Application of artificial intelligence in the identification of dental implant systems: a literature review

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Artificial intelligence (AI) can be used across multiple disciplines and has also found application in the dental field. Although there have not been many studies on AI-related to dental implants, identification of implant systems in radiographic images using AI is being actively researched. The purpose of this study was to review articles related to the application of AI for the identification of dental implant systems. A systematic review was conducted using the Pubmed and Scopus databases to identify English language articles about AI and dental implant systems. Factors such as implant systems, data modality, sample size, training time, validation method, AI method, accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) were extracted from the 4 selected articles. All the surveyed research adopted pre-trained convolutional neural networks as the AI method. The accuracy of AI in finding the correct implant system ranged from 51 to 99.5 percent. (JOURNAL OF DENTAL IMPLANT RESEARCH 2020;39(4):48-52)

Key Words: Artificial intelligence, Machine learning, Deep learning, Dental implant

INTRODUCTION

The concept of a strong artificial intelligence (AI) which is capable of mimicking the intelligence of humans has led to, the application of weak AI capable of answering specific questions or solving some disputes¹⁾. The concept of weak AI explores different methods for constructing algorithms which learns from a set of data and make predictions. Machine learning aids in developing algorithms supervised by data²⁾. Neural network (NN) was the earliest types of AI to be built consisting of nodes and weights²⁾. The training data attributes influences the computing skills of the network, allowing it to update the connections weight²⁾. A simple network structure involving a few layers is called a "shallow" learning neural networks, while a "deep" learning neural network structure involves a plentiful and large layers³⁾. Convolutional neural network (CNN) which is a deep learning structure, can be used for extracting many features from abstract filter layers. CNN are commonly useful for processing

large and complex figures⁴⁾. The progression made in self-learning back-propagation algorithms has accelerated deep learning by refining the outcome from the data, thereby increasing the computing capability. The advancements in AI today have made it possible to be implemented for solving real-life problems and is applicable in various fields of study⁵⁾.

Since dental implants were first introduced in the 1960s, they have now become the standard treatment method for replacing edentulous area. There are many implant manufacturers, and there are subtle differences in treatment protocols for each company. Jokstad et al. reported that approximately 220 implant brands from 80 companies exist worldwide⁶⁾. If mechanical complications such as screw loosening or screw fracture occur in the implant, accessories provided by the manufacturer should be used to overcome the complications. However, it may be difficult for certain dentists to identify new implant systems simply by only viewing the images of the fixtures in radiographs. Therefore, radiographic identi-

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fication of implants is especially important to provide appropriate diagnoses and treatments to patients.

For this reason, research to identify implant systems on radiographic images through AI is currently being actively conducted. In this article, papers about AI applied to find and detect dental implant system using dental plain radiography were reviewed.

MATERIALS AND METHODS

1. Search strategy

In PubMed and Scopus, a search was performed for 'Machine learning OR deep learning OR neural network' and 'dental implants AND (identification OR detection OR classification)' until September 2020, and 7, 7, and 9 search results were obtained, respectively. A total of 4 peer-reviewed papers were obtained by removing articles not written in English, those focusing on radiological artifact, papers not related to dental implant, as well as reviews, editorials, and letters.

2. Data extraction

The following items were investigated within each paper; Author and year, Implant system, Data modality, Sample Size, Training time, Validation method, AI method, Accuracy, Sensitivity, Specificity, and Area under the receiver operating characteristic curve (AUC).

Among the items listed, Accuracy, Sensitivity, Specificity, AUC are defined as follows.

$$\text{Accuracy}(\%) = \frac{TP + TN}{TP + FP + FN + TN} \times 100$$

$$\text{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100$$

$$\text{Specificity}(\%) = \frac{TN}{TN + FP} \times 100$$

TP: True positive, TN: True negative, FP: False positive, FN: False negative.

ROC curve: a curve that visualizes how the evaluation value changes according to the change of each threshold after placing the sensitivity on the y-axis and (1-specificity) on the x-axis.

AUC: The value by obtaining the area of the lower area of the ROC curve has a value between 0~1, and a higher value means better classification performance.

RESULTS

The summary of the data derived from the selected papers is given in Table 1.

In all studies, CNN was adopted and used as a main network component. The size of the data set was different for each paper, and it ranged from 801 to 10770. In order to maximize the learning effect of the computer, the number of original data was replicated and increased through cross-validation. Then, deep learning was conducted on more replicated data. In the papers, the frequency of learning was set between 500 and 1000 times. Most of them used pretrained networks such as Alexnet, VGG, GoogLeNet, and Inception in existing servers. For radiographs, two-dimensional images such as panorama or periapical view were used alone or in combination. In the case of implant systems, global-market-leading products such as Straumann and Nobel Biocare were commonly investigated in all paper. Additionally, Osstem and Dentium's products were investigated in a Korean author's paper, and Zimmer, Astra, GC, and Kyocera's

Table 1. Summary of artificial intelligence articles in identification of dental implants system

Author and year	Implant system	Data modality	Sample size	Training	Validation method	AI method	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
Lee et al. ²⁴⁾ 2020	3 types (Osstem TSIII, Dentium Superline, Straumann Bone level)	Panorama, periapical	10770	1000 epoch	10-fold cross-validation	Pretrained CNN (GoogLeNet Inception-v3)	99.5	95.3	97.6	0.971
Takahashi et al. ²⁵⁾ 2020	6 types (Nobel Biocare MK III/IIIIG/MKIV/SG, Straumann Bone level, GC Genesio)	Panorama	1282	1000 epoch		Pretrained CNN (YOLO)	51~85	50~82		0.72
Kim et al. ²⁶⁾ 2020	4 types (Nobel Biocare MK TiUnite, Dentium Implantium, Straumann Bone level/Tissue level)	Periapical	801	500 epoch	k-fold cross-validation	Pretrained CNN (SqueezeNet, GoogLeNet, ResNet-18, MobileNet-v2, and ResNet-50)	93~98	92~98	94~98	
Sukegawa et al. ²⁷⁾ 2020	11 types (Zimmer Full Osseotite, Dentsply Astra EV/TX/Microthread, Nobel Biocare MKIII/SG/CC, Kyocera Finesia, Straumann Tissue level)	Panorama	8859	700 epoch	4-fold cross-validation	Pretrained CNN (VGG16 and VGG19)	86.0~93.5	84.2~92.8	80.2~90.7	0.958~1.000

products were investigated in a Japanese author's paper. The accuracy of AI was 51~99.5%, and the AUC ranged from 0.72~1.00.

DISCUSSION

AI have been studied in various fields within dentistry. Most of them are machine or deep learning using radiographic images or clinical pictures. In the field of oral and maxillofacial surgery, studies have been reported to classify tongue muscles or to provide anatomical guides for segmenting the mandibular canal using AI^{7,8)}. In addition, studies to diagnose oral cancer using tissue slides or cytology images have been reported⁹⁾. There was also a study analyzing the accuracy of automatic diagnosis using ultrasonography in patients with Sjogren syndrome¹⁰⁾. Additionally, there have been studies on the correlation between TMD and TMJ changes on CBCT or MRI¹¹⁾. As for orthodontics, studies on automating measurement points in lateral cephalometry or cone-beam CT have been reported¹²⁻¹⁴⁾. On top of that, studies have been reported to discriminate the dentition on which orthodontic treatment was performed, or to analyze the relationship between age and face^{15,16)}. In cariology, studies to detect dental caries from radiographic or infrared images have been conducted^{17,18)}. Also, studies to find normal root morphology, root fracture, and periapical pathogen have also been reported¹⁹⁻²¹⁾. In prosthodontics, there have been studies to distinguish between restorations and normal teeth in clinical pictures, or to predict the color tone of porcelain powder or composite resin^{22,23)}.

Researches on dental implants using AI had yet to be conducted only on the determining the implant system. The reason that only studies on implant systems have been conducted is thought that AI research using radiographic images or clinical images is relatively easy to perform. However, clinicians' desperate need for grasping the implant system is probably the main reason. When a patient has undergone an implant procedure at another hospital, or when the clinical information is not available because of an implant treatment long ago, clinicians must infer the implant system only by looking at radiographs. As mentioned in the introduction, when prosthetic complications of implants occur, clinicians

need to know the implant system to solve the complications. Considering these issues, an AI based approach seems to be a potentially suitable solution to solve that problem, and most studies were conducted to focus on developing an automated identification system of implants from radiographic images using object detection.

The accuracy of AI was 51~99.5%, and a large difference in accuracy was observed between literatures. Takahashi et al.'s research showed relatively low accuracy of 51~85%, while other papers had an accuracy of 90% or more, and Kim's research showed that the accuracy was 93~98% even though the sample size was only 801²⁴⁻²⁷⁾. Presumably, this is likely to be the effect of sample size replication by cross-validation. In the study of Takahashi et al., the content of cross-validation was not mentioned²⁵⁾. Even though the sample size was not small, as a result, accuracy may be low because only a small scale of learning was performed.

Currently, the areas that AI must overcome are largely classified into four categories. The first is data acquisition. Establishing an open-access standard data set will play a more important role since the sample size is ultimately directly related to accuracy²⁸⁾. The second is interpretability. Data-based AI cannot explain the decision-making process because it uses a purely computational method, so it needs to be supplemented to compensate mistake²⁹⁾. The third is Computing Power. As the AI model becomes more complex, the output speed depends on the computing power of the computer, so the advancement of hardware must be accompanied³⁰⁾. The last is Ethical consideration. Since AI does not imply standards on human ethics, development with ethical issues must be done for symbiosis with humans³¹⁾.

Contemporary AI excels in utilizing formalized knowledge and extracting information from massive data sets. However, it is hard to involve human emotion in its algorithm. AI should be viewed as an augmentation tool and, at times, relieve dentists so that they can perform more valued tasks, such as integrating emotional sympathy of patient and improving dentist-patient interactions³²⁾. In dental implantology, where humans are currently in charge of a large part, it is expected that more development will be achieved through the help of AI in the near future.

CONFLICT OF INTEREST

No potential conflict of interest relevant to this article was reported.

REFERENCES

1. Park WJ, Park JB. History and application of artificial neural networks in dentistry. *Eur J Dent* 2018;12:594-601.
2. Mupparapu M, Wu CW, Chen YC. Artificial intelligence, machine learning, neural networks, and deep learning: futuristic concepts for new dental diagnosis. *Quintessence Int* 2018;49:687-8.
3. Hwang JJ, Jung YH, Cho BH, Heo MS. An overview of deep learning in the field of dentistry. *Imaging Sci Dent* 2019;49:1-7.
4. Shan T, Tay FR, Gu L. Application of Artificial Intelligence in Dentistry. *J Dent Res* 2020;22034520969115.
5. Shahid N, Rappon T, Berta W. Applications of artificial neural networks in health care organizational decision-making: a scoping review. *PLoS One* 2019;14:e0212356.
6. Jokstad A, Braegger U, Brunski JB, Carr AB, Naert I, Wennerberg A. Quality of dental implants. *Int Dent J* 2003;53(6 Suppl 2):409-43.
7. Alabi RO, Elmusrati M, Sawazaki-Calone I, Kowalski LP, Haglund C, Coletta RD, et al. Comparison of supervised machine learning classification techniques in prediction of locoregional recurrences in early oral tongue cancer. *Int J Med Inform* 2020;136:104068.
8. Gerlach NL, Meijer GJ, Kroon DJ, Bronkhorst EM, Berge SJ, Maal TJ. Evaluation of the potential of automatic segmentation of the mandibular canal using cone-beam computed tomography. *Br J Oral Maxillofac Surg* 2014;52:838-44.
9. Sunny S, Baby A, James BL, Balaji D, N VA, Rana MH, et al. A smart tele-cytology point-of-care platform for oral cancer screening. *PLoS One* 2019;14:e0224885.
10. Kise Y, Shimizu M, Ikeda H, Fujii T, Kuwada C, Nishiyama M, et al. Usefulness of a deep learning system for diagnosing Sjogren's syndrome using ultrasonography images. *Dentomaxillofac Radiol* 2020;49:20190348.
11. Shoukri B, Prieto JC, Ruellas A, Yatabe M, Sugai J, Styner M, et al. Minimally invasive approach for diagnosing TMJ osteoarthritis. *J Dent Res* 2019;98:1103-11.
12. Kok H, Acilar AM, Izgi MS. Usage and comparison of artificial intelligence algorithms for determination of growth and development by cervical vertebrae stages in orthodontics. *Prog Orthod* 2019;20:41.
13. Amasya H, Yildirim D, Aydogan T, Kemaloglu N, Orhan K. Cervical vertebral maturation assessment on lateral cephalometric radiographs using artificial intelligence: comparison of machine learning classifier models. *Dentomaxillofac Radiol* 2020;49:20190441.
14. Gupta A, Kharbanda OP, Sardana V, Balachandran R, Sardana HK. A knowledge-based algorithm for automatic detection of cephalometric landmarks on CBCT images. *Int J Comput Assist Radiol Surg* 2015;10:1737-52.
15. 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;48:77-83.
16. Wang X, Cai B, Cao Y, Zhou C, Yang L, Liu R, et al. Objective method for evaluating orthodontic treatment from the lay perspective: An eye-tracking study. *Am J Orthod Dentofacial Orthop* 2016;150:601-10.
17. Casalegno F, Newton T, Daher R, Abdelaziz M, Lodi-Rizzini A, Schurmann F, et al. Caries detection with near-infrared transillumination using deep learning. *J Dent Res* 2019;98:1227-33.
18. Schwendicke F, Elhennawy K, Paris S, Friebertshauser P, Krois J. Deep learning for caries lesion detection in near-infrared light transillumination images: a pilot study. *J Dent* 2020;92:103260.
19. Setzer FC, Shi KJ, Zhang Z, Yan H, Yoon H, Mupparapu M, et al. Artificial intelligence for the computer-aided detection of periapical lesions in cone-beam computed tomographic images. *J Endod* 2020;46:987-93.
20. Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Ozyurek T. Evaluation of artificial intelligence for detecting periapical pathology on cone-beam computed tomography scans. *Int Endod J* 2020;53:680-9.
21. Hiraiwa T, Aiji 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;48:20180218.
22. 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;98:1234-8.
23. Yoneda M, Yamada K, Izumi T, Matsuzaki E, Maruta M, Hatakeyama J, et al. Development of an error-detection examination for conservative dentistry education. *Clin Exp Dent Res* 2020;6:69-74.
24. Lee JH, Jeong SN. Efficacy of deep convolutional neural network algorithm for the identification and classification of dental implant systems, using panoramic and periapical radiographs: A pilot study. *Medicine (Baltimore)* 2020;99:e20787.
25. Takahashi T, Nozaki K, Gonda T, Mameno T, Wada M, Ikebe K. Identification of dental implants using deep learning-pilot study. *Int J Implant Dent* 2020;6:53.
26. Kim JE, Nam NE, Shim JS, Jung YH, Cho BH, Hwang JJ. Transfer learning via deep neural networks for implant fixture system classification using periapical radiographs. *J Clin Med* 2020;9.
27. 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.
28. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts H. Artificial intelligence in radiology. *Nat Rev Cancer* 2018;18:500-10.
29. 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;28:249-56.

30. Fabrizio A, Meyer B, Fabregat R, Corminboeuf C. Quantum chemistry meets machine learning. *Chimia (Aarau)* 2019;73: 983-9.

31. Currie G, Hawk KE, Rohren EM. Ethical principles for the appli-

cation of artificial intelligence (AI) in nuclear medicine. *Eur J Nucl Med Mol Imaging* 2020;47:748-52.

32. Recht M, Bryan RN. Artificial intelligence: threat or boon to radiologists? *J Am Coll Radiol* 2017;14:1476-80.