difficult when profound fissures, close interproximal joining. In fact, several damages are detected uniquely in the late phases of dental decay, which conduct to supplementary sophisticated treatment. Furthermore, most of diagnosis belong to dentists' experience despite of the wide use of dental radiography and explorer in dental caries diagnosis. Each pixel has a degree of grey in two-dimensional X-Ray which represents the object density. An AI algorithm may assimilate the model and provide auguries to several dental lesions from this concept. In fact, several studies performed a CNN algorithm dental caries detection on periapical x-rays and intraoral images [17,18]. Others found that AI in proximal caries detection was further productive and cheaper than dentists [19]. Actually, AI showed encouraging results in precocious detection of dental lesions, which accuracy was better than dentists or at less the same (Figure 3,4).

AI in periodontics

Periodontitis is one of the most prevalent troubles. It is a charge for billions of people and, if not well fixed, may conduct to tooth mobility or loss [20]. It is well known that Prompt discovery and care are required to avert acute periodontitis. In clinical practice, periodontal illness determination is based on assessing pocket probing profundity and gingival regress. Researchers used AI in diagnostic and periodontal disease classification [21,22].
Others researchers utilized CNN in the discovery of periodontal bone damage on panoramic radiographs [23]. In addition, studies started that periodontal status may be inspected by a CNN algorithm utilizing organizational health-related input [23].

AI in orthodontics

Orthodontic treatment organization is generally found on the experience and priority of the orthodontists. In fact, orthodontists spend a great effort to identify malocclusion, due to the multitude of changeable that must be examined in the cephalometric investigation, which makes difficult to establish the treatment program and anticipate the result [24].

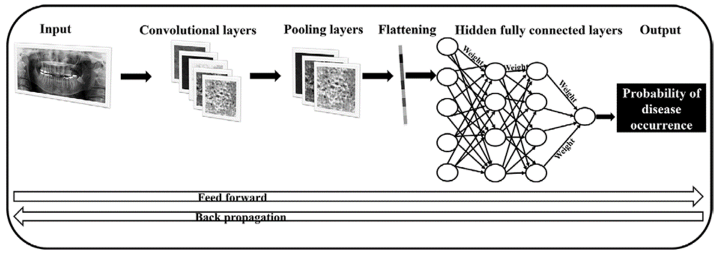

Figure 3: *CNN model to forecast the patient's dental condition from a panoramic radiograph (2).*

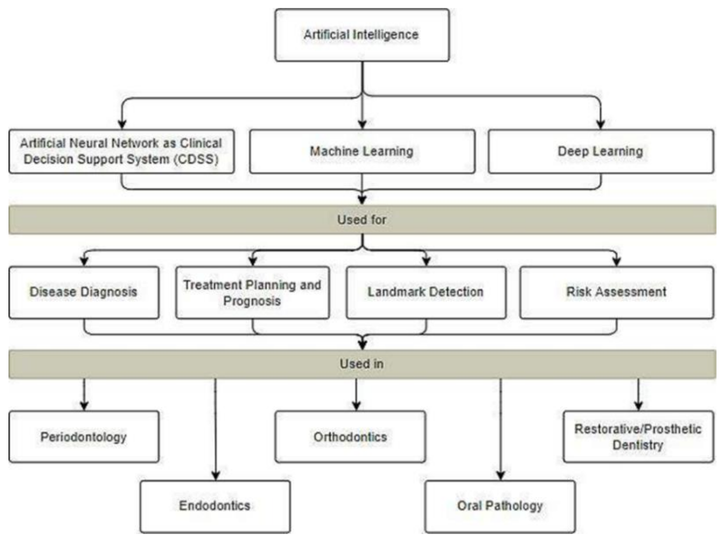

Figure 4: *Applications of AI in different subfields of dentistry (2).*

Moreover, treatment planning and prediction of treatment results, such as simulating the changes in the appearance of pre- and post-treatment facial photographs are the most applications of AI in orthodontics. Actually, thanks of AI, the orthodontic treatment outcome, the skeletal class, and the anatomic landmarks in lateral x-rays may be examined [25]. A study performed an algorithm to diagnose if there is a requirement for treatment by orthodontics on the base of orthodontics-related data [26]. On other study, an ANN model was proposed to estimate if there is need of extractions based on lateral cephalometric radiographs [27,28]. Also, several studies have demonstrated how AI may automatically locate cephalometric landmarks with high accuracy as well as the need of orthognathic surgery [29-32].

AI in oral and maxillofacial pathology

Oral and Maxillofacial Pathology (OMFP) is a specialty that examines pathological status and diagnoses sickness s in the buccal and maxillofacial area. The most serious kind of OMFP is buccal cancer. World Health Organization (WHO) reports over 657,000 patients with buccal cancer which cause more than 330,000 deaths per year [33]. By utilizing x-rays, pictures from microscope and ultrasonography AI may be utilized for tumour and cancer identification by CNN algorithms [34,35]. AI is used to handle cleft lip and palate in risk augury [36]. Further, with intrabuccal visual pictures and using a CNN model, it was possible to spot buccal latent malignant troubles and oral squamous cell carcinoma (OSCC). Also, optical Coherence Tomography (OCT) has been utilized in the recognition of benign and malignant lesions in the buccal mucosa in addition to intrabuccal visual pictures. In addition, a study has used ANN and Support Vector Machine (SVM) patterns to identify neoplastic buccal lesions [37]. In other study, researchers were able to mechanically identify oral squamous cell carcinoma using a CNN algorithm from confocal laser endomicroscopy pictures [34]. Finally, a study has used a CNN algorithm to recognize and determine ameloblastoma and keratocystic odontogenic tumour (KCOT) [38].

AI in prosthodontics

AI is mostly used in prosthodontics to perform the restoration design. CAD/CAM has digitalized the design work in profit-oriented yields, like CEREC, 3Shape, etc. Some studies demonstrated novel methods founded on 2D-GAN patterns creating a crown by studying shape technicians' designs. Transformed from 3D mouth models, the forming input was 2D depth maps. Other study utilized 3D data directly generating crown using a 3DDCGAN network [39,40]. In addition, associating AI and CAD/CAM or 3D/4D printing could bring a high effectiveness (88). Also, in debonding prediction and shade matching of restorations, AI may be an unavoidable support [41, 42]. However, in removable prosthodontics the design is more demanding as more elements and changeable must be reviewed. Assisting the conception process of partial dentures is the most used feature in recent ML algorithms [43,44].

AI in Endodontics

Using properties of periapical radiolucency, AI algorithms may identify periapical disease [45]. Also, radiolucencies can be recognized on periapical on panoramic radiographs with deep learning algorithm model [46,47]. A study utilizing AI system identified 142 out of 153 periapical lesions with a detection accuracy rate of 92.8%. In addition, utilizing artificial neural connections the detection of cystic lesions has been done [48]. Furthermore, a separation of granuloma from periapical cysts using CBCT images was performed and three-dimensional teeth segmentation using the CNN method was demonstrated [49,50]. AI can assimilate further on that human competence. Also, the growth of computer tech is vital to promote the AI development. Evidence-Based Dentistry (EBD) is "an approach to oral health care that requires the judicious integration of systematic assessments of clinically relevant scientific evidence, relating to the patient's oral and medical condition and history with the dentist's clinical expertise and the patient's treatment needs and preferences". ML models may be considered like another helpful instrument for health professionals. Indeed, EBD and ML are matching to better help dental professionals, in fact they may use it both to enhance their benefits and place them to medical exercise.

Conclusion

A multiple of AI systems are being developed for diverse dental disciplines and have produced encouraging results which predicts a bright future for AI in dentistry. Thereafter, it is now a necessity that institutions integrate AI into their theoretical and practical training programs without forgetting the continuous training of former dentists.

References

1. Stevenson A. Oxford Dictionary of English. USA: Oxford University Press. 2010.
2. Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. Commun ACM. 2017; 60: 84-90.
3. Fang G, Chow MC, Ho JD, He Z, Wang K, Ng T, et al. Soft robotic manipulator for intraoperative MRI-guided transoral laser microsurgery. Sci Robot. 2021; 6.
4. Flowers JC. Strong and weak AI: deweyan considerations. AAAI Spring symposium: towards conscious AI systems. 2019.
5. Hastie T, Tibshirani R, Friedman J. Overview of supervised learning. In: Hastie T, Tibshirani R, Friedman J, editors. The elements of statistical learning. New York, NY, USA: Springer. 2009; 9-41.
6. Hastie T, Tibshirani R, Friedman J. Unsupervised learning. In: Hastie T, Tibshirani R, Friedman J, editors the elements of statistical learning. New York, NY, USA: Springer. 2009; 485-585.
7. Zhu X, Goldberg AB. Introduction to semi-supervised learning. Synth Lect Artif Intell Mach Learn. 2009; 3:1-130.
8. Keser G, Namdar Pekiner F. Artificial intelligence applications in dentistry. In: Karaman, E. (ed.), Current researches in health sciences-I. Ozgur Publi. 2023.
9. Zhou ZH. A brief introduction to weakly supervised learning. Natl Sci Rev. 2017; 5: 44-53.
10. Agatonovic-Kustrin S, Beresford R. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. J Pharm Biomed Anal. 2000; 22: 717-727.
11. Nam CS. Neuroergonomics: Principles and practice. Gewerbestrasse, Switzerland: Springer Nature. 2020.
12. Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, et al. Generative adversarial nets. Adv Neural Inf Process Syst. 2014; 27: 2672-2680.

13. Gui J, Sun Z, Wen Y, Tao D, Ye J. A review on generative adversarial networks: algorithms, theory, and applications. arXiv preprint arXiv: 200106937. 2020.
14. Aggarwal A, Mittal M, Battineni G. Generative adversarial network: an overview of theory and applications. Int J Inf Manage Data Insights. 2021; 33.
15. Wu J, Zhang C, Xue T, Freeman WT, Tenenbaum JB. Learning a probabilistic latent space of object shapes via 3d generative-adversarial modelling. Proceedings of the 30th international conference on neural information processing systems. 2016.
16. Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. J Dent. 2018; 77: 106-111.
17. Kuhnisch J, Meyer O, Hesenius M, Hickel R, Gruhn V. Caries detection on intraoral images using artificial intelligence. J Dent Res. 2021; 101.
18. Schwendicke F, Rossi J, Gostemeyer G, Elhennawy K, Cantu A, Gaudin R, et al. Cost-effectiveness of artificial intelligence for proximal caries detection. J Dent Res. 2021; 100: 369-376.
19. Tonetti MS, Jepsen S, Jin L, Otomo-Corgel J. Impact of the global burden of periodontal diseases on health, nutrition and wellbeing of mankind: a call for global action. J Clin Periodontol. 2017; 445: 456-462.
20. 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: 1-6.
21. Kim EH, Kim S, Kim HJ, Jeong Ho, Lee J, Jang J, et al. Prediction of chronic periodontitis severity using machine learning models based on salivary bacterial copy number. Front Cell Infect. 2020; 10: 698.
22. Huang W, Wu J, Mao Y, Zhu S, Huang GF, Petritis B, et al. Developing a periodontal disease antibody array for the prediction of severe periodontal disease using machine learning classifiers. J Periodontol. 2020; 91: 232-243.
23. Proffita WR. The evolution of orthodontics to a data-based specialty. Am J Orthod Dentofacial Orthop. 2000; 117: 545-547.
24. Thanathornwong B. Bayesian-based decision support system for assessing the needs for orthodontic treatment. Healthc Inform Res. 2018; 24: 22-28.
25. 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.
26. Jung SK, Kim TW. New approach for the diagnosis of extractions with neural network machine learning. Am J Orthod Dentofacial Orthop. 2016; 1491: 127-133.
27. Park JH, Hwang HW, Moon JH, Yu Y, Kim H, Her SB, et al. Automated identification of cephalometric landmarks: part 1—comparisons between the latest deep-learning methods YOLOV3 and SSD. Angle Orthod. 2019; 89: 903-909.
28. Hwan HW, Park JH, Moon JH, Yu Y, Kim H, Her SB, et al. Automated identification of cephalometric landmarks: part 2-might it be better than human? Angle Orthod. 2020; 90: 69-76.
29. 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: 1986-1989.
30. Junaid N, Khan N, Ahmed N, Abbasi MS, Das G, Maqsood A. Development, application, and performance of artificial intelligence in cephalometric landmark identification and diagnosis: a systematic review. Healthcare. 2022; 10.
31. Kunz F, Stellzig-Eisenhauer A, Zeman F, Boldt J. Artificial intelligence in orthodontics: evaluation of a fully automated cephalometric analysis using a customized convolutional neural network. J Orofac Orthop. 2020; 81: 52-68.
32. World Health Organization. Cancer Prevention.
33. 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: 1-10.
34. James BL, Sunny SP, Heidari AE, Ramanjinappa RD, Lam T, Tran AV, et al. Validation of a point-of-care optical coherence tomography device with machine learning algorithm for detection of oral potentially malignant and malignant lesions. Cancers. 2021; 13.
35. Poedjiastoeti W, Suebnukarn S. Application of convolutional neural network in the diagnosis of jaw tumours. Healthc Inform Res. 2018; 24: 236-241.
36. Xu B, Wang N, Chen T, Li M. Empirical evaluation of rectified activations in convolutional network. arXiv preprint arXiv:150500853. 2015.
37. Dhillon H, Chaudhari PK, Dhingra K, Kuo R-F, Sokhi RK, Alam MK, et al. Current applications of artificial intelligence in cleft care: a scoping review. Front Med. 2021; 8: 1-14.
38. Hwang JJ, Azernikov S, Efros AA, Yu SX. Learning beyond human expertise with generative models for dental restorations. arXiv preprint arXiv:180400064. 2018.
39. Tian S, Wang M, Dai N, Ma H, Li L, Fiorenza L, et al. DCPR-GAN: dental crown prosthesis restoration using two-stage generative adversarial networks. IEEE J Biomed Health Inform. 2021; 26: 151-160.
40. Wei J, Peng M, Li Q, Wang Y. Evaluation of a novel computer color matching system based on the improved back-propagation neural network model. J Prosthodont. 2018; 27: 775-783.
41. Yamaguchi S, Lee C, Karaer O, Ban S, Mine A, Imazato S. Predicting the debonding of CAD/CAM composite resin crowns with AI. J Dent Res. 2019; 98: 1234-1238.
42. 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: 115-118.
43. Cheng C, Cheng X, Dai N, Jiang X, Sun Y, Li W. Prediction of facial deformation after complete denture prosthesis using BP neural network. Comput Biol Med. 2015; 66: 103-112.
44. 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.
45. 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. Comput Methods Programs Biomed. 2015; 121: 117-126.

46. Lin PL, Huang PY, Huang PW. Automatic methods for alveolar bone loss degree measurement in periodontitis periapical radiographs. Comput Methods Programs Biomed. 2017; 148: 1-11.
47. Carmody DP, McGrath SP, Dunn SM, van der Stelt PF, Schouten E. Machine classification of dental images with visual search. Acad Radiol. 2001; 8: 1239-1246.
48. Endres MG, Hillen F, Salloumis M, Sedaghat AR, Niehues SM, Quatela O, et al. Development of a deep learning algorithm for periapical disease detection in dental radiographs. Diagnostics (Basel). 2020; 10.
49. Lahoud P, EzEldeen M, Beznik T, Willems H, Leite A, Van Gerven A, et al. Artificial intelligence for fast and accurate 3-dimensional tooth segmentation on cone-beam computed tomography. J Endod. 2021; 47: 827-835.
50. American Dental Association. Policy on Evidence-Based Dentistry. 2001.