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Review article

Application of artificial intelligence in the dental field: A literature review

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Abstract

Purpose: The purpose of this study was to comprehensively review the literature regarding the application of artificial intelligence (AI) in the dental field, focusing on the evaluation criteria and architecture types.

Study selection: Electronic databases (PubMed, Cochrane Library, Scopus) were searched. Full-text articles describing the clinical application of AI for the detection, diagnosis, and treatment of lesions and the AI method/architecture were included.

Results: The primary search presented 422 studies from 1996 to 2019, and 58 studies were finally selected. Regarding the year of publication, the oldest study, which was reported in 1996, focused on "oral and maxillofacial surgery." Machine-learning architectures were employed in the selected studies, while approximately half of them (29/58) employed neural networks. Regarding the evaluation criteria, eight studies compared the results obtained by AI with the diagnoses formulated by dentists, while several studies compared two or more architectures in terms of performance. The following parameters were employed for evaluating the AI performance: accuracy, sensitivity, specificity, mean absolute error, root mean squared error, and area under the receiver operating characteristic curve.

Conclusion: Application of AI in the dental field has progressed; however, the criteria for evaluating the efficacy of AI have not been clarified. It is necessary to obtain better quality data for machine learning to achieve the effective diagnosis of lesions and suitable treatment planning.

Keywords: Artificial intelligence, Data mining, Machine learning, Neural Networks, Dental field

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1. Introduction

Recently, advanced in information science and technology have led to an explosive increase in data in various fields. Therefore, the importance of comprehensively processing enormous amounts of data, often called big data, has been highlighted, and hence, artificial intelligence (AI) has been widely used[1–3]. AI is a conceptual term denoting a series of basic technologies that enable digital systems or computers to perform functions involving human-like intelligence. The concept of AI was first defined by McCarthy in 1956[4]. In various industrial fields, many studies have considered the social implementations of big data analysis, robot control, voice or image recognition facilities, and automated driving using AI[5–7]. Studies have also been conducted to investigate the application of AI in the medical field. In particular, studies on expert systems such as MYCIN, which is a recommended antibacterial drug selection system for diagnosing infectious diseases, and INTERNIST-1, which is a general medical diagnosis support system, were reported in 1974[8,9]. Several decades later, Hinton et al. (2006) developed deep learning and convolutional neural networks (CNNs), which were presented at the ImageNet Large-Scale Visual Recognition Challenge in 2012[10]. Currently, many studies related to the application of CNNs to classify brain tumors or diagnose cancer from skin images are being conducted worldwide[11–13].

The application of digital technology has advanced rapidly in the dental field. Furthermore, computer-aided design and manufacturing (CAD/CAM) in prosthodontic treatment and implant simulation software or analysis systems in orthodontic treatment have been developed[14–16]. Although some research related to the application of AI in the dental field has been conducted, little information is available on its architecture and effectiveness.

The purpose of this study was to comprehensively review the literature concerning the application of AI in the dental field, focusing on the evaluation criteria and architecture types in different subfields.

2. Materials and Methods

In this study, we investigated the purpose of AI application in the dental field and the individual problems that it aimed to resolve.

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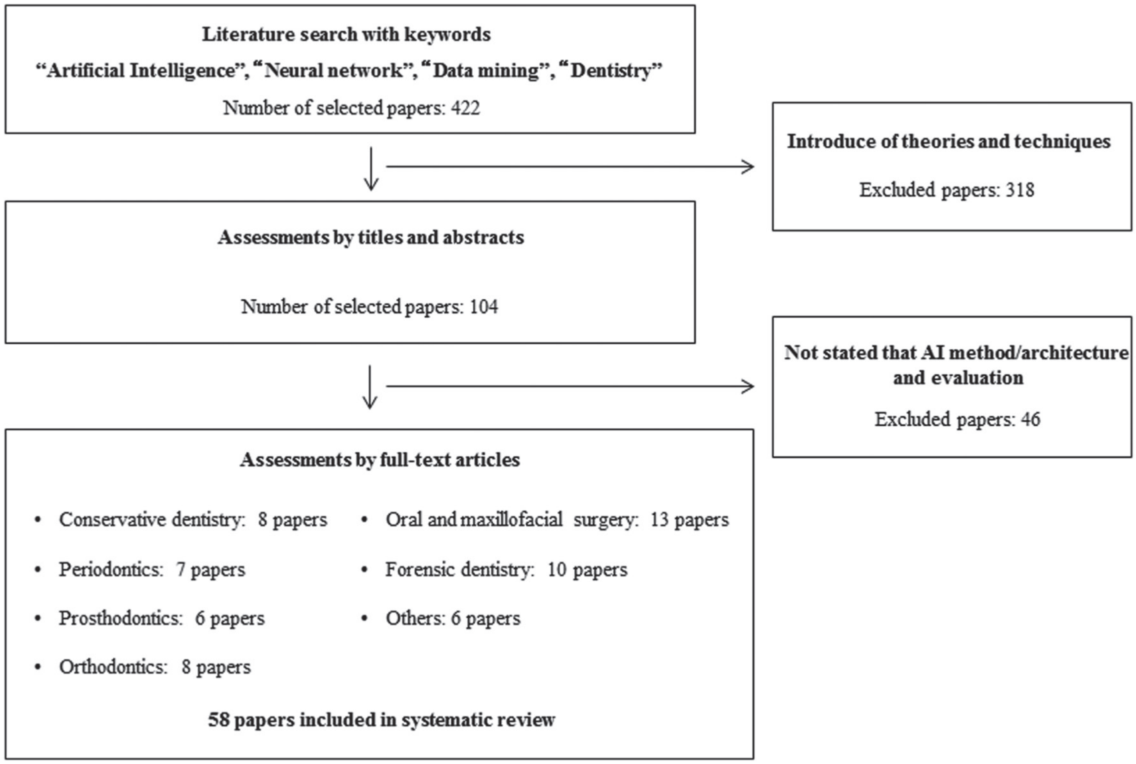

Fig. 1. Literature review strategy.

2.1. Information sources and search

An electronic search of English language literature published between January 1980 and June 2019 was performed using the MEDLINE (via PubMed), Cochrane Library (via Cochrane Central Register of Controlled Trials, CENTRAL), and Scopus. Electronic database searches were performed using keywords and MeSH terms based on a search strategy used for searching MEDLINE (via PubMed): ("Artificial Intelligence" [Mesh] OR "Neural Networks, Computer" [Mesh] OR "Neural network" [all fields] OR "Data Mining" [Mesh] OR "Data mining" [all fields]) AND "Dentistry" [all fields]. In addition to these database searches, manual searches were also performed.

2.2. Inclusion criteria

The articles were selected based on the following inclusion criteria: articles in which AI was applied clinically for the detection, diagnosis, and treatment of lesions in the dental field; articles that clearly stated the subject of the evaluation; articles describing the AI method/architecture used; and original articles written in English. Articles that merely introduced theories, architecture, and techniques were excluded.

2.3. Study selection

Figure 1 shows the literature search strategy used in this study. The literature search was evaluated by the two authors (T. K. and T. M.) who had previously confirmed the criteria independently.

First, the articles that adhered to the purpose of this study were selected from the titles and abstracts. After confirming that the results of the two examiners were identical, a full examination of the manuscripts was performed and the articles were screened again.

Articles that did not match the search results of the two authors were discussed with a third reviewer (T. G.), and finally, the documents to be used for researching AI application in the dental field were selected.

2.4. Data collection process and data items

An extraction sheet for data collection was created using Microsoft Excel software (Microsoft Office Professional 2016, CA, USA). The sheet listed the author, publication year, reference number, reporting institution, field, presence of human versus AI results, architecture of machine learning, evaluation items, number of datasets, type of input data, and evaluation results. After summarizing the results for each subfield, a literature review was performed.

3. Results

3.1. Study selection

As shown in **Figure 1**, the primary search presented 422 studies from January 1996 to June 2019. After reviewing the titles and abstracts, 104 studies were selected for full-text assessment. Finally, after applying the inclusion criteria, 58 studies were selected and classified into the following seven fields: "Conservative dentistry" (including endodontics), "Periodontitis," "Prosthodontics," "Orthodontics," "Oral and maxillofacial surgery," "Forensic dentistry," and "Others." The "Others" class consisted of studies concerning temporomandibular disorders (TMD), oral malodor, and fraud in dentistry.

Regarding the number of published studies, eight studies reported on “Conservative dentistry”[17–24], seven on “Periodontitis”[25–31], six on “Prosthodontics”[32–37], eight on “Orthodontics”[38–45], thirteen on “Oral and maxillofacial surgery”[46–58], and ten on “Forensic dentistry”[59–68], and six studies pertained to the class “Others”[69–74].

Regarding the year of publication, the oldest study was reported in 1996 and focused on “Oral and maxillofacial surgery.” The number of studies in each period was three in the 1990s, two in the early 2000s, six in the late 2000s, and seven in the early 2010s; while the last number was less than 10 initially, it increased to 40 studies rapidly in the late 2010s.

3.2. Architectures and evaluations

The selected studies employed the following machine-learning architectures: artificial neural networks (ANNs), CNNs, support vector machine (SVM), linear discriminant analysis (LDA), decision tree (DT), random forest (RF), natural language processing (NLP), k-nearest neighbor (k-NN), expert system (ExS), case-based reasoning (CBR), fuzzy logic (FL), Bayesian inference (BI), logistic regression (LR), and the k-means method (k-means). ANNs are computing systems that are inspired by the neuronal networks of the human brain, and utilize many neurons to classify input data. The data are then processed and transmitted to successive adjacent layers until the output layer provides an outcome. CNNs are specialized types of ANNs, and are considered deep learning technique. Deep learning is capable of automatically extracting image features using features provided by the machine itself. SVM and LDA are statistical algorithms that separate datasets into subgroups with different characteristics using an appropriate separation plane. DT is a machine-learning technique that is used to classify a statistical population by partition functions. RF consists of DT subsets and combines their outputs to improve performance. Furthermore, NLP is a technology that converts human natural language into computer language and searches for target keywords in text data. The k-NN algorithm finds k samples in newly added data with the most similar features among the training data; then, it uses sample categories to weigh the category candidates. ExS, CBR, and FL use a database of previously treated cases created by professionals to provide knowledge for treatment planning. BI predicts the outcome with the highest predicted probability given a particular input. LR is a data analytics tool used to estimate equations with binary-dependent variables. In addition, the k-means method is a machine-learning technique involving partitioning or grouping a given dataset with particular patterns into disjoint clusters.

The above-mentioned machine-learning architectures were employed in the selected studies; most studies (16/58) employed ANNs. With regard to the subject of evaluation, different types of subjects were used (e.g., patient information or the presence of bacteria in saliva); however, most studies (35/58) used digital images to detect and diagnose lesions. Regarding the evaluation criteria, 12 studies compared the results obtained by AI with the diagnoses formulated by dentists, while several studies compared two or more architectures in terms of performance. The following parameters were employed for evaluating AI performance: accuracy, sensitivity, specificity, precision, mean absolute error (MAE), root mean squared error (RMSE), and the area under the receiver operating characteristic curve (AUC).

3.3. Study characteristics

The characteristics of the selected studies are summarized in **Table 1**.

3.3.1. Conservative dentistry

In the field of conservative dentistry, including endodontics[17–24], most studies reported the detection of lesions on X-ray images, that is, dental caries (four studies), vertical root fracture (two studies), and apical lesion (one study). Al Haidan et al. proposed a mathematical model predicting tooth abrasion or erosion from input data, such as the frequency of brushing teeth, diet information, and a habit of tooth clenching[21]. Regarding architecture, the authors used ANNs in five studies, CNNs in two studies, and ExS in one study. Moreover, Ekert et al., Araki et al., and Devito et al.[17,23,24] compared the AI-obtained results with human diagnoses. In the five studies that presented assessment results, the accuracy, sensitivity, specificity, and AUC values were 70.0%–96.6%, 65.0%–100.0%, 60.0%–100.0%, and 0.662–0.850, respectively.

3.3.2. Periodontics

In the field of periodontics[25–31], two studies reported the radiographic detection of periodontal bone loss using periapical or panoramic radiographs. Three studies classified patients into plausible periodontal disease types based on various types of input data, such as bacterial species in subgingival biofilms, patient information and oral conditions, and clinical and immunologic data from previous studies. Meissner et al. detected calculus on the surface of extracted human teeth using a dental ultrasonic scaler and mechanical oscillation system[31]. Regarding architecture, four studies used ANNs or CNNs, and one compared the ANN results with those obtained from SVM and DT. In addition, some studies used only one type of architecture, namely, SVM, FL, or LDA. As regards assessment results, the accuracy, sensitivity, specificity, precision, and AUC values were 73.4%–98.6%, 46.0%–98.0%, 79.0%–98.1%, 93%, and 0.73–0.83, respectively. Finally, Krois et al. and Lee et al. compared the AI performance with the subjective assessment of dental practitioners in the diagnosis of periodontitis[25,27].

3.3.3. Prosthodontics

In the field of prosthodontics, three studies used image datasets, such as photographic and three-dimensional (3D) scanning data. The remaining three studies used text data, such as oral condition and radiographic findings[32–37]. Vaccaro et al. recognized mixture patterns on photographic images of masticated two-colored chewing gum, and assessed the masticatory efficiency[32].

Raith et al. classified specific features of teeth using a virtual model of tthe human dental arch[34]. Additionally, Cheng et al. proposed a method for predicting the change in facial appearance after complete denture placement using facial scan data[36]. Chen et al. investigated the decision models of removable partial denture designs based on information such as oral hygiene, oral soft tissue condition, and periodontal condition[35]. Papantonopoulos et al. predicted the stage of peri-implantitis based on oral condition assessments and radiography images[33]. Regarding architecture type, three studies used ANNs, while SVM, CBR, and k-NN were each used in one study. As for the assessment results, the accuracy, sensitivity,and specificity were 93.3%–93.5%, 52.6%–98.0%, and 70.7%–99.0%, respectively.

Table 1. Characteristics of included studies
Field: Conservative dentistry

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
Ekert T, et al	2019	vs human	CNNs	Apical Lesions	2001 images	Image data	Se: 0.65, Sp: 0.87, AUC: 0.85
Patil S, et al	2019	—	ANNs	Caries	120 images	Image data	A: 0.95, Se: 1.00, Sp: 0.90
Lee JH, et al	2018	—	CNNs	Caries	3000 images	Image data	A: 82.0%, Se: 81.0%, Sp: 83.0%,AUC: 0.845
Johari M, et al	2017	—	ANNs	Root fracture	240 images	Image data	Periapical radiographs = A: 70.00%, Se: 97.78%, Sp: 67.7% CBCT images = A: 96.6%, Se: 93.3%, Sp: 100.0%
Al Haidan A, et al	2014	—	ANNs	Tooth surface loss	61 subjects	Numerical data	A: 73.3%
Kositbowornchai S, et al	2012	—	ANNs	Root fracture	200 images	Image data	A: 88.3%, Se: 97.8%, Sp: 60.0%
Araki K, et al	2010	vs human	Logicon Caries Detector	Caries	50 images	Image data	AUC: 0.662
Devito KL, et al	2008	vs human	ANNs	Caries	160 images	Image data + Numerical data	AUC: 0.717

Field: Periodontics

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
Krois J, et al	2019	vs human	CNNs	Periodontal bone loss	2001 images	Image data + Numerical data	A: 0.81, Se: 0.81, Sp: 0.81
Feres M, et al	2018	—	SVM	Periodontal classification	435 patients	Numerical data	Se: 86%, Sp: 79%, AUC: 0.83
Lee JH, et al	2018	vs human	CNNs	Periodontal compromise teeth	1740 images	Image data + Numerical data	Premolars = A: 82.8%, AUC: 0.83 Molars = A: 73.4%, AUC: 0.73
Ozden FO, et al	2015	—	ANNs, SVM, DT	Periodontal classification	150 patients	Numerical data	SVM = Se: 98%, DT = Se: 98% NN = Se: 46%
Thyvalikakath TP, et al	2015	—	LDA	Periodontal risk	2370 patients	Numerical data	A: 92%, P: 93%
Papantonopoulos G, et al	2014	—	ANNs	Periodontal classification	347 patients	Numerical data	A: 98.6%, Se: 97.9%, Sp: 98.1%
Meissner G, et al	2006	—	FL	Calculus	234 teeth	Numerical data	Se: 76%, Sp: 86%

Moreover, the RMSE and AUC values were 0.149 and 0.96, respectively. Furthermore, Cheng et al. employed the average error as the evaluation criteria[36]. Chen et al. reported that removable partial denture designs selected by professionals were defined as the correct reference result for comparison with the AI results[35].

3.3.4. Orthodontics

In the field of orthodontics[38–45], three studies used image datasets; one of them examined the changes in appearance of pre- and post-treatment facial photographs to assess the impact of orthodontic treatment, and the remaining two studies conducted classification of skeletal patterns and recognition of anatomic landmarks using lateral cephalograms. In addition, the cephalometric variables in two studies and the orthodontic treatment records in three studies were used for the classification of skeletal patterns, diagnosis of tooth extraction for orthodontic treatment, appropriate selection of headgear type, and treatment planning. As regards the architecture type, FL was used in two studies, while ANNs, CNNs, SVM, DT, and ExS were each used in one study. Furthermore, Tanikawa et al. employed a system called the "projected principal edge distribution"[42]. Regarding assessment results, most studies in this field evaluated the performance using the success rate, achieving 80.0%–97%. Finally, experienced orthodontists evaluated the results obtained by AI in the studies by Akçam et al., Sorihashi et al., and Hammond et al.[43–45].

3.3.5. Oral and maxillofacial surgery

In the field of oral and maxillofacial surgery[46–58], most studies performed the detection of tumors using image data, that is, radiographic (six studies), microscopic (three studies), and ultrasonographic (one study) images. In addition, two studies used medical records, including medication consumption, and one study used the exosome spectrum obtained from saliva. These input data were used for the detection of oral cancers and tumors in five studies, osteoporosis in four studies, cystic lesions in three studies, and maxillary sinusitis in one study. Regarding architecture type, most studies employed ANNs, CNNs, SVM, DT, and RF, and compared more than two architectures. Florindo et al. developed a system that implemented the Bouligand-Minkowski fractal descriptors[50], and Caruntu et al. proposed the Zeiss KS400 environment[56]. With respect to the

Table 1. *(Continued)*
Field: Prosthodontics

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
Vaccaro G, et al	2018	—	ANNs	Masticatory efficiency	400 images	Image data	Se: 98%, Sp: 99%
Papantonopoulos G, et al	2017	—	SVM	Implant bone levels	72 patients	Numerical data	RMSE: 0.149
Raith S, et al	2017	—	ANNs	Dental cusps classification	129 images	Image data	A: 93.3–93.5%
Chen Q, et al	2016	vs human	CBR	Removable partial denture design	104 patients	Numerical data	AUC: 0.96
Cheng C, et al	2015	—	ANNs	Facial deformation after complete denture prosthesis	48 images	Image data	Average error: 22.94%
Papantonopoulos G, et al	2015	—	k-NN	Peri-implant bone levels	94 patients	Numerical data	Se: 52.6%, Sp: 70.7%

Field: Orthodontics

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
Patcas R, et al	2019	—	CNNs	Changes in facial appearance	2164 images	Image data	—
Auconi P, et al	2017	—	DT	Skeletal growth	91 subjects	Numerical data	Misclassification rate: 12.1%
Jung SK, et al	2016	—	ANNs	Teeth extractions	156 subjects	Numerical data	Success rates: 84%
Niño-Sandoval TC, et al	2016	—	SVM	Skeletal patterns	229 images	Image data	A: 74.51%
Tanikawa C, et al	2009	—	Projected principal edge distribution	Anatomic landmarks	465 images	Image data	Success rate: 88%
Akçam MO, et al	2002	vs human	FL	Types of headgear	85 cases	Numerical data	Satisfaction rate of examiners: 95.6%
Sorihashi Y, et al	2000	vs human	FL	Skeletal patterns	175 cases	Numerical data	Orthodontists agreed rate: 97%
Hammond RM, et al	1997	vs human	ExS	Treatment planning	330 cases	Numerical data	Success rate: 80.0%

assessment results, the above-mentioned studies achieved accuracy, sensitivity, specificity, and AUC values of 83.0%–98.9%, 81.8%–100.0%, 76.7%–98.4%, and 0.88, respectively. Finally, Tanaka et al. reported a successful computer-assisted diagnosis formulated by an unskilled clinician using an ExS system[57].

3.3.6. Forensic dentistry

In this review, forensic dentistry corresponds to the identification of victims of large-scale disasters based on dental records[59–68]. Most studies concerning dental identification handle information acquired from radiographic images. Input data were used for the recognition and identification of tooth types (four studies), age estimation using pulp-to-tooth ratio in canines or classification of stages of third molar development (two studies), and the identification of people based on dental records such as the shape, location, and treatment of teeth (two studies). The prediction of the mandibular bone morphology and classification of common dental diseases, such as decay and cracked dental root, were each conducted in one study. CNNs were used in five studies, while ANNs, FL, and k-means were each used in one study. Furthermore, Chen et al. experimented with the contour-matching algorithm, and Chomdej et al. explored an intelligent dental identification system[67,68]. The above-mentioned studies achieved accuracy and precision values of 52.0%–93.0% and 79.2%–95.8%, respectively. MAE and RMSE were 0.09–4.121 and 0.09–4.403, respectively.

3.3.7. Others

In this field, there were four studies on temporomandibular joint disorders, one study on the detection of fraud in dentistry, and one study on the classification of oral malodor[69–74]. De Dumast et al. classified five stages of degenerative condylar bone change in temporomandibular joint osteoarthritis using cone beam computed tomography scans[69]. Nam et al. used the same method to differentiate TMD-like symptoms, such as trismus and jaw pain, from genuine TMD by text mining using NLP. The text-mining technology extracted useful information from text data, including chief complaints,

Table 1. *(Continued)*
Field: Oral and maxillofacial surgery

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
Murata M, et al	2019	—	CNNs	Maxillary sinusitis	12000 images	Image data	A: 87.5%, Se: 86.7%, Sp: 88.3%, AUC: 0.88
Zlotogorski-Hurvitz A, et al	2019	—	LDA, SVM	Oral cancer	34 patients	Numerical data	LDA = A: 95%, Se: 100%, Sp: 89% SVM = A: 89%
Kim DW, et al	2018	—	ANNs, SVM, LR, DT, RF	Osteonecrosis	125 patients	Numerical data	Se: 100%, Sp: 76.7%
Poedjiastoeti W, et al	2018	—	CNN	Jaw tumors	500 images	Image data	A: 83.0%, Se: 81.8%, Sp: 83.3%
Florindo JB, et al	2017	—	Bouligand-Minkowski fractal descriptors	Radicular cyst	150 images	Image data	A: 98%
Hwang JJ, et al	2017	—	SVM	Osteoporosis	454 images	Image data	A: 96.9%, Se: 97.2%, Sp: 97.1%
Yilmaz E, et al	2017	—	ANNs, SVM	Periapical cyst and keratocystic odontogenic tumor	50 images	Image data	ANNs = A: 92.0%, F score: 91.7% SVM = A: 94.0%, F score: 94.0%
Kavitha MS, et al	2016	—	FL	Osteoporosis	141 images	Image data	At lumbar spine = A: 96.01%, Se: 95.3%, Sp: 94.7% At femoral neck = A: 98.9%, Se: 99.1%, Sp: 98.4%
Kavitha MS, et al	2015	—	BI, k-NN, SVM	Osteoporosis	141 patients	Image data	BI = A: 95.3%, Se: 96.1%, Sp: 87.3% k-NN = A: 92.1%, Se: 96.6%, Sp: 82.0% SVM = A: 96.8%, Se: 96.6%, Sp: 89.3%
Frydenlund A, et al	2014	—	SVM, LR	Odontogenic cyst	149 images	Image data	SVM = correctly predicted: 83.8%–92.3% LR = correctly predicted: 90%–95.4%
Caruntu ID, et al	2005	—	Zeiss KS400 environment	Tumoral cell	1500 images	Image data	—
Tanaka T, et al	1997	vs human	ExS	Tumors	30 images	Image data + Numerical data	Increase in A: 8.5%, Increase in Se: 10.7%, Increase in Sp: 6.4%
Firriolo FJ, et al	1996	vs human	ExS	Salivary gland neoplasms	20 cases	Numerical data	Performance: 90%–60%

Field: Forensic dentistry

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
Chen H, et al	2019	—	CNNs	Teeth recognition	1250 images	Image data	—
Farhadian M, et al	2019	—	CNNs	Age	300 images	Image data	MAE: 4.121, RMSE: 4.403
Zhang K, et al	2018	—	CNNs	Teeth recognition	1000 images	Image data	P: 95.8%, F score: 0.96
De Tobel J, et al	2017	—	CNNs	Age	400 images	Image data	A: 0.52, Linear kappa coefficient: 0.82
Miki Y, et al	2017	—	CNNs	Teeth recognition	52 images	Image data	A: 88.8%
Niño-Sandoval TC, et al	2017	—	ANNs	Mandibular morphology	229 images	Image data	Coefficients: 0.84–0.99 Support vector regression: 0.7
Wang L, et al	2017	—	k-means method	Teeth recognition	280 images	Image data	A: 0.769–0.848. P: 0.792–0.910
Ngan TT, et al	2016	—	FL	Medical diagnosis	66 images	Image data	A: 93.0%, MAE: 0.09, MSE: 0.09
Chen H, et al	2005	—	Contour matching algorithm	Dental identification	235 images	Image data	A: 72.0%
Chomdej T, et al	2005	—	Intelligent dental identification system	Dental identification	4000 patients	Numerical data	Identification range: 82.61–100% Minimal error: 0–1.19%

Table 1. *(Continued)*
Field: Others

Author	Year	Comparison to human assessment	Architecture	Outcome	Number of datasets	Type of input data	Evaluation
de Dumast P, et al	2018	—	CNNs	TMD	259 images	Image data	—
Nam Y, et al	2018	—	NLP	TMD	319 patients	Numerical data	The predictive performance: 96.6%, Se: 69.0%, Sp: 99.3%
Wang SL, et al	2017	—	ZeroR classifier	Fraud in dentistry	500 dentists	Numerical data	A: 0.94
Iwasaki H	2015	—	BI	TMD	295 cases	Numerical data	Resubstitution validation: 99.5–100%
Nakano Y, et al	2014	—	ANNs, SVM, DT	Oral malodor	309 subjects	Numerical data	SVM = A: 82.5%, Se: 95.0%, Sp: 51.1% ANNs = A: 81.9%, Se: 90.5%, Sp: 60.2% DT = A: 71.5%, Se: 82.3%, Sp: 45.5%
Bas B, et al	2012	vs human	ANNs	TMD	219 patients	Numerical data	ADDwR = Se: 80–100%, Sp: 95–89% ADDwoR = Se: 37–69%, Sp: 91–100%

medical history, and objective examination results[70]. Nakano et al. presented an SVM-based method for classifying oral malodor from oral microbiota in saliva[73]. Wang et al. deployed social networks to evaluate the trustworthiness of dentists and to detect fraudulent ones. If a large number of patients who had received an initial treatment from a dentist also received subsequent treatment from other dentists for the same dental problem within a short period, the first dentist was suspected of providing inadequate treatment[71]. Iwasaki et al. applied BI to determine the progression of TMD, and investigated the relationship between condylar bone changes, bony space, and joint disc deformation and displacement[72]. Bas et al. used ANNs for the prediction of two TMD subgroups, anterior disc displacement with and without reduction, and the use of input data such as clicking noise, maximal mouth opening, and pain during mandibular movement[74]. The accuracy, sensitivity, and specificity were 71.5%–94.0%, 37.0%–100.0%, and 45.5%–100.0%, respectively. Finally, using the resubstitution validation method, Iwasaki et al. achieved a performance of 99.5%–100%[72].

4. Discussion

There has been rapid progress in research on the development of AI, particularly with the advancement of high-performance computers during the 1980s. In fact, many types of architectures were established for statistical analysis, laying the foundation for contemporary AI technology in the 1990s. Thus, the studies that were considered also employed various architectures. The machine-learning part of AI-based statistics is broadly divided into supervised machine learning (SML) and unsupervised machine learning (UML)[75]. SML constructs a regression or classification structure by training a classifier that is adjustable to new data using labeled data. Examples of SML include CNNs, SVM as a pattern recognition structure, and RF consisting of DT[76,77]. In contrast, UML implements rules to categorize input data by their features without using labeled data as a reference. Examples of UML include principal component analysis (PCA), clustering, and k-means methods. PCA reveals the simplified structures hidden in complex datasets by reducing them to lower dimensions. The methods of clustering and k-means classify data into categories based on similarity between data samples[78,79]. In this review, most studies considered the application of AI to the dental field by using SML, and only one study used the UML method of k-means. In addition, data mining is an important element of AI applications. Data mining is a generic term that refers to data analysis conducted using various calculation algorithms[80].

Scoping reviews on the application of AI in the dental field have already been reported[81–83]. However, these past reviews only focused on dental image diagnosis using digital images[82,83] and ANN architectures without keywords and search formulas[81]. In this research, we focus not only on image diagnosis but also on diagnoses based on patient information and treatment planning decisions. Moreover, the architectures deployed in each study were surveyed, and a comprehensive literature review was conducted on the application of AI in the dental field.

In our literature search, we focused on three keywords: artificial intelligence, neural networks, and data mining. These keywords are MeSH terms and belong to separate disjoint categories without duplication. However, we obtained the same results when searching for additional keywords that were related to each analysis method. Therefore, we consider our search strategy to be reasonable, and claim to have collected an adequate number of research papers to perform a literature review on AI applications in the dental field. Moreover, for a comprehensive discussion, we included studies without considering the dataset size or evaluation values such as accuracy.

Since the 1970s, many researchers have attempted to apply AI in the medical field. Nevertheless, the oldest study in the dental field was reported in 1996; thus, there is a relatively short history of the application of AI in the dental field. Medical companies have developed various products that aim to perform segmentation of target areas (e.g., organs) and detection of lesion areas via radiography (i.e., computer-aided detection) and to improve work efficiency in the reading of radiographs[84,85]. In the dental field, joint research with dental companies has not been reported.

Most studies included in the review used radiographic images as data samples for the diagnosis or detection of lesions. In oral and maxillofacial surgery, conservative dentistry, and orthodontics, diagnoses are often formulated from conventional radiographs. Moreover, a correlation has been observed between the reading time of radiographs per case and misdiagnosis; for example, Berlin et al. reported that when the reading time was reduced by 50%, the misdiagnosis rate increased by 16.6%[86]. It is desirable that AI would be applicable not only for imaging diagnosis but also for comprehensive diagnosis in the stomatognathic system.

We also reviewed many studies that focus on forensic dentistry, such as personal identification from dental records. When large-scale disasters occur (e.g., tsunamis, earthquakes, and typhoons), if a body is severely damaged, identification using belongings, clothes, and fingerprints is often challenging. Dental records are considered strong and reliable evidence in such situations[87,88]. Matching radiographic images of the victims' remains with those taken at a medical facility while they were alive may be a quick and reliable method of identification. In this field, we expect the use of AI to be particularly beneficial.

In many situations in the dental field, direct vision is sufficient for diagnosis; therefore, there are limited diseases and clinical conditions that need to be diagnosed otherwise. Furthermore, in the restorative, prosthodontic, and orthodontic fields, where treatment skills are considered more important than diagnosing ability, the potential applicability of AI is limited. However, in the future, imaging information sources such as X-rays will not be the only data source; 3D data, such as those of the dental arch obtained when using an intraoral scanner, will be easily obtained. Therefore, for the restorative and orthodontic fields, AI is also expected to facilitate medical treatment planning and prosthesis design, including structural calculations such as computer-aided engineering.

Moreover, it is assumed that a vague medical treatment plan in the dental field can be made objective by considering the evaluation value of AI and by ensuring that each report shows progress. The optimal answer to a dental problem can be automatically predicted by AI using a large amount of data, as AI can automatically learn a large number of features and explanatory variables. Nevertheless, to utilize AI exhaustively, data should not only be plentiful but also of high quality; therefore, the process of data cleansing is crucial[89]. In the medical field, across local and university hospitals, attempts have been made to construct an image database of cases aimed at the collection of learning data. To utilize AI in the dental field, it is necessary to standardize the evaluation methods and to create a database of X-ray and intraoral images.

5. Conclusion

The present literature review revealed that the oldest study regarding the use of AI in the dental field was reported in the 1990s. Additionally, most studies that were included in this review showed good results; however, the criteria for evaluating the efficacy of AI have not been clarified. It is necessary to collect better quality data for machine learning to realize the effective diagnosis of lesions and suitable treatment planning. This can be accomplished using AI through the construction of public case databases and by the standardization of the evaluation methods and criteria.

Conflicts of interest

The authors declare that they have no conflict of interest.

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