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# Application of Artificial Intelligence in Dentistry

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**Abstract**

Artificial intelligence (AI) is a technology that utilizes machines to mimic intelligent human behavior. To appreciate human-technology interaction in the clinical setting, augmented intelligence has been proposed as a cognitive extension of AI in health care, emphasizing its assistive and supplementary role to medical professionals. While truly autonomous medical robotic systems are still beyond reach, the virtual component of AI, known as software-type algorithms, is the main component used in dentistry. Because of their powerful capabilities in data analysis, these virtual algorithms are expected to improve the accuracy and efficacy of dental diagnosis, provide visualized anatomic guidance for treatment, simulate and evaluate prospective results, and project the occurrence and prognosis of oral diseases. Potential obstacles in contemporary algorithms that prevent routine implementation of AI include the lack of data curation, sharing, and readability; the inability to illustrate the inner decision-making process; the insufficient power of classical computing; and the neglect of ethical principles in the design of AI frameworks. It is necessary to maintain a proactive attitude toward AI to ensure its affirmative development and promote human-technology rapport to revolutionize dental practice. The present review outlines the progress and potential dental applications of AI in medical-aided diagnosis, treatment, and disease prediction and discusses their data limitations, interpretability, computing power, and ethical considerations, as well as their impact on dentists, with the objective of creating a backdrop for future research in this rapidly expanding arena.

**Keywords:** big data, clinical decision making, dental, informatics, machine learning, neural networks

Advancement in digitized technology for clinical examination has rendered health care data collection from dental patients less complex and cumbersome. Personalized dentistry requires taking massive data sets into consideration for each patient. Conventional statistical analytics relies on specific assumptions and handcrafted markers, making it impractical in dealing with such high-volume data (Ayala Solares et al. 2020). Artificial intelligence (AI) intends to reproduce the cognitive process of humans and can achieve the same outcome as medical professionals within a much shorter time frame. It excels in extracting information from historical data and benefits physicians by automating time-consuming tasks. Although the current development of AI is preliminary and medical tasks that contemporary AI can complete can almost be performed by humans, the emergence of AI in dentistry heralds an era of disruptive technology with the potential to reengineer the landscape in which dental clinical care is practiced. The present review outlines the progress and potential dental applications of AI and discusses their challenges as well as the potential impact on dentists. A glossary of AI terms used in the review is included in the Appendix.

## Artificial Intelligence

AI is a new branch of applied computer science that endows machines with the ability to mimic intelligent human behavior. Two types of AI are available for general health care delivery: physical and virtual. Physical applications are represented by sophisticated robots or automated robotic arms (Wang et al. 2014). Virtual components are software-type algorithms that support clinical decision making.

Attempts at implementing AI were initially based on the assumption that human intelligence can be fully digitized and integrated into machines. As early as the 1970s, commentators predicted that AI would bring careers in medicine to an end (Maxmen 1976). However, the development of strong AI is limited by the finite storage and data-processing capacity of bit-based computers as well as the complexity of human cognition. Persuaded by these intractable barriers, weak (narrow) AI was developed to partially solve problems in distinct application areas by learning specific perception and thinking mechanisms instead of comprehensive intelligence (Park and Park 2018). Augmented intelligence, introduced by the American

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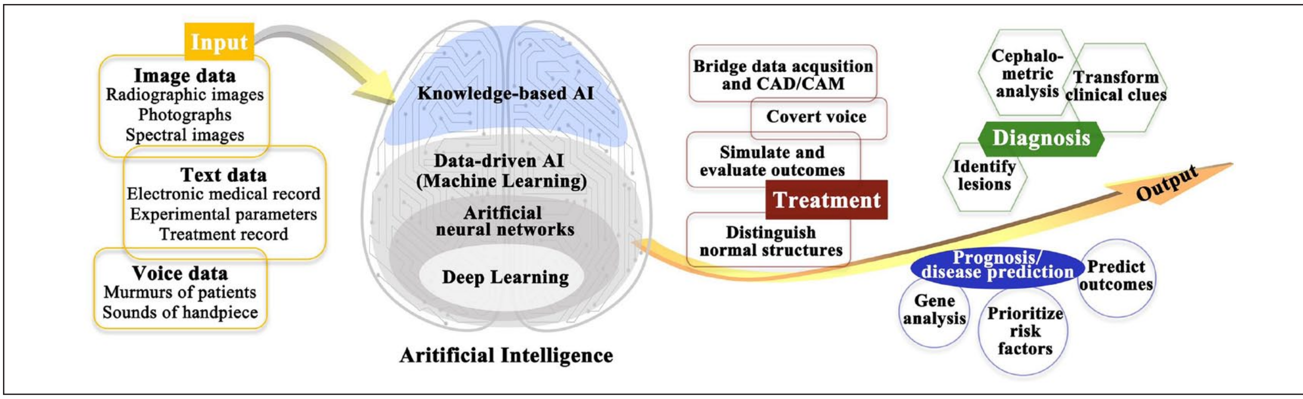


**Figure 1.** Overview of the hierarchy and major dental applications of artificial intelligence (AI). CAD/CAM, computer-aided design/computer-aided manufacturing.

Medical Association (2018), is an alternative conceptualization of narrow AI in health care, emphasizing its assistive and supplementary role to medical professionals (Crigger and Khoury 2019). Admittedly, human intelligence is still superior in complex cognitive tasks. Nonhominid intelligent systems guided by augmented intelligence are designed to cooperate with humans, augmenting human intelligence rather than replacing human expertise.

In dentistry, the applications of AI are mostly virtual, employing AI algorithms to distinguish between lesions and normal structures, prioritize risk factors, and simulate and evaluate prospective results. According to the Barcelona Declaration for the Proper Development and Usage of Artificial Intelligence in Europe (Steels and Lopez de Mantaras 2017), virtual AI methodologies are fundamentally divided into knowledge-based and data-driven AI (Fig. 1). Knowledge-based AI attempts to model human knowledge and is built in a top-down fashion from the self-reported concepts and knowledge that humans use to solve problems. However, knowledge acquisition and formalization are 2 major bottlenecks, which consume development time and require significant initial effort (Montani and Striani 2019). Conversely, data-driven AI, commonly known as machine learning (ML), commences in a bottom-up approach by training mathematical models with data derived from human activities. Because of the large amount of dental data available in electronic form, data-driven AI receives a lot of attention in dentistry.

Data-driven AI or ML may be divided as supervised, unsupervised, and semisupervised learning (Handelman et al. 2018). On the supervised platform, algorithms employ manually labeled training data sets to learn the correlations between data instances and labels, yielding the desired and known outcomes (Krittanawong et al. 2017). Support vector machines (SVMs), decision tree (DT), random forest (RF), and artificial neural networks (ANNs) are all ML algorithms that can be used in supervised learning. SVMs set up an imaginary high-dimensional space, place samples according to their features, and separate them by a hyperplane, resulting in data classification (Amasya et al. 2020). DT is a hierarchical data structure (Kok et al. 2019). Each node is a specific attribute, and branches are followed until a leaf node is reached. Classification is completed once a leaf node is reached. RF is an extension of DT, in which each DT is independently trained and subsequently combined with others (Krittanawong et al. 2017). ANNs are highly interconnected models (Fig. 2) inspired by vertebrate nervous systems. Every neuron receives signals from neurons in the previous layer, performs mathematical transformation, and transmits signals to neurons in the next layer as output.

In unsupervised learning, algorithms are provided with unlabeled data, and they involve recognizing hidden data patterns that investigators may not have conceived, yielding unknown results. Principal component analysis and *k*-means clustering are common methods used in unsupervised learning. They employ discrete or continuous data as input to identify latent regularities (i.e., *k*-means clustering) or lower dimensional representations (i.e., principal component analysis). Deep neural networks, commonly known as deep learning (DL), is a subset of ML; they can also be operated in unsupervised scenarios. The term "deep" refers to multiple neural layers between the input and output layers (Park and Park 2018). Convolutional neural networks (CNNs; Fig. 2A) are the most widely used DL architecture in dentistry, employing a convolutional process to learn features contained within data (Hiraiwa et al. 2019). Although it is frequently mentioned that supervised learning is limited by the lack of annotated data, unsupervised learning has also been criticized for failing to identify the initial pattern. Semisupervised learning is an amalgamation of supervised and unsupervised learning that analyzes a collection of data while augmenting the pattern recognition abilities with a small amount of labeled data (Handelman et al. 2018). All these techniques offer the promise of more powerful endeavors to enhance human capability in dealing with massive and complex data.

## Applications of AI in Dentistry

### *Medical-Aided Diagnosis*

Diagnostic logic for a certain disease is based on a clinician's analysis of symptoms, diagnostic test results, and other factors, which are vulnerable to the clinician's imperfect memory and

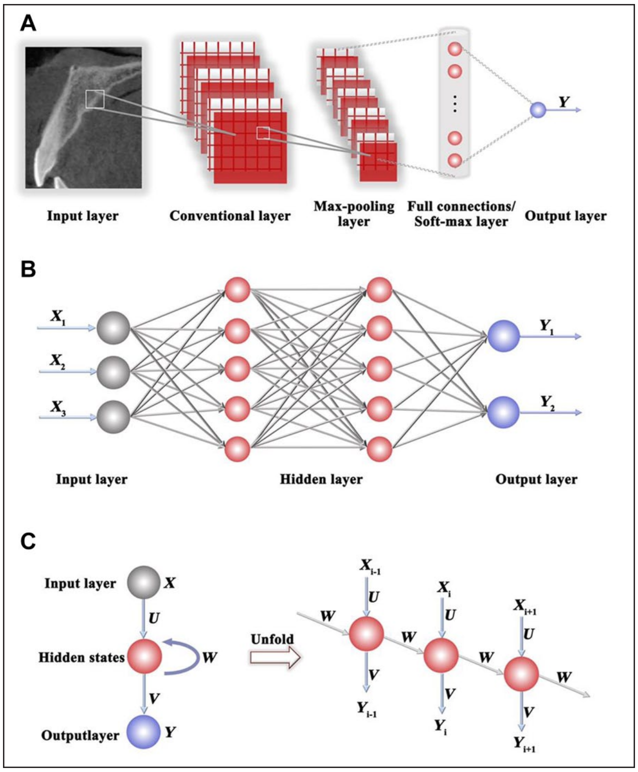


**Figure 2.** Topology of 3 artificial neural networks: (**A**) convolutional, (**B**) multilayer perceptron, and (**C**) recurrent. $X_i$, input data set; $Y_i$, output data set. *U, V*, and *W* are the weights.

cognitive bias. When "educated" with hundreds of thousands of cases, AI surpasses the clinical experience of even the most proficient specialist (Bouletreau et al. 2019). This infers that more accurate and efficient diagnosis will be achieved with the integration of AI into existing dental clinical workflow (Table 1).

*Oral and Maxillofacial Surgery.* ML algorithms, including SVM, ANN, RF, and *k*-nearest neighbors, have been experimentally investigated for their ability to identify cysts, benign tumors, oral cancer, and lymph node metastasis. Fed with handcrafted engineered features in cone beam computed tomography (CBCT), SVM was 94% accurate in differentiating periapical cysts from keratocystic odontogenic tumors (Yilmaz et al. 2017). A risk stratification model based on brush biopsy and cytology was also constructed with ML algorithms such as SVM and RF. Utilizing CNN to score the malignancy of cytology images derived from a telemedicine platform, this model showed high sensitivity in detecting oral malignant (93%) and high-grade potential malignant (73%) lesions (Sunny et al. 2019). Despite these excellent results, contemporary AI models for oral and maxillofacial surgery diagnosis focus on only 1 type of data, such as radiographic results or cytopathologic images. For highly accurate diagnosis, models that integrate more medical information about the patient are required.

*Cariology and Endodontics.* With the ability to perform automated lesion segmentation, DL with CNN has become the predominant AI component used in cariology and endodontic diagnostics. The segmentation process divides radiographs or images into multiple nonoverlapping regions using sets of rules, such as similar pixels or intrinsic features, to convert them into a meaningful form that can be conveniently analyzed (Anwar et al. 2018). Based on an encoder-decoder architecture (U-Net), DL segmented CBCT voxels into "lesion," "tooth structure," "bone," "restorative materials," and "background," achieving results comparable to those of clinicians in diagnosing periapical lesions (Setzer et al. 2020). Focusing on the binary presence or absence of lesions, DL identified proximal carious lesions from near-infrared transillumination images with an area under the receiver operating characteristic curve of 0.856 (Casalegno et al. 2019). Volumetric measurement in CBCT, following DL-based segmentation, was reported to be comparable to the results obtained from manual segmentation of periapical lesions (Orhan et al. 2020). However, this research failed to report outcomes such as the volume deviation of lesions and the Intersection over Union metric. This oversight challenges the reliability of the results.

*Periodontics.* Periodontal disease is a complex inflammatory disease contributed by multiple causal factors simultaneously and interactively. Focusing on periapical radiographs, CNN achieved 81.0% and 76.7% accuracy in diagnosing periodontally compromised premolars and molars (Lee et al. 2018). However, due to the hysteresis of imaging characteristics and the visual field of periapical radiographs, this technique cannot distinguish incipient lesions or make a final diagnosis of periodontal disease. DT and SVM performed well in classifying healthy periodontium, gingivitis, chronic periodontitis, and aggressive periodontitis by integrating a patient's medical history, clinical information, and radiographs. Although immunologic responses and microbial composition in relation to the etiology of periodontitis have not been fully elucidated, AI-based classifiers—such as a multilayer perceptron neural network (a class of feedforward ANN; Fig. 2B) focusing on leukocytes, interleukins, and IgG antibody titers, as well as an SVM focusing on the relative bacterial load—performed satisfactorily in distinguishing aggressive from chronic periodontitis (Feres et al. 2018). In addition to promoting our understanding of periodontitis, AI serves as a bridge to incorporate conventional indicators and immunologic and microbiological parameters into periodontal diagnosis.

*Temporomandibular Joint Disorder.* Clinical clues from a patient's complaint and history are important for diagnosing temporomandibular joint disorders (TMDs). Natural language processing is a technology that transforms natural human language into structured computer language. A natural language processing–based model was successful in differentiating TMD-mimicking conditions from genuine TMDs, according to the frequency of word usage in the patient's chief complaint and mouth-opening size (Nam et al. 2018). ANNs based on

**Table 1.** Dental Applications of AI in Diagnosis.

| Field | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Diagnosed Disease | Clinical or Experimental Data | Sample Size, Training: Testing | Validation Method | AI Methods | Accuracy | Sensitivity | Specificity | AUC |
| **Oral and maxillofacial surgery** | | | | | | | | |
| Oral cancer | Fourier-transform infrared spectra of salivary exosomes (Zlotogorski-Hurvitz et al. 2019*) | 34: — | *k*-fold cross-validation | PCA and LDA | 95% | 100% | 89% | |
| | | | | SVM | 89% | | | |
| | Hyperspectral images (Jeyaraj and Samuel Nadar 2019*) | 100: — | 7-fold cross-validation | CNN | 91.4% | 94% | 91% | |
| | X-ray images (Al-Ma'aitah and AlZubi 2018*) | | Mean square error rate | GSOESNN | 99.2% | >95% | >95% | |
| Oral squamous cell carcinoma | Laser endomicroscopy images (Aubreville et al. 2017*) | 7,894 augmented 2 times: — | Leave-1-patient-out cross-validation | CNN | 88.3% | 86.6% | 90% | 0.955 |
| | | | | LBP-based RF | 81.4% | 84.7% | 78.2% | 0.895 |
| | | | | GLCM-based RF | 73.1% | 77.5% | 69.5% | 0.807 |
| | Oral tissue histopathologic slides (Das et al. 2018*) | 80: 20 | | CNN and RF | 96.9% (keratin pearl) | | | |
| | Brush cytology specimens (McRae et al. 2020*) | | | *k*-nearest neighbors | 96.9% | | | |
| | Cytology images (Sunny et al. 2019) | 11,981: — | | Pretrained ANN (inception V3) | | 73% (high potential malignant), 93% (malignant) | | |
| Cervical lymph node metastasis | CT images (Ariji et al. 2019*) | 441 augmented to 21,362: — | 5-fold cross-validation | Pretrained CNN (Alex Net) | 78.20% | 75.4% | 81.0% | 0.8 |
| Ameloblastoma, keratocystic odontogenic tumor | Panoramic images (Poedjiastoeti and Suebnukarn 2018*) | 400 augmented to 800: 100 augmented to 200 | | Pretrained CNN (VGG-16) | 83% | 81.8% | 83.3% | 0.88 |
| Dentigerous cysts, keratocystic odontogenic tumor and periapical cysts | Panoramic radiography (Lee et al. 2020*) | 648 augmented 100 times: 228 | | Pretrained CNN (GoogLeNet) | | 96.1% | 77.1% | 0.914 |
| | CBCT images (Lee et al. 2020*) | 592 augmented 100 times: 197 | | Pretrained CNN (GoogLeNet) | | 88.2% | 77.0% | 0.847 |
| Periapical cyst and keratocystic odontogenic tumor | CBCT images (Yilmaz et al. 2017) | | 10-fold cross-validation | SVM | 94% | | | |
| | | | | ANN | 92% | | | |
| | | | | Naïve Baves | Inferior to ANN | | | |
| **Cariology and endodontics** | | | | | | | | |
| Dental caries | Periapical radiographic images of premolar and molar (Lee et al. 2018*) | 2,400: 600 | | Pretrained CNN (GoogLeNet) | 82% | 81% | 83% | 0.845 |
| | Near-infrared transillumination images (Casalegno et al. 2019) | 185: 32 | Monte Carlo cross-validation | CNN | | | | 0.836 (occlusal), 0.856 (proximal) |
| | Near-infrared-light transillumination images (Schwendicke et al. 2020*) | 226 with augmentation: — | 10-fold cross-validation | Pretrained CNN (Resnet18) | 69% | 85% | 46% | 0.73 |
| | | | | Pretrained CNN (Resnext50) | 68% | 76% | 59% | 0.74 |
| Root fracture | Panoramic images (Fukuda et al. 2019*) | 240: 60 | | Pretrained CNN (DetectNet) | 93% | | | |
| | Periapical radiographs (Johari et al. 2017*) | 180: 60 | | PNN | 70% | 93.3% | 63.6% | |
| | | 120: 120 | | PNN | 65% | 81.7% | 61.3% | |
| | | 60: 180 | | PNN | 63.9% | 88.9% | 59.3% | |
| | CBCT images (Johari et al. 2017*) | 180: 60 | | PNN | 96.7% | 93.3% | 100% | |
| | | 120: 120 | | PNN | 95.0% | 90% | 100% | |
| | | 60: 180 | | PNN | 93.3% | 86.7% | 100% | |
| Periapical pathosis | Panoramic radiographs (Ekert et al. 2019*) | 2,001 teeth from 85 panoramic images: — | 10-fold repetition | CNN | | 65% | 87% | 0.84 |
| | CBCT images (Setzer et al. 2020) | 20: — | 5-fold cross-validation | Pretrained CNN (U-net) | 93% | 93% | 88% | |
| | CBCT images (Orhan et al. 2020) | 3,900: 153 | | CNN | | 0.89 estimated recall | | |
| Cracked dental root, caries, hypodontia and bone resorption | X-ray images (Ngan et al. 2016*) | | | Fuzzy aggregation operators | 93.0% | | | |
| **Periodontics** | | | | | | | | |
| Gingivitis and periodontitis | Risk factors, clinical periodontal parameters (Ozden et al. 2015*) | 100: 50 | | SVM | 98% precision | | | |
| | | | | DT | 98% precision | | | |
| | | | | BPNN | 46% precision | | | |
| Periodontally compromised teeth | Periapical radiographs (Lee et al. 2018) | 1,044 augmented to 104,400: 348 | | CNN | 82.8% (premolar) | | | 0.826 (premolar) |
| | | | | | 73.4% (molar) | | | 0.734 (molar) |

*(continued)*

**Table 1.** (continued)

| Field | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Diagnosed Disease | Clinical or Experimental Data | Sample Size, Training: Testing | Validation Method | AI Methods | Accuracy | Sensitivity | Specificity | AUC |
| Aggressive and chronic periodontitis | Clinical and immunologic data sets (Papantonopoulos et al. 2014*) | | 10-fold cross-validation | MLP neural network | 90% to 98% | | | |
| | Microbial profiles (Feres et al. 2018) | 2,740: 1,175 | | SVM | | 86% | 79% | 0.83 |
| **TMDs** | | | | | | | | |
| TMD-mimicking conditions | Mouth opening size and the frequency of word usage in chief complaint (Nam et al. 2018) | 29 (TMD-mimicking cases), 290 (TMD): — | 10-fold cross-validation | Text-mining method | 96.6% | 69.0% | 99.3% | |
| Bone changes and disc displacement | Magnetic resonance images (Iwasaki 2015*) | 590: — | Resubstitution validation | BBN with path condition | 99.8% | | | |
| | | | 10-fold cross-validation | BBN with path condition | 99.5% | | | |
| Deformation of condyles with osteoarthritis | CBCT images (Shoukri et al. 2019) | 259: 34 | | ANN | 97.1% | | | |
| **Orthodontics** | | | | | | | | |
| Cervical vertebral maturation | Measurement data from lateral cephalometric radiographs (Kok et al. 2019) | 300: — | 5-fold cross-validation | ANN | 93.0% (CVS 1) | | | |
| | | | | *k*-nearest neighbors | 78.7% (CVS 1) | | | |
| | | | | Naïve Bayes | 92.1% (CVS 1) | | | |
| | | | | DT | 97.1% (CVS 1) | | | |
| | | | | SVM | 84.8% (CVS 1) | | | |
| | | | | RF | 91.8% (CVS 1) | | | |
| | Measurement data from lateral cephalometric radiographs (Amasya et al. 2020) | 498: 149 | | ANN | 0.926 ($\kappa$ value) | | | |
| | | | | SVM | 0.874 ($\kappa$ value) | | | |
| | | | | RF | 0.908 ($\kappa$ value) | | | |
| | | | | DT | 0.921 ($\kappa$ value) | | | |
| Automated cephalometric analysis | Lateral cephalometric radiographs (Kunz et al. 2020*) | 96.6% of 1,792 samples after augmentation: — | | CNN | High correlation with humans ($r > 0.864$) | | | |
| | CBCT images (Gupta et al. 2015) | —: 30 | | A knowledge-based algorithm | $2.01 \pm 1.23$ mm (mean error) | | | |
| **Others** | | | | | | | | |
| Oral lichen planus | Clinical data, normalized expression of interleukin-12 receptor $\beta$2 and tumor necrosis factor receptor superfamily member 8 (Jeon et al. 2015) | 81: — | | SVM | 0.76 | 0.77 | 0.75 | 0.87 |
| | | | | RF | 0.86 | 0.90 | 0.80 | 0.92 |
| | | | | ANN | 0.78 | 0.79 | 0.77 | 0.83 |
| | | | | LDA | 0.82 | 0.87 | 0.75 | 0.88 |
| | | | | Naïve Bayes | 0.80 | 0.77 | 0.85 | 0.87 |
| Sjögren's syndrome | Ultrasonography images of parotid gland (Kise et al. 2020) | 160 augmented to 8,000: 40 | 5-fold cross-validation | Pretrained CNN (VGG16) | 89.5% | 90.0% | 89.0% | 0.948 |
| | Ultrasonography images of submandibular gland (Kise et al. 2020) | 160 augmented to 8,000: 40 | 5-fold cross-validation | Pretrained CNN (VGG16) | 84.0% | 81.0% | 87.0% | 0.894 |

*References marked with an asterisk are included in the Appendix.
AI, artificial intelligence; ANN, artificial neural network; AUC, area under the receiver operating characteristic curve; BBN, Bayesian belief network; BPNN, back propagation neural network; CBCT, cone beam computed tomography; CNN, convolutional neural network; CT, computed tomography; CVS, cervical vertebrae stage; DT, decision tree; GLCM, gray-level co-occurrence matrix; GSOESNN, gravitational search optimized echo state neural network; LBP, local binary pattern; LDA, linear discriminant analysis; MLP, multilayer perceptron; PCA, principal component analysis; PNN, probabilistic neural network; RF, random forest; SVM, support vector machine; TMD, temporomandibular disorder.

CBCT revealed a 91.2% degree of conformity as compared with clinician consensus in classifying condylar morphology (Shoukri et al. 2019). By integrating patients' chief complaints, clinical and biochemical indicators, and objective radiomic features into training data sets and collecting larger samples of these data sets, a computer-assisted diagnosis system is warranted to improve TMD diagnostic accuracy.

*Orthodontics.* Given the availability of clearly definable cephalometric landmarks, a knowledge-based algorithm has been developed to detect them. This algorithm revealed only a 2.01-mm mean error for all 20 landmarks tested (Gupta et al. 2015). Diagnostic modeling based on lateral cephalometric radiographs was also constructed with ML algorithms, such as ANN, SVM, RF, and DT, to evaluate cervical vertebral maturation. Among the ML algorithms tested, ANN achieved the best results in classifying cervical vertebral maturation stage and DT for vertebral body shape classification (Amasya et al. 2020). In the future, hybrid approaches that combine knowledge-based algorithms and ML should be able to achieve more accurate and precise automated cephalometric analysis.

*Others.* Focusing on the expression of inflammatory cytokines genes, ANN, SVM, and RF were all capable of distinguishing oral lichen planus from other white lesions of the oral mucosa (Jeon et al. 2015). When used for recognizing steatosis (i.e., abnormal retention of lipids) of the salivary gland parenchyma in ultrasonography images, ANN was superior to inexperienced radiologists in differentiating patients with true Sjögren's syndrome from those with xerostomia (Kise et al. 2020).

## Treatment

The versatility of AI in distinguishing anatomic structures and simulating prospective results renders it a valuable adjunct in providing anatomic guidance, planning treatment, and evaluating outcomes of dental treatment (Table 2). Although truly autonomous medical robotic systems are still beyond reach, these virtual AI applications have immense potential in simplifying clinical operations. They are the keystone in the development of precision dentistry.

*Oral and Maxillofacial Surgery.* To date, much of the clinical potential of AI relies on its ability to trace critical anatomic structures by analyzing patients' radiographic data or diffuse reflectance spectra produced by a laser scalpel. Examples of these anatomic structures include interdigitated tongue muscles, the mandibular canal, nerves, and the parotid gland. Although the difference between AI-based segmentation and expert measurement or true anatomic position is only in the millimeter range (Gerlach et al. 2014), it is still substantial for fine structures, such as neurovascular canals, and may lead to severe surgical complications. In terms of postoperative rehabilitation, an ML-based voice conversion technique has been used to transform nonaudible murmurs of source speakers into the normal speech of target speakers. By learning a set of bases that is representative of the entire set of voice and target dictionary, this technique adapted well to a limited amount of training data and acquired satisfactory short-time objective intelligibility scores (Fu et al. 2017). This is instrumental in improving the speech intelligibility of oral surgical patients.

*Prosthodontics.* Computer-aided design/computer-aided manufacturing (CAD/CAM) is gaining acceptance in prosthetic dentistry. Integrating AI with CAD/CAM improves its chairside application (Raith et al. 2017). ANNs based on panoramic radiographs, periapical radiographs, micro–computed tomography images, and 3-dimensional scanning of dental surfaces have been explored for tooth segmentation and classification. With >90% accuracy, such automatic classification is instrumental for bridging the gap between data acquisition and manufacturing in CAD/CAM technology. For abutment tooth preparation, an ablation system combining robotics and picosecond laser has been developed. In vitro results indicated that the average linear ablation errors of this system were only 0.06 mm for wax resin and 0.05 mm for dentin (Wang et al. 2014). However, the long ablation time for dentin (3.5 h) precluded its clinical application. An automatic robotic system is still an underdeveloped area of research in fixed prosthodontics. In removable prosthodontics, a clinical decision support model that applies ontology and case-based reasoning was capable of recommending a design of individualized removable partial dentures (Chen et al. 2016). Unfortunately, this model makes recommendations based on the most similar case in the database. Because clinical scenarios are ever changing, a skeptical attitude must be maintained with respect to its output.

*Orthodontics.* Treatment need assessment and outcome scoring are the 2 potential applications of AI in orthodontics. The Bayesian network, based on orthodontics-related data, attained a high level of agreement with orthodontists in diagnosis of orthodontic treatment needs (Thanathornwong 2018). SVM enabled analysis of the fixation time of lay persons viewing patients and utilized observer attention as an indicator of orthodontic treatment need (Wang et al. 2016). CNNs achieved attractiveness scoring and apparent age estimation by characterizing specific facial traits (Patcas et al. 2019). Whereas professional appraisal of attractiveness relies on the perception of "ideal facial features," AI evaluation is a quantifiable representation of social attractiveness. Introducing AI into orthodontics is helpful in objectively and reproducibly interpreting facial appearance. Nevertheless, AI will never replace a patient's own perception and expectations.

*Others.* Fed with data extracted from experiments, a prediction model integrating ANN obtained 0.81 coefficient of determination in predicting the viability of dental pulp stem cells under different bacterial lipopolysaccharide concentrations and treatment times (Bindal et al. 2017). This may be a future tool for evaluating regenerative dentistry protocols in a simulated inflammatory microenvironment.

## Disease Prediction and Prognosis

Recent advances in AI provide valuable frameworks for integrating all clinical symptoms–related attributes, including patient history, demographics, lifestyle, and clinical and gene factors. Classifier and predictive AI models help prioritize risk factors and predict long-term outcomes of dental diseases by exploring associations between diseases and patient data (Table 3).

*Oral and Maxillofacial Surgery.* In dental extraction scenarios, an ANN that established associations among personal, anatomic, and surgical factors was 98% accurate in predicting facial swelling after extraction of impacted mandibular third molars (Zhang et al. 2018). In oral cancer prognosis, ML-based predictive models that integrate all patient performance metrics have been constructed. Decision forest, SVM, and gradient boosting algorithms all reached ~0.70 area under the receiver operating characteristic curve in predicting occult nodal metastasis (Bur et al. 2019). Boosted DT, SVM, decision forest, and

**Table 2.** Dental Applications of AI in Treatment of Diseases.

| Fields | | | | | | |
|---|---|---|---|---|---|---|
| Aim | Function | Data | Sample Size, Training: Testing | Assessment | AI Method | Results |
| **Oral and maxillofacial surgery** | | | | | | |
| Provide anatomic guidance | Distinguish interdigitated tongue muscles (Ye et al. 2015*) | Limited diffusion MRI | | | Bayesian approach | |
| | Segmentate the mandibular canal (Gerlach et al. 2014) | CBCT images | 13: — | Compared with histologic sections of the same region | ASM | The difference ranged from −3.45 to 3.27 mm |
| | | | | | AAM | The difference ranged from −4.44 to 4.44 mm |
| | Segmentate parotid gland (Yang et al. 2014*) | MRI | | Compared with the physicians' manual contours | SVM combined with Atlas registration | The average volume differences were 7.98% (left) and 8.12% (right) |
| | Classifying different tissue types (Engelhardt et al. 2014*) | Diffuse reflected spectra of laser scalpel | 1,000: 1,000 | Calculated misclassification rate | *k*-nearest neighbors | 0.26 misclassification rate |
| | | | | | ANN | 0.98 misclassification rate |
| | | | | | LDA | 0.34 misclassification rate |
| | | | | | QDA | 0.27 misclassification rate |
| | | | | | PDA | 0.02 misclassification rate |
| | | | | | Random forests | 0.34 misclassification rate |
| | | | | | Classification and regression trees | 0.50 misclassification rate |
| Improve speech intelligibility of patients | Voice conversion (Fu et al. 2017) | Sentences uttered by oral surgical patients and target speakers | 70: 40 | Compared with conventional exemplar-based NMF method | Joint dictionary learning based non-NMF algorithm | Higher short-time objective intelligibility scores in the proposed algorithm |
| **Prosthodontics** | | | | | | |
| Classify tooth | Classify dental cusps (Raith et al. 2017) | 3D surface scans of dental casts | 119: 10 | | ANN | 93.3% accuracy (cusp distance method), 93.5% accuracy (range image method) |
| | Classify and number tooth (Tuzoff et al. 2019*) | Panoramic radiographs | 1,352: 222 | Compared with experts | Pretrained CNN (VGG-16) | 0.9941 sensitivity and 0.9945 precision |
| | Detect and classify tooth (Zhang et al. 2018*) | Periapical radiographs | 700: 200 | | Pretrained CNN (VGG-16) | 95.8% accuracy and 96.1% recall in total |
| | Classify enamel, dentin, and pulp layer (Wang et al. 2017*) | Micro–computed tomography data sets | | | *k*-means++ | 0.83, 0.85, and 0.77 accuracy in classifying enamel, dentin, and pulp |
| Optimize conditions | Correlate resin composite hardness with light conditions (Deniz Arısu et al. 2018*) | Processing parameters and corresponding results | | | ANN | The mean square error value of the model was 0.0373 |
| | Predict color outcomes of porcelain powder (Li et al. 2015*) | Parameters from spectrophotometer colorimetric instrument | 75% of 119 sets of data: 25% of 119 sets of data | | Back propagation neural network with genetic algorithm | Smaller mean square error than back propagation neural network |
| Resin restoration removal and tooth preparation | Discriminate tooth and restorative materials (Zakeri et al. 2015*) | Cutting sounds of an air-turbine handpiece | | | SVM | 89% accuracy for resin composite, 92% accuracy for amalgam |
| | Achieve tooth crown preparation (Wang et al. 2014) | Shape of the target tooth acquired by a laser scanner | | Matched with expected tooth preparation | Automatic laser ablation system | Wax resin: 0.05-mm linear error, 4.33° angel error, and 0.1-mm depth error. Dentin: 0.06-mm linear error, 0.5° angel error, and 0.1-mm depth error |
| | Achieve tooth preparation for porcelain laminate veneers (Otani et al. 2015*) | Image of tooth models scanned with 3D laser scanner | 10: — | Compared with freehand tooth preparation | A robotic arm | The mean absolute deviation was 0.112 mm in the control group and 0.133 mm in the experimental group |
| Assist designing RPDs | Produce RPD designs according to the most similar cases (Chen et al. 2016) | Data about of oral conditions | 104: — | Compared with professionals | An ontology-driven, case-based clinical decision support model | The mean average of precision was 0.61; AUC = 0.96; normalized discounted cumulative gain = 0.74 |
| Measure masticatory efficiency | Identify patterns of masticated chewing gums (Vaccaro et al. 2018*) | Images of chewing gums obtained by flatbed scanner | 400: — | | Expert system | Mathews correlation coefficient score = 0.97 |

(continued)

**Table 2.** (continued)

| Fields | | | | | | |
|---|---|---|---|---|---|---|
| Aim | Function | Data | Sample Size, Training: Testing | Assessment | AI Method | Results |
| **Orthodontics** | | | | | | |
| Assist therapeutic decisions | Evaluate the orthodontic treatment needs (Thanathornwong 2018) | Patients' oral examination data sets | 800: 200 | Compared with 2 orthodontists on the newly recruited patients | Bayesian network | A high degree of agreement between the system and orthodontists (kappa value was 1.00 and 0.894) |
| | Identify pretreatment patients from posttreatment and normal individuals (Wang et al. 2016) | The eye-tracking data of observers | 440: — | Leave-1-out cross-validation | SVM | 97.2% and 93.4% accuracy for classifying pretreatment patient from posttreatment patient and normal people, respectively |
| Evaluate aesthetic outcome | Assess facial attractiveness and apparent age (Patcas et al. 2019) | Pre- and posttreatment photographs | 469: — | | Pretrained CNN (VGG-16) | Facial attractiveness was scaled from 0 to 100; apparent age was compared with real age |
| | Assess facial attractiveness (Patcas et al. 2019*) | Frontal and left-side profile images | | Compared with lay people, orthodontists, and oral surgeons | Pretrained CNN (VGG-16) | No significant differences with regard to the evaluation of attractiveness |
| **Endodontics** | | | | | | |
| Produce anatomic guidance | Identify root morphology (Hiraiwa et al. 2019) | Panoramic images | 22,476: 64 | Examined on CBCT images | Pretrained CNN (AlexNet) | 87.4% accuracy, 77.3% sensitivity, 97.1% specificity |
| | | | | | Pretrained CNN (GoogleNet) | 85.3% accuracy, 74.2% sensitivity, 95.9% specificity |
| | Measure root canal curvature (Christodoulou et al. 2018*) | CBCT images | 30: — | | An algorithm for the 3D measurement | |
| Optimize conditions | Predict the viability of stem cells (Bindal et al. 2017) | Processing variables and cell viability | | | Fuzzy inference system with ANN | The root mean square error was 0.028855. The coefficient of determination was 0.8111 |
| **Dental implantology** | | | | | | |
| Classify implant types | Identify 4 types of implant fixtures (Kim et al. 2020*) | Periapical radiographs | 60% of 801 images: 20% of 801 images | | Pretrained CNN (MobileNet-v2) | 97% accuracy, 96% precision |
| | | | | | Pretrained CNN (ResNet-50) | 98% accuracy, 98% precision |
| | | | | | Pretrained CNN (ResNet-18) | 98% accuracy, 98% precision |
| | | | | | Pretrained CNN (GoogleNet) | 93% accuracy, 92% precision |
| | | | | | Pretrained CNN (SqueezeNet) | 96% accuracy, 96% precision |

*References marked with an asterisk are included in the Appendix.
3D, 3-dimensional; AAM, active appearance model; AI, artificial intelligence; ANN, artificial neural network; ASM, active shape model; AUC, area under the receiver operating characteristic curve; CBCT, cone beam computed tomography; CNN, convolutional neural network; LDA, linear discriminant analysis; MRI, magnetic resonance imaging; NMF, negative matrix factorization; PDA, penalized discriminant analysis; QDA, quadratic discriminant analysis; RPD, removable partial denture; SVM, support vector machine.

naïve Bayes were ~70% accurate in predicting locoregional recurrence of squamous cell carcinoma (Alabi et al. 2020); these algorithms outperformed a contemporary clinical model that focused exclusively on tumor invasion depth. Because of the small sample size of training data sets and the large number of variables, the accuracy of these predictive models is inadvertently affected by irrelevant features (i.e., the overfitting problem) and is still below satisfaction.

*Cariology and Endodontics.* Predictive models based on ML algorithms, including SVM, RF, and *k*-nearest neighbors, were used to identify individuals prone to tooth surface loss and root caries. SVM demonstrated the best performance, with 97% accuracy and 99.6% sensitivity, by analyzing information derived from the demographic, nutrition, lifestyle, and clinical data of patients (Hung et al. 2019). Utilizing 83 features from the American Association of Endodontists' "Endodontic Case Difficulty Assessment Form" as input, SVM and ANN obtained >90% accuracy in predicting the level of difficulty of cases requiring root canal treatment. This illustrated the potential of ML to improve the decision making of general dental practitioners in their referrals to endodontists (Mallishery et al. 2020).

**Table 3.** Dental Applications of AI in Disease Prediction.

| Field | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Prediction | Data | Sample Size, Training: Testing | Validation Method | AI Methods | Accuracy | Sensitivity | Specificity | AUC |
| **Oral and maxillofacial surgery** | | | | | | | | |
| Survivability of patients with oral cavity squamous carcinoma | 5 factors related to quantitative nuclear histomorphometric features of tissue sections (Lu et al. 2017*) | 50: 65 | | Wilcoxon rank sum test and quadratic discriminant analysis | 70.8% | 61.5% | 73.1% | 0.72 |
| Nodal metastasis in early oral cavity squamous cell carcinoma | 5 factors pertaining to clinical and pathologic features of patients (Bur et al. 2019) | 1,570: 391 | 5-fold cross-validation | Decision forest | | 0.753 | 0.492 | 0.712 |
| | | | | Kernel SVM | | 0.649 | 0.636 | 0.698 |
| | | | | Gradient boosting | | 0.773 | 0.492 | 0.704 |
| Stage, type, and survivability of oral cancer | 12 attributes regarding clinical details, personal history, and habits of patients (Sharma and Om 2015*) | 1,025 | Leave-1-out method | PNN and general regression neural networks | | Benign and malignant | | |
| | | | | | 70.0% | 91.0% | 55.7% | 0.7491 |
| | | | | | | Survivability | | |
| | | | | | 67.0% | 91.0% | 55.7% | 0.7491 |
| Locoregional recurrence of oral tongue squamous cell carcinoma | 11 features pertaining to clinical, pathologic, and treatment features of patients (Alabi et al. 2020) | 50% of 254 cases: 59 | 5-fold cross-validation | SVM | 68% | 0.84 | 0.60 | |
| | | | | Boosted DT | 81% | 0.79 | 0.83 | |
| | | | | Decision forest | 78% | 0.79 | 0.78 | |
| | | | | Naïve Bayes | 70% | 0.84 | 0.63 | |
| 3-y survival rate of patients with oral cancer | 10 features selected from 17 features pertaining to patients (Tan et al. 2016*) | 31: — | 5-fold cross-validation | Genetic programming | 83.9% | | | 0.8341 |
| | | | | SVM | 64.8% | | | 0.5000 |
| | | | | Logistic regression | 64.5% | | | 0.5000 |
| Occurrence of bisphosphonate-related osteonecrosis after dental extraction | 9 factors related to medical history, tooth conditions (Kim et al. 2018*) | 70%: 30% of the 125 patients | | RF | | 100% | 83.3% | 0.973 |
| | | | | ANN | | 100% | 76.7% | 0.915 |
| | | | | SVM | | 81.8% | 86.7% | 0.882 |
| | | | | DT | | 90.9% | 79.0% | 0.821 |
| | | | | Logistic regression | | 90.9% | 70.0% | 0.844 |
| Facial swelling after impacted mandibular third molars extraction | 15 factors related to patients, the third molars, bone, and surgical conditions (Zhang et al. 2018) | 300: 100 | 5-fold cross-validation | ANN based on improved conjugate grads BP algorithm | 98.00% | | | |
| **Cariology and endodontics** | | | | | | | | |
| Root caries | 15 factors related to personal, nutrition, lifestyle, and clinical factors (Hung et al. 2019) | 7,272: 1,818 | | SVM | 97.1% | 99.6% | 94.3% | 0.997 |
| | | | | XGBoost | 94.7% | 100.0% | 88.9% | 0.987 |
| | | | | RF | 94.1% | 100.0% | 87.5% | 0.999 |
| | | | | *k*-nearest neighbors | 83.2% | 97.1% | 67.9% | 0.881 |
| | | | | Logistic regression | 74.2% | 77.1% | 71.1% | 0.818 |
| Tooth surface loss index | 11 factors related to patients and teeth (Al Haidan et al. 2014*) | 81: 15 | | ANN | 73.3%, ±5 scores | | | |
| Gene expression of radicular cyst and periapical granuloma | Times of the gene associated to the diseases in the PubMed database (Poswar et al. 2015*) | | | MLP neural network | | | | |
| Difficulty of endodontic cases | 83 features from AAE case difficulty assessment form (Mallishery et al. 2020) | | 10-fold cross-validation | SVM | 94.8% | 95.0% | 94.6% | |
| | | | | Deep neural network | 93.4% | 93.0% | 93.8% | |
| **Dental implantology** | | | | | | | | |
| Failure of dental implants | 20 attributes pertaining to patients and surgeon (Liu et al. 2018*) | 747: — | 10-fold cross-validation | DT | 0.679 | 0.590 | 0.768 | 0.670 |
| | | | | SVM | 0.628 | 0.581 | 0.675 | 0.628 |
| | | | | Logistic regressions | 0.624 | 0.607 | 0.641 | 0.644 |
| Individual implant mean bone levels | 6 factors related to demographic and clinical features (Papantonopoulos et al. 2017) | 237: — | 10-fold resampling cross-validation | Ensemble selection | | 55% | 91% | |
| | Age, tooth number, and implant surface (Papantonopoulos et al. 2017) | 237 | 10-fold resampling cross-validation | SVM with Particle Swarm Optimization | | 62% | 85% | |
| Successive rate of implant treatment | Dental data, patient self-behavior, health condition, and attitude (Alarifi and AlZubi 2018) | | | Memetic search optimization with genetic scale RNN | 99.2% | 97.6% | 98.3% | |
| **Periodontics** | | | | | | | | |
| Presence of oral malodor | 16s ribosomal RNA sequence from microbiota in saliva (Nakano et al. 2018*) | 90: — | Leave-1-out cross-validation | DL | 96.7% | 100% | 93.3% | |
| | | | | SVM | 78.9% | 77.8% | 80.0% | |
| Tooth mobility | 9 factors related to patients (Yoon et al. 2018) | | 10-fold cross-validation | MLP and deep neural networks | 88.4% | | | 0.72 |
| **Orthodontics** | | | | | | | | |
| Perioperative blood loss in orthognathic surgery | Demographic, clinical and surgical data (Stehrer et al. 2019*) | 760: 190 | | RF | 7.4-mL mean difference | | | |

*(continued)*

**Table 3.** (continued)

| Field | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Prediction | Data | Sample Size, Training: Testing | Validation Method | AI Methods | Accuracy | Sensitivity | Specificity | AUC |
| **Prosthodontics** | | | | | | | | |
| Longevity of dental restorations | Attributes related to patients and teeth (Aliaga et al. 2015) | 4,336: 1,714 | Leave-1-out validation | Bayesian network and MLP neural network | Error: 0.42 y (composites), 0.21 (amalgam) | | | |
| Debonding probability of CAD/CAM composite resin crowns | 2D images captured from 3D stereolithography (Yamaguchi et al. 2019) | 6,480: 2,160 | | CNN | 98.5% | | | 0.998 |
| Facial deformation after complete denture prosthesis | 3D pre- and postoperative models (Cheng et al. 2015*) | 43: 5 | | BP neural network | | | | |

*References marked with an asterisk are included in the Appendix.
2D, 2-dimensional; 3D, 3-dimensional; AAE, American Association of Endodontists; AI, artifical intelligence; ANN, artificial neural network; AUC, area under the receiver operating characteristic curve; BP, back propagation; CAD/CAM, computer-aided design/computer-aided manufacturing; CNN, convolutional neural network; DL, deep learning; DT, decision tree; MLP, multilayer perceptron; PNN, probabilistic neural network; RF, random forest; RNN, recurrent neural network; SVM, support vector machine.

*Dental Implantology.* Predictive AI models are useful in 2 aspects of dental implantology. First, predictive models focusing on clinical outcome and individual bone levels (Papantonopoulos et al. 2017) have been constructed with ML algorithms. By simultaneously analyzing the patients' data, the implant system, and the surgeons' operations, recurrent ANN (Fig. 2C) with memetic search optimization attained 99.2% accuracy in success rate prediction (Alarifi and AlZubi 2018). Second, AI was introduced as a surrogate to contemporary technology in predicting the mechanical performance of a bio-implant system, relieving high computational cost in optimizing implant design variables. By automatically learning the explicit relationship among variables, support vector regression was almost equivalent to contemporary mathematical models in predicting stresses at the implant-bone interface (Li et al. 2019). Nevertheless, this study was conducted by using vertical loading and is not representative of a genuine chewing cycle. Application of AI in the uncertainty optimization of bio-implants still requires improvement.

*Others.* Based on patients' attributes, a multilayer perceptron neural network performed satisfactorily in predicting tooth mobility (Yoon et al. 2018) and longevity of resin composite restorations (Aliaga et al. 2015). CNNs achieved 98.5% accuracy in predicting the debonding probability of CAD/CAM resin composite crowns by analyzing images captured from abutment models (Yamaguchi et al. 2019). These systems are useful in forecasting prognosis and enable dentists to provide patients with the most suitable maintenance program.

## Limitations and Challenges

### Data Acquisition

Application of AI in dentistry is lagging behind medicine by several years (Schwendicke et al. 2019). Apart from limitations encountered in other medical fields, such as insufficient data curation and sharing (Hosny et al. 2018), the lack of information on data processing, measuring, and validating is another blemish in dental AI research (Schwendicke et al. 2020). Sample size used for training and testing as well as the information for reference and comparative tests are sometimes unclear (Schwendicke et al. 2019), challenging the robustness, comparability, and generalizability of the results. It is imperative to improve data quantity, quality, and readability by standardizing methodology in data curation and reporting. Establishing an open-access standard data set, which contains comprehensive demographic, clinical, experimental, and treatment data, would be a crucial task in the next stage of AI development to facilitate evaluation and comparison of different algorithms.

### Interpretability

Data-driven AI calculates output in a purely computational manner; however, it fails to illustrate the decision-making process in a medically acknowledgeable format. The lack of interpretability and transparency reflects the black-box nature of many ML approaches, which are not conducive to verification (Magrabi et al. 2019). Interpretability matters for 2 reasons. First, ensuring that the algorithm is a reasonable interpretation of medical incidents is important for the rapport between technology and humans. Failure to explain the inner working will inevitably disrupt practitioners' trust in the clinical value of AI. Second, the lack of transparency and interpretability makes it difficult to predict failures and generalize specific algorithms for similar contexts. Enhancing visualization has become a pivotal task. Rigorous scientific inquiry and humanistic treatment models that respond to patient and practitioner narrative exchanges are critical to understanding the clinical phenotypes of AI as well as its relationship to personalized care (Kulikowski 2019).

### Computing Power

Extracting information from constantly updating medical and dental databases for the application of AI requires continuous upgrading of processing power. Because the computational power of classical computers has been largely saturated (Solenov et al. 2018), the insufficient computational resources in data processing have become one of the obstacles that constrain the efficacy of AI (Sunny et al. 2019). Quantum computing processes data by using quantum bits (qubits), in accordance with the laws and restrictions of quantum mechanics. Since quantum particles can exist in multiple states at the same time—a phenomenon known as superposition—quantum computation is exponentially faster than classical approaches (Ranjan and Hopper 2019). The ability to handle data simultaneously from very different data sets makes quantum computing a valuable platform to accelerate AI, especially ML (Sarma et al. 2019), from algorithms to data acquisition and modeling.

### *Ethical Considerations*

Development of AI should ensure that such intelligent technologies do no harm to humans and the moral status of the machines themselves (Keskinbora 2019). Nevertheless, demands for health care privacy may no longer be attainable with a colossal scale of data sharing (Char et al. 2018). Incorporating AI into health care would inevitably replace some established services and potentially exacerbate current health inequalities (Fiske et al. 2019). These ethical paradoxes emphasize the need to establish clear guidelines for the manner in which AI is applied clinically. Judgment of legal responsibility is another ethical dilemma. At present, AI is not accountable, irrespective of whether it is employed in a supervised or unsupervised manner. The physician takes responsibility for each patient and for how information is used (Currie et al. 2020). Applying the same social and ethical norms acceptable to humans is inappropriate when the border of human responsibility is increasingly blurred by the advent of chatbot-based, unsupervised AI–based diagnosis (Hauser-Ulrich et al. 2020).

## Impact of AI on Dentists

Dentistry is an excellent discipline for applying virtual AI algorithms because of its regular use of digitized imaging and electronic health records. While there is plenty of active discussion on how AI may revolutionize dental practice, concerns remain regarding whether AI will eventually replace dentists.

Contemporary AI excels in utilizing formalized knowledge and extracting information from massive data sets. However, it fails to make associations like a human brain and can only partially perform complex decision making in a clinical setting. Higher-level understanding that relies on the expertise of dentists is required, especially in ambiguous conditions, to conduct physical examinations, integrate medical histories, evaluate aesthetic outcomes, and facilitate discussion. Fleshless, machine-led dentistry does not embody the wreath of clinical care. Issues such as clinical intuition, ineffable perception, and empathy, which are keys to the delivery of personalized health care and professionalism, cannot be delivered by machines. Although there have been intense discussions whether empathy should be incorporated into algorithms so that artificial emotions may be expressed by affective robotics, it is important to stress that effective communication between a dentist and a patient involves nonverbal evaluation of the person's hopes, fears, and expectations. Such channels of communication are intuitive and spontaneous. The most intriguing dimension of human-to-human interaction cannot simply be replicated in computer language. AI should be viewed as an augmentation tool to enhance and, at times, relieve dentists so that they can perform more valued tasks, such as integrating patient information and improving professional interactions (Recht and Bryan 2017). Pedagogy for dental students should walk hand-in-hand with AI development.

## Conclusion

AI is progressing rapidly, with potential applications in diagnosis, treatment, and prognosis predictions. Although roadblocks that arise from data acquisition, interpretation, computing power, and moral issues exist and need to be overcome, AI is perceived to be an excellent adjunct for dentists. With thoughtful design and long-term clinical validation, AI can be user-friendly, transparent, reproducible, and unbiased. Future AI development should continue to consider human interest as its primary mission, with increasing capability in handling big data.

### Author Contributions

T. Shan, contributed to data acquisition, analysis, and interpretation, drafted the manuscript; F.R. Tay, L. Gu, contributed to conception and design, critically revised the manuscript. All authors gave final approval and agree to be accountable for all aspects of the work.

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### References

Alabi RO, Elmusrati M, Sawazaki-Calone I, Kowalski LP, Haglund C, Coletta RD, Makitie AA, Salo T, Almangush A, Leivo I. 2020. Comparison of supervised machine learning classification techniques in prediction of locoregional recurrences in early oral tongue cancer. Int J Med Inform. 136:104068.

Alarifi A, AlZubi AA. 2018. Memetic search optimization along with genetic scale recurrent neural network for predictive rate of implant treatment. J Med Syst. 42(11):202.

Aliaga IJ, Vera V, De Paz JF, Garcia AE, Mohamad MS. 2015. Modelling the longevity of dental restorations by means of a CBR system. Biomed Res Int. 2015;2015:540306.

Amasya H, Yildirim D, Aydogan T, Kemaloglu N, Orhan K. 2020. Cervical vertebral maturation assessment on lateral cephalometric radiographs using artificial intelligence: comparison of machine learning classifier models. Dentomaxillofac Radiol. 49(5):20190441.

American Medical Association. 2018. Augmented intelligence in health care: report 41 of the AMA Board of Trustees [accessed 2020 June 10]. https://www.ama-assn.org/system/files/2019-01/augmented-intelligence-policy-report.pdf.

Anwar SM, Majid M, Qayyum A, Awais M, Alnowami M, Khan MK. 2018. Medical image analysis using convolutional neural networks: a review. J Med Syst. 42(11):226.

Ayala Solares JR, Diletta Raimondi FE, Zhu Y, Rahimian F, Canoy D, Tran J, Pinho Gomes AC, Payberah AH, Zottoli M, Nazarzadeh M, et al. 2020. Deep learning for electronic health records: a comparative review of multiple deep neural architectures. J Biomed Inform. 101:103337.

Bindal P, Bindal U, Lin CW, Kasim NHA, Ramasamy T, Dabbagh A, Salwana E, Shamshirband S. 2017. Neuro-fuzzy method for predicting the viability of stem cells treated at different time-concentration conditions. Technol Health Care. 25(6):1041–1051.

Bouletreau P, Makaremi M, Ibrahim B, Louvrier A, Sigaux N. 2019. Artificial intelligence: applications in orthognathic surgery. J Stomatol Oral Maxillofac Surg. 120(4):347–354.

Bur AM, Holcomb A, Goodwin S, Woodroof J, Karadaghy O, Shnayder Y, Kakarala K, Brant J, Shew M. 2019. Machine learning to predict occult nodal metastasis in early oral squamous cell carcinoma. Oral Oncol. 92:20–25.

Casalegno F, Newton T, Daher R, Abdelaziz M, Lodi-Rizzini A, Schürmann F, Krejci I, Markram H. 2019. Caries detection with near-infrared transillumination using deep learning. J Dent Res. 98(11):1227–1233.

Char DS, Shah NH, Magnus D. 2018. Implementing machine learning in health care—addressing ethical challenges. N Engl J Med. 378(11):981–983.

Chen Q, Wu J, Li S, Lyu P, Wang Y, Li M. 2016. An ontology-driven, case-based clinical decision support model for removable partial denture design. Sci Rep. 6(1):27855.

Crigger E, Khoury C. 2019. Making policy on augmented intelligence in health care. AMA J Ethics. 21(2):E188–E191.

Currie G, Hawk KE, Rohren EM. 2020. Ethical principles for the application of artificial intelligence (AI) in nuclear medicine. Eur J Nucl Med Mol Imaging. 47(4):748–752.

Feres M, Louzoun Y, Haber S, Faveri M, Figueiredo LC, Levin L. 2018. Support vector machine-based differentiation between aggressive and chronic periodontitis using microbial profiles. Int Dent J. 68(1):39–46.

Fiske A, Henningsen P, Buyx A. 2019. Your robot therapist will see you now: ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy. J Med Internet Res. 21(5):e13216.

Fu SW, Li PC, Lai YH, Yang CC, Hsieh LC, Tsao Y. 2017. Joint dictionary learning-based non-negative matrix factorization for voice conversion to improve speech intelligibility after oral surgery. IEEE Trans Biomed Eng. 64(11):2584–2594.

Gerlach NL, Meijer GJ, Kroon DJ, Bronkhorst EM, Berge SJ, Maal TJ. 2014. Evaluation of the potential of automatic segmentation of the mandibular canal using cone-beam computed tomography. Br J Oral Maxillofac Surg. 52(9):838–844.

Gupta A, Kharbanda OP, Sardana V, Balachandran R, Sardana HK. 2015. A knowledge-based algorithm for automatic detection of cephalometric landmarks on CBCT images. Int J Comput Assist Radiol Surg. 10(11):1737–1752.

Handelman GS, Kok HK, Chandra RV, Razavi AH, Lee MJ, Asadi H. 2018. Edoctor: machine learning and the future of medicine. J Intern Med. 284(6):603–619.

Hauser-Ulrich S, Künzli H, Meier-Peterhans D, Kowatsch T. 2020. A smartphone-based health care chatbot to promote self-management of chronic pain (SELMA): pilot randomized controlled trial. JMIR Mhealth Uhealth. 8(4):e15806.

Hiraiwa T, Ariji Y, Fukuda M, Kise Y, Nakata K, Katsumata A, Fujita H, Ariji E. 2019. A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on panoramic radiography. Dentomaxillofac Radiol. 48(3):20180218.

Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts H. 2018. Artificial intelligence in radiology. Nat Rev Cancer. 18(8):500–510.

Hung M, Voss MW, Rosales MN, Li W, Su W, Xu J, Bounsanga J, Ruiz-Negrón B, Lauren E, Licari FW. 2019. Application of machine learning for diagnostic prediction of root caries. Gerodontology. 36(4):395–404.

Jeon SH, Jeon EH, Lee JY, Kim YS, Yoon HJ, Hong SP, Lee JH. 2015. The potential of interleukin 12 receptor beta 2 (IL12RB2) and tumor necrosis factor receptor superfamily member 8 (TNFRSF8) gene as diagnostic biomarkers of oral lichen planus (OLP). Acta Odontol Scand. 73(8):588–594.

Keskinbora KH. 2019. Medical ethics considerations on artificial intelligence. J Clin Neurosci. 64:277–282.

Kise Y, Shimizu M, Ikeda H, Fujii T, Kuwada C, Nishiyama M, Funakoshi T, Ariji Y, Fujita H, Katsumata A, et al. 2020. Usefulness of a deep learning system for diagnosing Sjogren's syndrome using ultrasonography images. Dentomaxillofac Radiol. 49(3):20190348.

Kok H, Acilar AM, Izgi MS. 2019. Usage and comparison of artificial intelligence algorithms for determination of growth and development by cervical vertebrae stages in orthodontics. Prog Orthod. 20(1):41.

Krittanawong C, Zhang H, Wang Z, Aydar M, Kitai T. 2017. Artificial intelligence in precision cardiovascular medicine. J Am Coll Cardiol. 69(21):2657–2664.

Kulikowski CA. 2019. Beginnings of artificial intelligence in medicine (AIM): computational artifice assisting scientific inquiry and clinical art—with reflections on present AIM challenges. Yearb Med Inform. 28(1):249–256.

Lee JH, Kim DH, Jeong SN, Choi SH. 2018. Diagnosis and prediction of periodontally compromised teeth using a deep learning–based convolutional neural network algorithm. J Periodontal Implant Sci. 48(2):114–123.

Li H, Shi M, Liu X, Shi Y. 2019. Uncertainty optimization of dental implant based on finite element method, global sensitivity analysis and support vector regression. Proc Inst Mech Eng H. 233(2):232–243.

Magrabi F, Ammenwerth E, McNair JB, De Keizer NF, Hyppönen H, Nykänen P, Rigby M, Scott PJ, Vehko T, Wong ZS, et al. 2019. Artificial intelligence in clinical decision support: challenges for evaluating AI and practical implications. Yearb Med Inform. 28(1):128–134.

Mallishery S, Chhatpar P, Banga KS, Shah T, Gupta P. 2020. The precision of case difficulty and referral decisions: an innovative automated approach. Clin Oral Investig. 24(6):1909–1915.

Maxmen JS. 1976. The post-physician era: medicine in the 21st century. New York (NY): Wiley.

Montani S, Striani M. 2019. Artificial intelligence in clinical decision support: a focused literature survey. Yearb Med Inform. 28(1):120–127.

Nam Y, Kim HG, Kho HS. 2018. Differential diagnosis of jaw pain using informatics technology. J Oral Rehabil. 45(8):581–588.

Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Ozyurek T. 2020. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endod J. 53(5):680–689.

Papantonopoulos G, Gogos C, Housos E, Bountis T, Loos BG. 2017. Prediction of individual implant bone levels and the existence of implant "phenotypes." Clin Oral Implants Res. 28(7):823–832.

Park WJ, Park JB. 2018. History and application of artificial neural networks in dentistry. Eur J Dent. 12(4):594–601.

Patcas R, Bernini DAJ, Volokitin A, Agustsson E, Rothe R, Timofte R. 2019. Applying artificial intelligence to assess the impact of orthognathic treatment on facial attractiveness and estimated age. Int J Oral Maxillofac Surg. 48(1):77–83.

Raith S, Vogel EP, Anees N, Keul C, Güth J-F, Edelhoff D, Fischer H. 2017. Artificial neural networks as a powerful numerical tool to classify specific features of a tooth based on 3D scan data. Comput Biol Med. 80:65–76.

Ranjan M, Hopper H. 2019. What if quantum computer combined with artificial intelligence? Sci Insigt. 29(2):48–51.

Recht M, Bryan RN. 2017. Artificial intelligence: threat or boon to radiologists? J Am Coll Radiol. 14(11):1476–1480.

Sarma S, Deng D, Duan L. 2019. Machine learning meets quantum physics. Phys Today. 72(3):48–54.

Schwendicke F, Golla T, Dreher M, Krois J. 2019. Convolutional neural networks for dental image diagnostics: a scoping review. J Dent. 91:103226.

Schwendicke F, Samek W, Krois J. 2020. Artificial intelligence in dentistry: chances and challenges. J Dent Res. 99(7):769–774.

Setzer FC, Shi KJ, Zhang Z, Yan H, Yoon H, Mupparapu M, Li J. 2020. Artificial intelligence for the computer-aided detection of periapical lesions in cone-beam computed tomographic images. J Endod. 46(7):987–993.

Shoukri B, Prieto JC, Ruellas A, Yatabe M, Sugai J, Styner M, Zhu H, Huang C, Paniagua B, Aronovich S, et al. 2019. Minimally invasive approach for diagnosing TMJ osteoarthritis. J Dent Res. 98(10):1103–1111.

Solenov D, Brieler J, Scherrer JF. 2018. The potential of quantum computing and machine learning to advance clinical research and change the practice of medicine. Mo Med. 115(5):463–467.

Steels L, Lopez de Mantaras R. 2017. Barcelona declaration for the proper development and usage of artificial intelligence in Europe. AI Commun. 31(6):485–494.

Sunny S, Baby A, James BL, Balaji D, NV A, Rana MH, Gurpur P, Skandarajah A, D'Ambrosio M, Ramanjinappa RD, et al. 2019. A smart tele-cytology point-of-care platform for oral cancer screening. PLoS One. 14(11):e0224885.

Thanathornwong B. 2018. Bayesian-based decision support system for assessing the needs for orthodontic treatment. Healthc Inform Res. 24(1):22–28.

Wang L, Wang D, Zhang Y, Ma L, Sun Y, Lv P. 2014. An automatic robotic system for three-dimensional tooth crown preparation using a picosecond laser. Lasers Surg Med. 46(7):573–581.

Wang X, Cai B, Cao Y, Zhou C, Yang L, Liu R, Long X, Wang W, Gao D, Bao B. 2016. Objective method for evaluating orthodontic treatment from the lay perspective: an eye-tracking study. Am J Orthod Dentofacial Orthop. 150(4):601–610.

Yamaguchi S, Lee C, Karaer O, Ban S, Mine A, Imazato S. 2019. Predicting the debonding of CAD/CAM composite resin crowns with AI. J Dent Res. 98(11):1234–1238.

Yilmaz E, Kayikcioglu T, Kayipmaz S. 2017. Computer-aided diagnosis of periapical cyst and keratocystic odontogenic tumor on cone beam computed tomography. Computer Methods Programs Biomed. 146:91–100.

Yoon S, Odlum M, Lee Y, Choi T, Kronish IM, Davidson KW, Finkelstein J. 2018. Applying deep learning to understand predictors of tooth mobility among urban latinos. Stud Health Technol Inform. 251:241–244.

Zhang W, Li J, Li ZB, Li Z. 2018. Predicting postoperative facial swelling following impacted mandibular third molars extraction by using artificial neural networks evaluation. Sci Rep. 8(1):12281.