Review

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Dental Artificial Intelligence Systems: A Review of Various Data Types

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With the rapid development of dental artificial intelligence systems (DAIS), a new field known as "Data Dentistry", proposed by Schwendicke in 2021, has successfully bridged the gap between medicine and engineering. This literature review introduces advanced techniques in data collection, outlines the current state of DAIS in data processing, and anticipates the future of DAIS by emphasizing the importance of more extensive and enhanced datasets. The key findings include: Versatility of imaging data: Various types of imaging data, such as X-ray, cone beam computed tomography (CBCT), facial photos, and face and oral scans, can be transformed into datasets used by artificial intelligence systems. Uniform rules in electronic dental record (EDR) systems: EDR systems require standardized rules for general use in DAIS, ensuring compatibility and seamless integration. Potential of wearable device data: Data from wearable devices, including bioelectric signals (such as electromyography), stress sensors, AR glasses, etc., show great potential for enhancing DAIS capabilities. Current DAIS performance focus: Presently, DAIS demonstrate superior performance in object location and disease diagnosis compared to information integration and clinical decision-making. Need for data quality and quantity improvement: Further improvements are needed in both the quality and quantity of data for DAIS.

Keywords: artificial intelligence; oral diagnosis and therapy; database

Introduction

The field of artificial intelligence (AI) is evolving rapidly, seeking to simulate or enhance human intelligence through the exploration of various theories, methods, technologies, and application systems [1]. The integration of AI into clinical decision-making has gained momentum and maturity, as certain systems have effectively transitioned from scientific research to practical application in clinical practice. These AI systems now offer valuable assistance to medical professionals.

To develop highly accurate AI models for medical decision-making, it is imperative to collect diverse data types, extract pertinent information, integrate the data, and label the results according to established standards or expert judgments. However, unlike other AI applications, such as image collection for autonomous driving or text collection for popular AI tools like ChatGPT, medical data pose unique challenges related to availability, integrality, and reproducibility [2].

Firstly, ensuring the availability of medical data proves challenging as multiple sources must be integrated, encompassing patient demographics, medical history, symptoms, laboratory results, imaging findings, and more. The collection of this information demands a comprehensive understanding of the patient's condition.

Secondly, the integrity of medical data relies heavily on the responsibility of healthcare professionals and the cooperation of patients. Standardized medical record writing and the timely nature of patients' return visits are pivotal factors influencing the completeness of the collected data.

Thirdly, the absence of standardized methods for collecting, storing, and processing medical data poses challenges for data reproducibility. Furthermore, transparency is crucial for ensuring data reproducibility, as researchers require access to and comprehension of the complete details of the data to accurately replicate findings.

In this review, our objective is to consolidate diverse data types employed in dental research and clinical care for the development of medical decision-making AI systems. Subsequently, we outline existing challenges and anticipate exploitable data resources to meet the genuine clinical demands.

Data from Different Types of Dental Images

X-ray

X-ray examinations have become a routine practice for stomatologists, offering a valuable means to observe internal structures and diagnose diseases (Fig. 1). Addi-

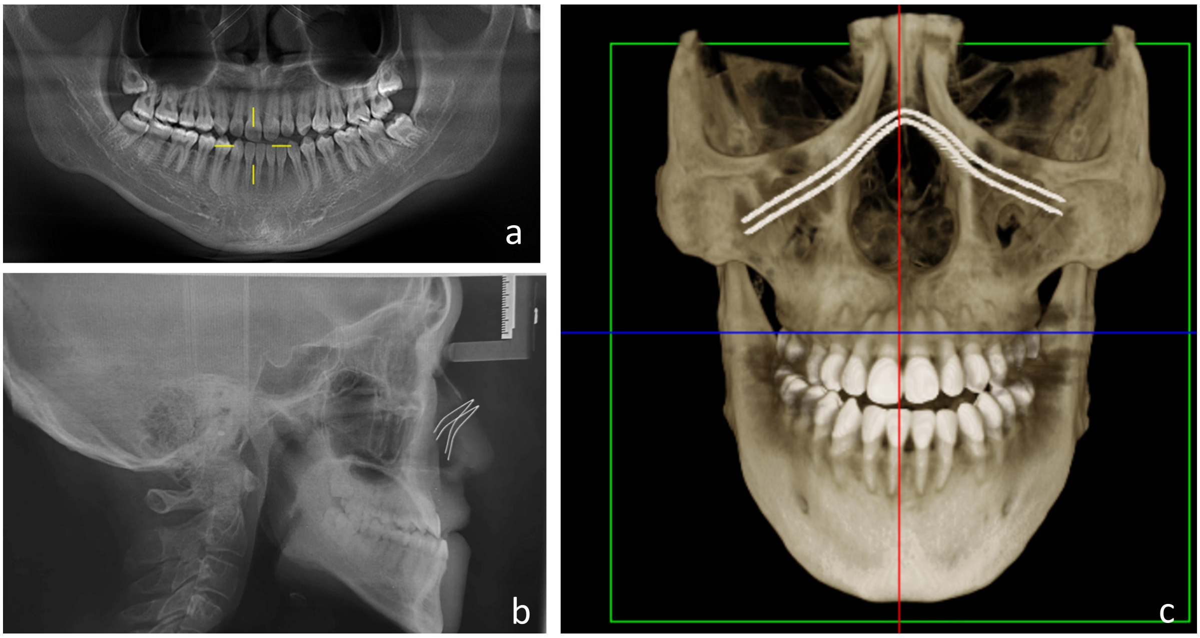

Fig. 1. Dental X-ray imaging data which are commonly used in orthodontics. (Department of Orthodontics, School of Stomatology, Air Force Military Medical University, Nov.14th 2021) (a) Panoramic images (OC100 D-1-4-1, Instrumentarium Dental, Tuusula, Finland). (b) Lateral cephalograms (OC200 D, Instrumentarium Dental, Tuusula, Finland). (c) Cone Beam CT (New Tom VGi, Verona, Italy).

tionally, the integration of X-ray technology with artificial intelligence represents one of the earliest and most mature fields in AI development. Table 1 (Ref. [3–12]) illustrates the synergy between these two domains.

Caries and Chronic Periapical Diseases

The gold standard for diagnosing caries and chronic periapical diseases relies on identifying the low-density shadows evident on X-ray films. Lee *et al*. [3] employed preprocessing and transfer learning of the pretrained GoogLeNet Inception V3 CNN (convolutional neural network), utilizing periapical slices to construct a caries prediction model. To enhance the model's performance on a limited dataset, image augmentation techniques were regularly applied, encompassing rotation (10° range), width and height shifting (0.1 range), zooming (0.8–1.2 range), shearing (0.5 range), and horizontal flipping.

Ekert *et al*. [4] manually cropped single tooth-specific local images from panoramic radiography. Following a series of digital preprocessing steps for augmentation and standardization (such as transforming to grayscale and resizing to certain pixels), these images served as input to a 7-layer CNN model for diagnosing apical diseases.

While dental cone beam computed tomography (CBCT) is the gold standard for assessing root morphology, its application is limited due to the high radiation dose for patients. Consequently, researchers [5] explored the use of panoramic radiography in conjunction with deep learning systems to assess the number of distal roots of mandibular first molars, achieving an accuracy of 86.9%.

Periodontal Diseases

In assessing certain periodontal diseases, the extent of alveolar bone resorption depicted in X-ray films is a crucial factor for evaluating disease severity (Table 1). Lee *et al*. [6] employed periapical radiographic images to create a CNN model capable of providing three distinct diagnoses corresponding to different degrees of severity. Similarly, Krois *et al*. [7] utilized panoramic images to develop a customized seven-layer feed-forward CNN model for their study.

Malocclusion

Lateral cephalograms are widely employed by orthodontists for a more precise understanding of the qualitative relationships between the tooth and alveolar bone, upper and lower teeth, and soft and hard tissues. The precise location and measurement of landmarks on soft and hard tissues in lateral cephalograms contribute to this detailed analysis. Despite the emergence of software designed to assist with measurements, these tools have not entirely replaced the manual process of locating and measuring landmarks. However, the integration of AI algorithms may revolutionize this aspect.

In 2017, Arık *et al*. [8] pioneered the application of a CNN combined with a shape model to perform cephalometric analysis, identifying 19 landmarks. The accuracy within a clinically acceptable error range of 2 mm for the three test groups was reported at 75.58%, 75.37%, and 67.68%, respectively.

Table 1. Dental artificial intelligence systems based on X-ray images.

Authors	Year	Image	Disease diagnosis/Image processing	Total image database	Neural network architecture	Outcome metrics	Outcome metrics values
Lee *et al*. [3]	2018	Periapical	Caries	3000	GoogLeNet Inception v3	Accuracy	premolar caries 89.0% molar caries 88.0%
Ekert *et al*. [4]	2019	Panoramic	Apical diseases	2001	a custom-made CNN	AUC	0.85
Hiraiwa *et al*. [5]	2019	Panoramic	Root numbers	2001	AlexNet and GoogleNet	Accuracy	86.90%
Lee *et al*. [6]	2018	Periapical	Alveolar bone resorption	1740	a custom-made CNN	Accuracy	premolars 81.0% molars 76.7%
Krois *et al*. [7]	2019	Panoramic	Alveolar bone resorption	2001	a custom-made CNN	Accuracy	0.81
Arık *et al*. [8]	2017	Lateral cephalograms	Cephalometry	400*	a custom-made CNN	Accuracy	Class I 75.58%; Class II 75.37%; Class III 67.68%
Kunz *et al*. [9]	2020	Lateral cephalograms	Cephalometry	1792	a custom-made CNN	Correlation	r > 0.864
Hwang *et al*. [10]	2020	Lateral cephalograms	Cephalometry	1028	YOLOv3	Error	1.46 ± 2.97 mm
Yu *et al*. [11]	2020	Lateral cephalograms	Skeletal classification	5890	DenseNet	Accuracy	95.7%
Liu *et al*. [12]	2021	Lateral cephalograms	Adenoid Hypertrophy	1023	VGG	F1 score	0.89

* Public database; AUC, area under curve; CNN, convolutional neural network; YOLOv3, you-only-look-once version 3; VGG, visual geometry group.

In 2020, Kunz *et al*. [9] customized open-source CNN deep learning algorithms (Keras and Google Tensorflow) to automatically output cephalometric landmarks, demonstrating a high correlation ($r > 0.864$, $p < 0.001$) between the AI system and human experts.

Hwang *et al*. [10] utilized the deep learning method you-only-look-once version 3 (YOLOv3) to identify 80 landmarks in lateral cephalograms, achieving an average detection error between AI and experts of 1.46 ± 2.97 mm. Notably, the average difference between human experts was 1.50 ± 1.48 mm. These advancements suggest a promising role for AI in transforming the precision and efficiency of cephalometric landmark identification.

Cephalometric analysis, having been in practice for decades, has traditionally relied on numerous measurement indicators, potentially missing valuable information due to its limitations and time-consuming nature over the past decade. In contrast, deep learning (DL) offers a more comprehensive approach, capable of directly learning from all input data and achieving end-to-end diagnoses.

In a groundbreaking study, Yu *et al*. [11] leveraged a multimodal CNN architecture. This innovative model could directly classify the sagittal or vertical type of bone by incorporating patients' sex and lateral cephalograms. By passing intermediary steps in cephalometric analysis, this approach significantly increased accuracy to over 90%, surpassing the performance of human experts. This highlights the potential of DL to streamline and enhance the efficiency of cephalometric analysis while extracting more nuanced information from the available data.

In addition to cephalometry, orthodontists utilize lateral cephalometric radiographs for a preliminary assessment of adenoid hypertrophy severity. In a study by Liu *et al*. [12], the researchers developed the VGG16 deep-learning neural network to evaluate the relative airway size of adenoids. This assessment could be performed either through complete machine judgment or by combining the judgment of machines with expert evaluation. The results demonstrated that both the speed and accuracy of these two methods surpassed those of human experts. This indicates the potential of deep learning models to enhance efficiency and accuracy in assessing adenoid hypertrophy from lateral cephalometric radiographs.

Table 2. Dental artificial intelligence systems based on CBCT images.

Authors	Year	Disease diagnosis/Structure detection	Total image database	Neural network architecture	Outcome metrics	Outcome metrics values
Sherwood *et al*. [24]	2021	C-shape canal	135	Xception U-Net (the best of the three)	mDSC	0.768 ± 0.0349
Orhan *et al*. [25]	2021	the impacted teeth	130	deep CNN (Diagnocat, Inc.)	——	——
Hung *et al*. [20]	2022	maxillary sinus	445	a custom-made CNN	AUC	Low-dose CBCT:0.91 Full-dose CBCT:0.89
Chai *et al*. [26]	2022	Ameloblastoma (AME) and odontogenic keratocysts (OKC)	178AMEs 172OKCs	Inception V3 DL	Accuracy	84.6%
Liu *et al*. [27]	2022	the third molar (M3) and mandibular canal (MC) and their relationship	254	U-Nets and ResNET-34	mDSC Accuracy	M3:0.9730 MC:0.9248 93.3%

AUC, area under curve; DL, deep learning; mDSC, mean dice coefficients; CNN, convolutional neural network; CBCT, cone beam computed tomography.

Cone Beam Computed Tomography (CBCT)

CBCT can present anatomical structures in three dimensions, offering clinicians a broader perspective. Subsequently, AI tools can autonomously recognize and segment distinct teeth [13–15], skull structures, including the sella turcica [16], maxillary [17], and mandible [18,19]. Additionally, they can identify features such as maxillary sinus mucosa [20], inferior alveolar canal [21], and pharyngeal airway [22,23], within precise three-dimensional (3D) images for diagnostic and printing applications in the medical field.

Beyond identification and segmentation, CBCT boasts irreplaceable advantages in diagnosis and detection (Table 2, Ref. [20,24–27]). CBCT stands as the gold standard for discerning the number of root canals. Utilizing CBCT data, Sherwood *et al*. [24] developed a DL model to categorize C-shaped canal anatomy in mandibular second molars. They explored three different architectures, among which Xception U-Net demonstrated the most outstanding performance, achieving the highest Dice coefficients of 0.768 ± 0.0349, the highest mean sensitivity values of 0.786 ± 0.0378, and the highest mean positive predictive values of 0.800 ± 0.1098.

Moreover, CBCT is considered the gold standard for evaluating impacted third molars due to its ability to detect root canal shapes, the relationship between upper jaw teeth and the maxillary sinus, the relationship between lower jaw teeth and the inferior alveolar canal, etc. Orhan *et al*. [25] utilized a CNN (Diagnocat, Inc.) with annotated information on impacted teeth. The results demonstrated accurate determination of the number of roots in 99 out of 112 teeth (78.6%) and 82 out of 112 canals (68.1%). The relationship between impacted teeth and adjacent anatomical structures was predominantly determined in good agreement with the judgment of human experts.

CBCT also offers irreplaceable advantages when observing other anatomical structures. The CNN developed by Hung *et al*. [20] can automatically detect and segment the maxillary sinus on both low-dose and full-dose CBCT, subsequently diagnosing thickening mucosal or mucosal retention cyst of the maxillary sinus. In the study by Chai *et al*. [26], the Inception V3 deep learning algorithm was employed to identify ameloblastoma and odontogenic keratocysts on CBCT. Liu *et al*. [27] constructed a DL model based on U-Nets and ResNet-34 modules to automatically detect and assess the relationship between mandibular third molars and mandibular canals through CBCT. This can provide additional evidence for stomatologists to inform patients about the risk of tooth extraction before surgery.

Furthermore, some AI systems utilize CBCT for the diagnosis of temporomandibular joint osteoarthritis with sufficient accuracy to assist clinicians in their judgment [28–30].

Facial Photos

Facial photo data are commonly collected for the assessment of facial aesthetics and to compare changes before and after treatments aimed at enhancing appearances (Fig. 2 and Table 3, Ref. [31–37]). Patcas *et al*. [31] utilized a CNN trained on thousands of photos from dating websites to evaluate changes in facial attractiveness and apparent age based on images captured before and after orthognathic surgery.

Similarly, Zhang *et al*. [32], through the use of patient face images, employed four public convolutional neu-

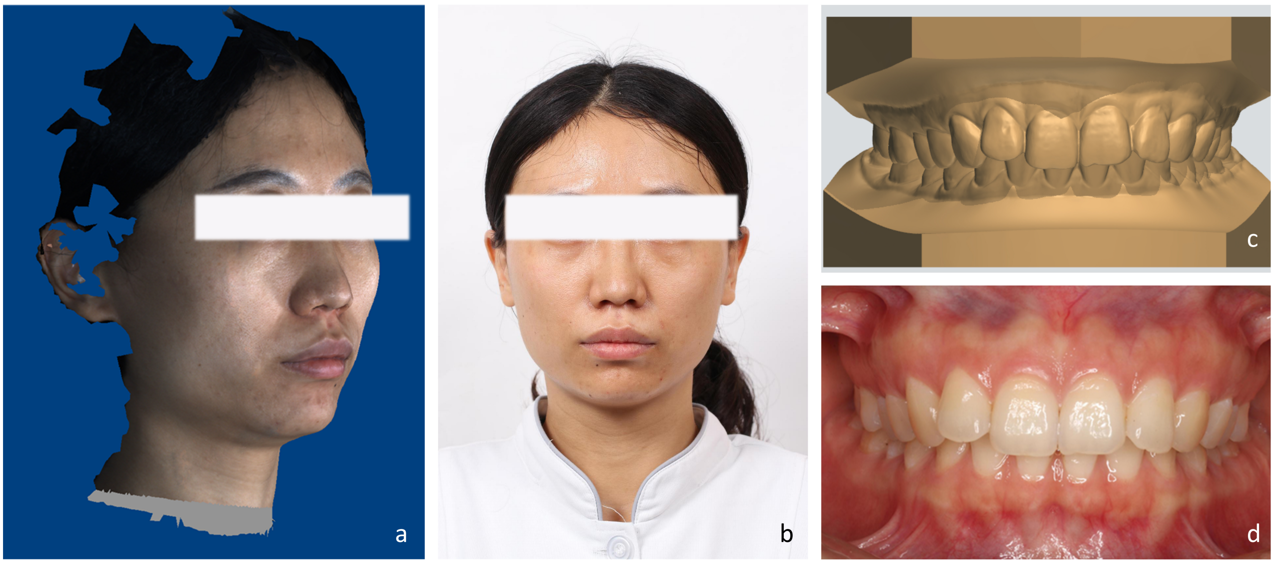

Fig. 2. Dental photography imaging data which are commonly used in orthodontics. (Department of Orthodontics, School of Stomatology, Air Force Military Medical University, Nov.14th 2021) (a) Three-dimensional facial scanners (3DMD face system, Atlanta, GA, USA). (b) Facial photos (Canon EOS 80D, Tokyo, Japan). (c) Intraoral scanners (3shape Trios 3 scanners, Copenhagen, Denmark). (d) Intraoral photos (Canon EOS 90D, Tokyo, Japan).

ral networks (FacePlusPlus, Amazon, Microsoft, and IBM) to estimate the reduction in apparent age following plastic surgery. Exploiting artificial intelligence systems for the objective evaluation of facial symmetry and aesthetics, Hidaka *et al.* [33] used an AI system to analyze facial photos of individuals treated with mandibular joint resection. When comparing photos from the group undergoing temporomandibular joint reconstruction surgery with those of the group retaining the original condylar, the results indicated no significant differences in terms of aesthetics and function between the two groups.

Several studies have explored the prediction of virtual profiles post-surgeries with the assistance of a DL-based algorithm (Table 3). Ter Horst [34] employed DL in conjunction with 3D photographs obtained using a stereophotogrammetric camera and CBCT before and after mandibular advancement surgery. Their 3D virtual soft-tissue simulation achieved a mean absolute error of the lower face region of 1.0 ± 0.6 mm and a root-mean-squared error of 1.2 ± 0.6 mm.

Through facial photos, artificial intelligence systems can also diagnose diseases (Table 3). Although these photos can only capture part of the lesion information on a two-dimensional level, the accuracy of clinical decisions made by AI is often comparable to those made by human experts. Zhang *et al.* [35] established a CNN model with 3932 intraoral photos to automatically detect caries in oral photos (AUC = 86.65%). The CNN established by Warin *et al.* [36] can detect and classify oral precancerous lesions in oral photographs, with a sensitivity of 100% and a specificity of 90%.

Intraoral Scans

Beyond 2-dimensional data, including X-rays and photos, facial and intraoral scans can provide high-precision 3-dimensional data for doctors. In Omnia's [38] research, the intraoral scanners they employed could capture tooth details of less than 10 microns. Utilizing unique texture features such as contours, dimensions, bite marks, and more, the automated convolutional neural network can aid in biometric identification for forensic and prosthetic applications. Nozomi [39] also developed an artificial intelligence-based algorithm using intraoral scans, significantly reducing the time required for identifying antemortem records compared to conventional forensic dentistry methods.

Intraoral scans can provide precise 3-dimensional (3D) anatomical details of crowns and gingiva, while CBCT offers 3D representations of bone-teeth-jaw structures. However, the widespread use of CBCT is constrained by the limitation of radiation exposure. A novel approach leverages the complementarity between intraoral scans and CBCT through crown registration and root segmentation [40,41]. By supplying intraoral scan and CBCT data to artificial intelligence algorithms, the tasks of registration and segmentation can be efficiently and accurately executed by dental artificial intelligence systems (DAIS) [42,43]. Additionally, intraoral scans can complement periodontium morphology with CBCT. Yang *et al.* [44] introduced an AI-based technique for measuring gingiva thickness and classifying gingival phenotypes by overlaying the CBCT scan with the intraoral scan.

By comparing intraoral scans before and after treatment, dentists can readily assess the movement of teeth,

Table 3. Dental artificial intelligence systems based on facial photos.

Authors	Year	Purpose	Treatment	Total image database	Neural network architecture
Patcas *et al*. [31]	2019	Comparison of attractive and apparent age	Orthognathic surgery	146	VGG16
Zhang *et al*. [32]	2021	Recognition of age reduction	Plastic surgery	50	four public convolutional neural networks (FacePlusPlus, Amazon, Microsoft and IBM)
Hidaka *et al*. [33]	2023	Analysis of Mandibular Asymmetry	TMJ Reconstruction	10 CR 18 CP	A public AI algorithm
Horst *et al*. [34]	2021	Prediction of the virtual soft tissue profile	mandibular advancement surgery	133	A custom-made DL-based model
Zhang *et al*. [35]	2022	Diagnosis of caries	——	3932	Adapted from Single Shot MultiBox Detector (SSD) [37]
Warin *et al*. [36]	2022	Diagnosis of oral precancerous lesions	——	600	Classification: DenseNet-121 and ResNet-50 Detection: Faster R-CNN and YOLOv4

TMJ, Temporomandibular Joint; CR, condylar resection; CP, native condyle preservation.

playing a crucial role in return visits. Recently, a novel AI-based method has enabled the remote monitoring of clear aligner therapy. Data for this monitoring were supplied through a smartphone application rather than traditional intraoral scanners. Despite potential disparities between decisions made by DAIS and experts, this approach may offer a viable solution for remote monitoring [45,46].

Data from Clinical Information

Extraction of Measurement Indicators

To attain a multimodal representation in the model, crucial indicators must initially be extracted from the original data. However, utilizing indicators instead of the original images presents a contradiction. On one hand, multimodal fusion stands as a crucial approach to enhancing the model's accuracy. On the other hand, the involvement of human experts in selecting parameters may heavily depend on the experts' experience, potentially restricting the role of AI in further increasing accuracy.

Takada *et al*. [47] pioneered the development of a mathematical model to assist orthodontists in optimizing tooth-extraction decisions for malocclusion cases lacking objective standards. They selected 27 feature variables from medical records, dental casts, and lateral and posteroanterior head films. The model's outputs coincided with actual treatment at a rate of 90.4%. Addressing the same issue, Xie *et al*. [48] employed a neural network with 23 quantification indices and 2 non-quantification indices, achieving an 80% success rate with 20 test samples.

Jung *et al*. [49] selected 18 indicators of soft and hard tissue measurements to train another backpropagation neural network. This model not only provided tooth extraction decisions but also specified the tooth extraction position, achieving a decision-making success rate of 93% across training, test, and validation sets. Li *et al*. [50] and Suhail *et al*. [51] constructed similar artificial neural network (ANN) models using 24 and 19 feature variables, respectively. Li's model could output teeth extraction patterns and corresponding anchorage patterns, while Suhail's work expanded teeth extraction patterns from 4 to 14 options. Research employing different indicators and artificial intelligence models can aid in tooth extraction decisions and align closely with expert judgment [52,53].

In addition to addressing tooth-extraction issues, Thanathornwong *et al*. [54] selected 15 variables and employed Bayesian networks (BN) as the base model to assess the necessity of orthodontic treatment. Bianchi *et al*. [28] utilized 52 variables from CBCT, clinical information, and laboratory tests as input for XGBoost and LightGBM models to achieve an 82.3% accuracy in the early diagnosis of temporomandibular joint osteoarthritis.

Electronic Health Records

A human medical expert relies on retrieving information from basic medical records, including age, sex, and medical history, for accurate diagnosis. AI systems that rely solely on imaging data may suffer from reduced accuracy due to missing information. The efficiency and data comprehensiveness can be ensured by combining electronic health records (EHR) with artificial intelligence. However, a challenge lies in the fact that basic information is often presented in the form of natural language. The crucial step in integrating medical records with AI models is the transformation of natural language into a structured format that algorithms can comprehend. Refer to Fig. 3 for a schematic diagram of the entire process.

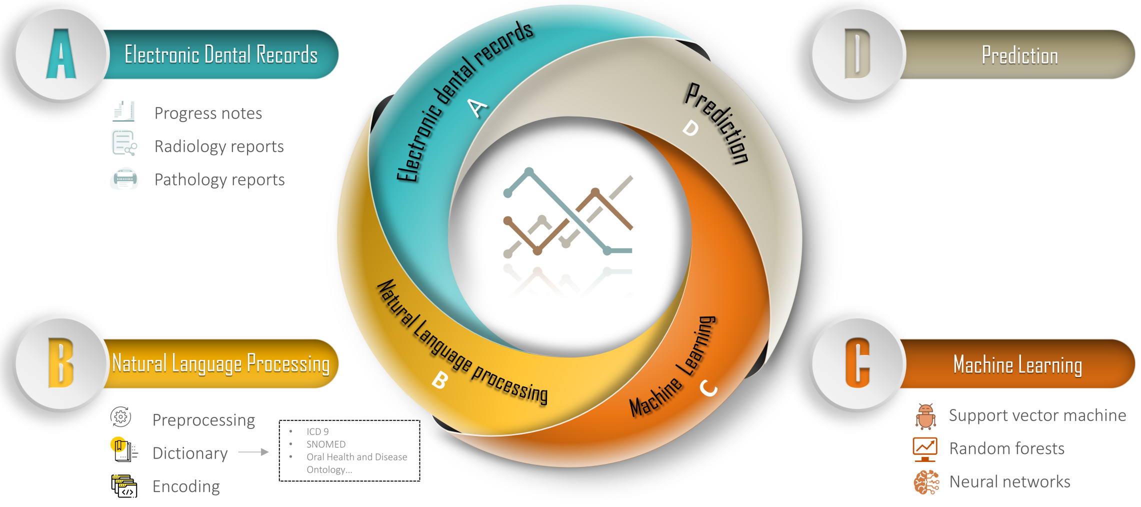

Fig. 3. Sequential phases of the natural language process. (The diagram was created by Microsoft PowerPoint software 365, Redmond, WA, USA. with vector drawing materials sourced from Alibaba Vector Gallery. All materials are licensed for commercial use).

One method involves compiling a list of common terms [55]. This encompasses a list of target terms (i.e., International Classification of Diseases Codes ICD-9 and ICD-10), and a list of modifiers (i.e., words that modify the target terms, including negative words, time, family members, anatomical location, etc.). In the transformation of the doctors' medical records into structured language, only sentences containing at least one target term (as an entity) are selected, deeming other medical records as irrelevant information. Some studies have directly employed open-source natural language processing (NLP) systems directly, with cTAKES being the most widely used system developed by the Mayo Clinic. For instance, in a study exploring new associations between sleep apnea and diseases through electronic health records [56], cTAKES was utilized to process natural language data.

Unfortunately, ICD codes lack specificity for dentistry. To integrate an electronic dental record system with AI and establish electronic dental record (EDR)-based clinical decision support systems (CDSS), it becomes imperative to institute a dental coding system. Several proposals and revisions for dental coding systems have been put forth since the 1920s, but currently, only two persist: SNOMED and its subset, which require access permission, and the open-source Oral Health and Disease Ontology. Additionally, there are other standardized diagnostic coding systems developed by dental faculty members, initially applied to the school's dental practice first with the hope of expanding their usage to clinics [57].

While there have been limited developments in AI models for dentistry utilizing Electronic Health Records (EHRs), significant strides have been made in other medical domains [55,57]. It is foreseeable that the continuous enhancements in EDRs and standard coding systems will create more opportunities for the advancement of dental AI.

Data from Wearable Devices

With the remarkable advancement of medical sensors and electronic chips, wearable devices have emerged as novel data sources, facilitating the exploration of more DAIS. Possessing wearable characteristics, devices like wristwatches, glasses, chest straps, rings, and prosthetic sockets can capture various human signals and convert them into data formats compatible with AI systems (Fig. 4).

Among various data types, electromyography signals stand out as one of the most advanced data with practical applications in acute disease prediction and physical therapy [58–60]. The provision of chin electromyogram signals for deep learning models has led to the development of a simpler and faster method for obstructive sleep apnea (OSA) diagnosis [61–63].

Various types of sensors can collect data for monitoring. Gao *et al*. [64] integrated a stress sensor into a splint for occlusion stabilization to acquire occlusal force data. A machine learning algorithm was employed for data processing and parameter configuration. The intelligent occlusion stabilization demonstrated its feasibility for bruxism diagnosis and treatment. Sebkhi *et al*. [65] utilized permanent magnet sensors for tongue tracking, with the tracking module embedded in a headset as part of their system.

Discussion

The Problems in the Database Construction and Possible Resolutions

To enhance the effectiveness of AI models supporting experts in clinical decision-making, improving the quality and quantity of data is crucial. Presently, databases in the field of stomatology encounter various challenges.

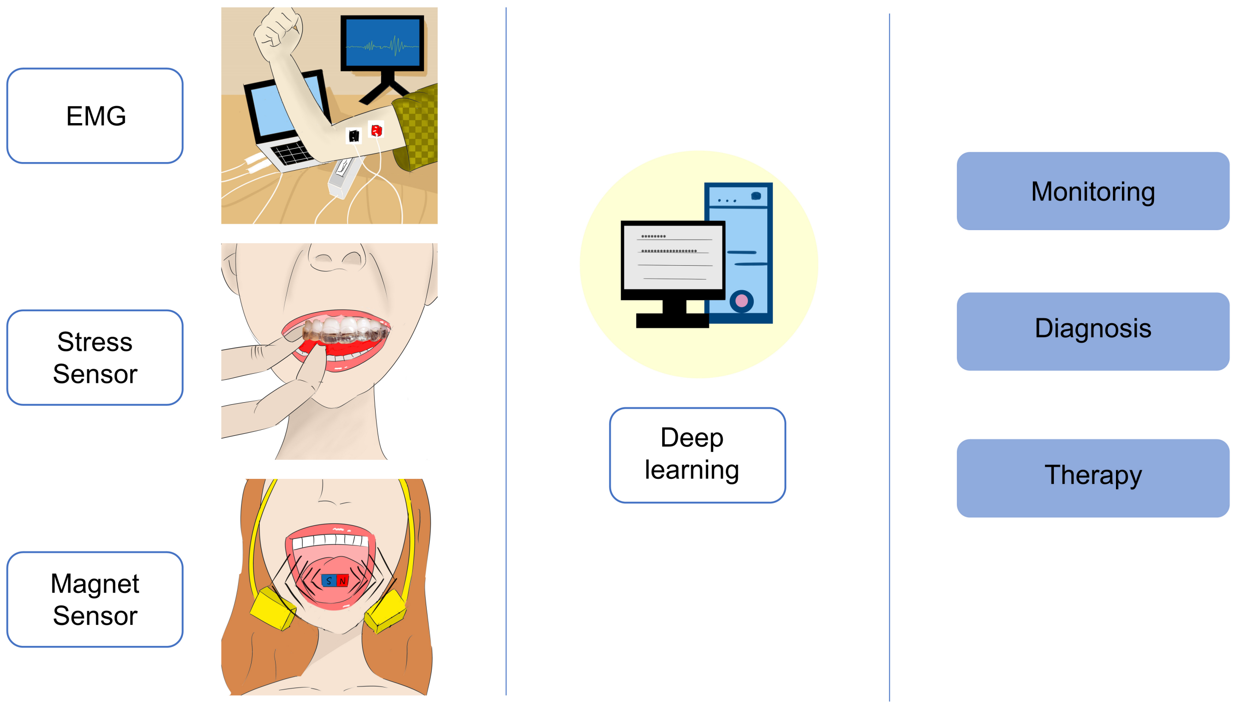

Fig. 4. Data sources from wearable devices. (Drawn by Paint Tool SAI Ver.1.2.5, SYSTEMAX, Tokyo, Japan).

Primarily, most shared dentistry databases are designed for Caucasian populations. Notable databases include the Tufts Dental Database (TDD) [66], comprising 1000 panoramic X-ray films with marked regions of interest in teeth, upper and lower jaw, and the BigMouth shared database [57], providing data from ten medical institutions covering over 3 million patients, contributing to numerous clinical research efforts by four dental schools.

However, other regions need to establish open and shared databases tailored to their specific racial backgrounds. For example, most studies in China rely on single institutions, with limited data availability in published papers. The reluctance to share data impedes model updates, and reliance on data from a single institution introduces bias based on doctors' diagnostic criteria, potentially undermining credibility. It is crucial to open the databases to the public, fostering collaboration for multicentral research efforts.

Secondly, the training model needs a large amount of data, making data annotation a labor-intensive task. Relying solely on a few experts for all data annotation work is challenging. Leveraging crowdsourcing workers through online platforms proves effective in significantly reducing labeling time. These workers can convert unstructured text from EHR into structured data directly used in supervised learning models [67,68] and can assist in classifying imaging data [69].

Although concerns were raised that the participation of these "non-specialists" potentially impacting annotation accuracy, indicate that, with careful interface design and strict quality control, no statistical difference exists between the annotation tasks completed by crowdsourcing workers and those done by experts. In fact, the time and quality of completion have been shown to improve.

Thirdly, utilizing a single data type is akin to the approach of human experts. Just as human experts benefit from comprehensive considerations, the accuracy of AI diagnosis results tends to improve when transitioning from a single modality to multimodality [70]. In many fields, including galactophore [70], ophthalmology [71,72], neurology [73], and other disciplines, the achievement of multimodal information fusion and complementarity is evident. While the dental field has progress to make, there have been significant advancements in dental auxiliary examinations in recent years, expanding beyond traditional X-ray examinations. CBCT and digital intraoral scanning are now routine examination items. Establishing an AI model that integrates various modalities of data could potentially enable information fusion between bone and soft tissue, crown, and root, among other aspects.

Fourthly, the data integrity is unsatisfying. A study conducted in the United States in 2000 showed that 9.4% to 87.1% of EDR patients had incomplete clinical records [74]. Clinicians must ensure the highest level of completeness in each medical record for professional integrity and clinical research. Besides, the medical record system should be highly efficient so that doctors can spend the minimal time completing the records, especially during periods of heavy clinical workload. Xu *et al*. [75] addressed this challenge by integrating a voice recognition system with a universal electronic medical record system, facilitating the ease of medical record documentation, even when doctors' hands are occupied.

The Outlook for Interdisciplinary Integration between Medicine and Engineering

As an emerging discipline, the field of medical engineering holds significant potential for development. Unlike the relatively mature development model in pharmaceutical research, which involves "clinicians-clinical trial organization-pharmaceutical companies", the collaboration between "clinicians-software engineers-medical device companies" is still in the early stages. It's crucial to acknowledge that this field is rapidly evolving, encompassing both scientific advancements and clinical implementation. The following perspective outlines an effective development model in medical engineering.

First and foremost, hospitals should implement a comprehensive electronic health record system and an intelligent joint database as the fundamental basis for the rapid advancement of DAIS. Integrating AI plug-ins into the hospital's electronic information platform can significantly contribute to this objective by automating the classification of medical data and extracting necessary information from records [76]. Moreover, the integration of multi-center data plays a pivotal role in enhancing the robustness and generalizability of DAIS. Leveraging federated learning technology helps safeguard patient privacy regarding their medical records while ensuring information security during big data exchanges [77].

Secondly, clinicians should systematically propose clinically relevant needs for DAIS, ensuring a balanced approach that integrates both medical and engineering perspectives. Striking this balance involves avoiding an overemphasis on accuracy at the expense of clinical significance or favoring clinical practice to an unattainable extent. Achieving this equilibrium requires effective communication and close collaboration between clinicians and algorithm engineers, particularly in the era of the "black box effect" caused by deep learning.

Subsequently, physicians must meticulously undertake precise data labeling, with an ideal scenario being the availability of datasets to the public. In most medical research cases, the "crowdsourcing model" is unsuitable due to the stringent requirements on data labeling, necessitating experienced doctors for this critical and intricate task. Although the sample size labeled in existing studies has often been inadequate, incorporating intelligent auxiliary software to streamline the annotation process could potentially address this limitation.

The next step involves back-end algorithm engineers establishing an artificial intelligence network architecture, training the model for accurate input-output mapping, and then software engineers integrating the algorithm into a user-friendly interface for clinicians. Ultimately, scientific research findings will evolve into products that can be marketed by medical AI companies, clear aligner companies, or other oral device manufacturers for advanced AI research and development.

This model has already been implemented in certain areas of dentistry, such as automated cephalometric positioning and data classification. The anticipation is that artificial intelligence integration will extend to various other domains, encompassing oral disease detection, evaluation, diagnosis, prediction, and efficacy assessment. This development is expected to significantly aid healthcare professionals and elevate the overall standard of medical care.

Availability of Data and Materials

All data are available upon request from the corresponding authors.

Author Contributions

RZ performed the literature searching, literature analysis and manuscript writing. HC contributed to literature searching. ZJ and YM provided help and advice on literature analysis. All authors contributed to the conception and design. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Ethics Approval and Consent to Participate

The study protocol adheres to the principles outlined in the Declaration of Helsinki. Informed written consent was obtained from all patients and their families, explicitly authorizing the utilization of orthodontic records for research purposes and granting permission for publication.

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Conflict of Interest

The authors declare no conflict of interest.

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