Review Article

University J Dent Scie 2025; Vol. 11, Issue 2

Artificial Intelligence in Periodontics- A Review

Abstract:
Early detection of supporting periodontal tissue destruction is crucial and beneficial for establishment of the correct diagnosis and prognosis for better patient management. There is a significant amount of inter-observer heterogeneity in the way that clinicians now evaluate radiographs. The concept of machines being able to carry out human functions is known as "artificial intelligence" (AI). In order to maximize the use of these multi-level data and comprehend their interaction, AI enables the integration of many heterogeneous data domains, such as medical/dental history, socio-demographic and clinical data, imaging data, biomolecular data, social network data, etc. Data proving use of AI in dentistry and oral care needs to be reinforced. Technological approaches like federated learning should be actively applied to dental AI tasks, and harmonization of data to improve interoperability should be actively pursued.

Key-words: Artificial intelligence, Machine learning, Deep learning, AI task, Periodontics and human autonomy

Introduction:

Artificial Intelligence is one of the most significant contributions of the new digital era brought about by the fourth industrial revolution. Built-in machines that can execute tasks that are typically performed by humans are referred to as artificial intelligence (AI), a term that was first used in the 1950s.

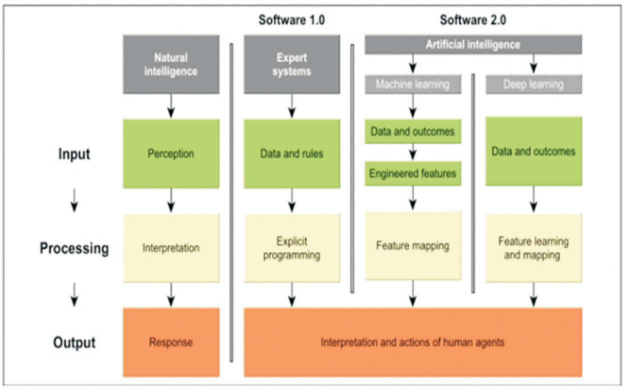

Figure 1: Perception, interpretation, and bodily reaction are the traits of natural intelligence. Contrarily, machine intelligence mostly aids human interpretation and action rather than replacing it as of now. Rules-based expert systems underpin traditional software (1.0), one of the pillars of computer intelligence. They use data and explicitly specified logical rules to produce specific, limited results, exceeding humans in these tasks. Instead, Software 2.0 infers the rules based on data and results: Regression modelling, where characteristics are first designed by human specialists and subsequently learned. Without the need for human feature engineering, pertinent features are learned and mapped in a single step in deep learning; (2019) Kolossváry et al [1]

"Barr and Feigenbaum" define AI as the branch of computer science that focuses on creating intelligent computer systems that display traits associated with intelligence in human behavior, such as grasping language, learning, reasoning, problem solving, and many more [2].

Access this article online

Website: www.ujds.in

Quick Response Code

DOI: https://doi.org/10.21276/ujds.2025.v11.i2.17

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Received : 31 Dec., 2024, **Published :** 30 June, 2025

How to cite this article: kapoor, D. A., Soni, D. P., & Soni, D. S. R. (2025). Artificial Intelligence in Periodontics- A Review. UNIVERSITY JOURNAL OF DENTAL SCIENCES, 11(2).

History:

Alan Turing wrote in his paper "Computing Machinery and Intelligence" (3) in the 1950 issue of Mind: "I believe that at the end of the century (20th), Words and the general consensus of educated opinion will have changed to the point where discussing machines thinking won't be met with resistance.

Turing described AI as "machines thinking". He proposed that "humans solve problems and make decisions by utilising available information and inference, machines *also can do the same thing"*.[3]

Turing proposed a test to determine if a machine is capable of reaching human-level intelligence (*Turing Test)*.

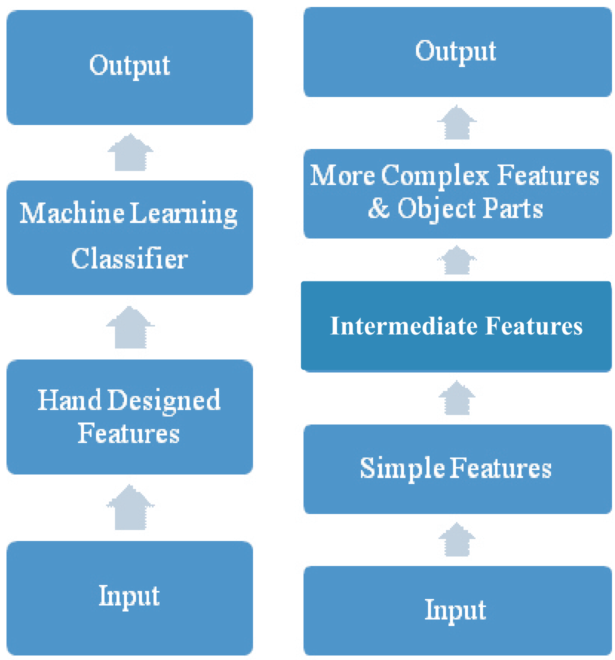
In 1955, John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon organized the two-month Dartmouth Summer Research Project on Artificial Intelligence[4], where the term AI was first introduced.

Examples of AI include: **Deep Blue**-a chess-playing expert system, **Google's AlphaGo**(2017) **ChatGPT (2022).**

Classification:

Nowadays, when we talk about artificial intelligence we often refer to ***machine learning (ML)*** and ***deep learning (DL):***

a) Machine learning b) Deep learning



ML can be classified as ***supervised, semi-supervised and unsupervised*** learning based on ***the theory of the methods***.\

The difference between ML and DL is the **feature extraction**, i.e. the procedure for converting unprocessed data into numerical characteristics so that the information in the original data set may be processed(5).

Ai In Dentistry:

The most often used application of AI in dentistry is diagnosis. AI can make more accurate and efficient diagnoses, thus reducing dentist's workload.

Ai In Operative Dentistry:

Dentists used to employ radiographic or visual-tactile examinations to identify caries. When deep fissures, strong interproximal contacts, and secondary lesions are present, it is occasionally difficult to detect lesions in the early stages. Eventually, a lot of lesions are only found when dental caries grows worse, requiring a more involved course of care.

AI system by **Fukuda M (2020)[6]** for detecting vertical root fracture on panoramic radiography, **Setzer FC (2020)[7]** detection of periapical lesions in CBCT images, **Jaiswal P (2021)[8]** classification of tooth wear, **Lee J-H (2018)[9]** detection and diagnosis of dental caries, **Kühnisch J (2021)[10]** caries detection on intraoral images.

AI in Orthodontics:

It takes a lot of effort for orthodontists to diagnose malocclusion, as many variables need to be considered in the cephalometric analysis to determine the treatment plan and predict outcome[56].

Based on AI **Tanikawa C (2021)[11]** predict facial morphology after orthognathic surgery, **Thanathornwong B (2018)[12]** assessed the needs for orthodontic treatment, **Park J-H (2019)[13]** automated identification of cephalometric landmarks, **Yu H (2020)[14]** automated skeletal classification with lateral cephalometry, **Cui Z (2022)[15]** tooth and alveolar bone segmentation from CBCT images.

AI in Oral and Maxillofacial surgery:

Statistics from the WHO show that every year there are over 657,000 patients diagnosed with oral cancer globally, among which there are more than 330,000 deaths[16].

With AI **Choi E (2022)**[17] position between mandibular third molar and inferior alveolar nerve on panoramic radiography, **Aubreville M (2017)**[18] Automatic classification of cancerous tissue in laserendomicroscopy images of oral cavity, **Warin K (2022)**[19] analysis of oral lesions for early detection of oral cancer, **James BL (2021)**[20] Validation of a point-of-care optical coherence tomography device for detection of oral potentially malignant and malignant lesions, **Heidari AE (2020)**[21] distinguish normal and abnormal oral mucosa, **Poedjiastoeti W (2018)**[22] diagnosis of jaw tumors.

AI Tools in Periodontics:

Periodontitis is one of the most widespread diseases and if untreated, can lead to tooth mobility and even tooth loss[23]. Early detection and treatment of periodontitis is necessary to prevent severe cases.

1) Haptics-based virtual reality periodontal training simulator (Luciano et al)

This was the first haptics-based dental simulator, exclusively for Periodontics. This simulator helps students develop the necessary skills to diagnose and treat periodontal diseases. A haptic device along with 3D images of upper and lower teeth along with gingival, can be felt by "touch". When employing dental instruments, the haptic feedback that generates simulates the clinical feel of an operator's hand. **Steinberg et al (2007)** incorporated recording and playback of the trainee's performance. The simulator was designed to reduce class duration and enhance the learning curve.[24]

2) Ultrasonographic periodontal probe Companion et al (1998) :

Published the results of an ultrasonographic periodontal probe at NASA Langley. The probe was intended to reduce the pain and inaccuracy that is common in manual probing. In order to couple the ultrasonic beam into the tissues, it contains a hollow conical tip filled with water. So as to mimic ultrasonic propagation in the tip and the intricate geometries of the periodontal tissues, **Kevin Rudd et al. (2009)** used a 3D parallel acoustic finite integration technique. The periodontal tissue structures and the tip's 2D and 3D geometry are then created by software, which also runs simulations to generate data that is realistic and echoes in accordance with which echoes corresponding to the periodontal pocket depths.[25]

3) Artificially intelligent olfaction in halitosis:

Breath analyzers have been developed to replace the subjective organoleptic assessment.

The major drawbacks of assessment of VSCs alone, is that

1) Bad breath does not disappear just because VSCs are not present;
2) Non-sulfur volatile compounds, found in upto 15% of halitosis cases are ignored.

Artificial Olfaction, is a non-invasive technique, assess the full spectrum of exhaled volatile compounds **(Barash et al, 2009; Haick et al, 2014; Nakhleh, Broza et al, 2014)**. It consists of an array of sensors, based on nanomaterials, that semi-selectively and/or collectively assess the composition of exhaled breath using analysis software and a database of breath patterns and then is processed toward a pattern-recognition application. A decision tree classifier determines whether the subject suffers from oral or extra-oral halitosis and in the second case, draw association to different systemic diseases. **Nakhleh et al 2017** reported 20 functionalized nanomaterials-based sensors designed to successfully distinguish among 17 different systemic diseases, by analysing exhaled breath with an overall accuracy of 86%[26]

4 Differentiation between aggressive and chronic periodontitis:)

Feres et al 2017, tested the hypothesis by using 40 bacterial species of the subgingival microbial complexes and a linear Support Vector Machine based classifier to differentiate between Generalised AgP and Generalised CP.[27]

5) Automated segmentation of gingival diseases from oral images:

Rana et al 2017 reported a machine learning classifier that could distinguish between inflamed and healthy gums. After irradiation with light of 405-450 nm wavelength, the corresponding fluorescence from biomarker porphyrin was recorded using an oral imaging device. Plaque was displayed in shades of yellow whereas inflamed gums displayed in shades of magenta and red.[28]

6) Automated procedure utilizing machine learning segmentation and systemic health-oral disease correlation:

Rana et al 2019 reported an automated process that combines the aforementioned intra-oral fluorescent porphyrin biomarker imaging, clinical examinations and machine learning to correlate systemic and periodontal health. Here, intra-oral images were collected, segmentation was done using the aforementioned classifier and then analysis of co-occurrence rates between subject's Modified Gingival Index and three other sources of screenings like a self-reported medical history questionnaire, Blood Pressure (BP) and Body Mass Index (BMI) as well as single-lead ECG, optic nerve disorders etc were performed.[29]

7) Diagnosis and prediction of periodontally compromised teeth:

Lee et al 2018 started a computer-aided recognition system. In order to evaluate the diagnosis and prediction of periodontally compromised teeth (PCT), a prelabeled periapical radiograph dataset was provided. The diagnostic accuracy for PCT was 81.0 % for premolars and 76.7 % for molars and that for predicting extraction was 82.8% for premolars and 73.4% for molars. The results of study showed similar diagnostic and predictive accuracy to that obtained by a board certified Periodontist.[30]

8) Diagnosis of periodontal bone loss using deep learning:

Krois et al 2019 used AI to discover periodontal bone loss on panoramic dental radiographs. Results showed that given the limited dataset of radiographic image segments, the trained AI software showed at least dentist like discriminating power to assess PBL on panoramic radiographs. The authors believe that the applicability and accuracy of CNNs can be improved by integrating more imaging.[31]

9) Huang W et al (2020):

Assessed simultaneously and quantitatively the expression levels of 20 periodontal disease-related proteins in GCF from normal controls and severe periodontitis (SP) patients with an antibody array. Seven proteins (CRP, IL-1α, IL -1β, IL-8, MMP-13, osteoprotegerin, and osteoactivin) were significantly upregulated in SP patients compared with NOR, while receptor activator of nuclear factor-kappa was significantly downregulated. The highest diagnostic accuracy was observed for IL-1β. Osteoprotegerin, osteoactivin, MMP-13, IL-1β, and IL-8 were the five proteins that were found to be significant characteristics for classification. Linear discriminant analysis showed highest accuracy across the five classification models that were tested. Study highlights the potential of antibody arrays to diagnose periodontal disease[32].

Applications In Implantology:

1. **Sadat et al (2016)** developed a hybrid method to predict dental implant success and presented a combined predictive model with various classifiers like Neural networks, SVM, W-J48, K-NN. The results showed, performance of the combined classifiers were better than a single classifier with increase in sensitivity by up to 13.3 %.[33]

2. Lerner and associates (2020) a process for fabricating monolithic zirconia crowns (MZCs) supported by implants and cemented to separate hybrid abutments using artificial intelligence. Here, CAD and AI were used to design the crown. It was time saving, reduced the possibility of errors and the costs of prosthetic therapy. A retrospective study of 106 implant-supported MZCs was performed and a 3-year survival and success rates of the MZCs were 99.0% and 91.3% respectively.[34]

3. Sometimes, the dentist is unable to solve the implant related issues, therefore, a need to identify the implant systems without depending on the dentist's knowledge or experience. **Takahashi et al 2020** successfully conducted a study using a AI based object detection software to identify implant systems from panoramic radiographs.[35]

Challenges During The Development Of Ai For Health Applications:

1. **Bias:** Data may suffer from biases introduced during the data collection, data being collected from only a few populations. For *example*, in the USA, the majority (71%) of AI for health applications were trained on data from three states: California, Massachusetts, and New York[36].

Data generated in clinical routine may itself suffer from **confounding bias**. In a recent study on radiographs to classify the severity of COVID-19 from chest radiographs, standing and lying patients were included. Because lying patients by large suffered from more severe disease, the model erroneously learned to classify severity according to the patient's position.[37]

2. Accessibility:

Biases and limited generalizability are often grounded in the overall limited and selective accessibility of data. In many cases, data is not available due to data protection reasons. A range of approaches to broaden the access to health data, improving AI performance, fairness.[38]

3. Interoperability:

Limited interoperability of healthcare data remains a significant hurdle. The **two major aspects** to consider are:

Syntactic interoperability:

Defines the format and structure of data. It is backed by the International Standards Development Organizations such as Health Level Seven International (HL7) and its Fast Health Interoperability Resource (FHIR).

Semantic interoperability:

Is ensured by agreed terminologies, nomenclatures, and ontologies being employed, such as SNOMED CT, the Logical Observation Identifiers Names and Codes or the identification of Medicinal Products for medicines.

None of these theories are really well-liked or well accepted in the field of oral and dental research. Even terminologies and classifications defined by dental experts themselves are not necessarily adopted or interchangeably usable. An *example* is differing the WHO and the International Caries Detection and Assessment System criteria for caries diagnosis.[39]

4. Authenticity:

It is frequently the case that a hard gold standard, like histological examination, is unavailable. Instead, multiple human annotators provide the reference test for *example* towards the presence of pathology on an image.

Here, aspects around usefulness, acceptability, implementation, and maintenance of the resulting software product are relevant. For *example*, during the COVID-19 pandemic, hundreds of models were developed to predict the risk for COVID-19 but none have been found clinically useful by a recent systematic review.[37]

GOVERNANCE

WHO's Consensus Principles on AI:

WHO (2021) guidance provides six consensus principles to ensure that AI works for people's benefit:

1. **Preserve human autonomy:** Using AI or other computer systems shouldn't take away person's sense of self.
2. **AI must not harm people:** Regulatory requirements and, generally, governance are needed to ensure the safety, accuracy, and efficacy of AI for health.
3. **Ensuring transparency, explain ability, and intelligibility:** AI-based technologies must be understandable to developers, medical professionals, patients, users, and regulators. AI must be sufficiently documented prior to clinical implementation, and all methods or processes should allow humans to understand and trust the results.
4. **Fostering responsibility and accountability:** Humans require clear, transparent specifications of the tasks that an AI can perform and the conditions under which the AI can achieve this task. Humans should supervise the AI upstream, and downstream accountability remains with the human user.
5. **Ensuring inclusiveness and equity:** AI for health should ensure the widest possible appropriate, equitable use and access, irrespective of age, sex, gender, income, race, ethnicity, sexual orientation, ability, or other characteristics protected under human rights codes.
6. **Encouraging sustainable and responsive AI:** To be responsive, AI technologies must be adequately monitored in real-world applications in a methodical, transparent, and ongoing manner. Sustainability also requires governments and companies to anticipate and address the disruptions caused by the implementation of AI technologies.

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