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A review of the use of artificial intelligence in orthodontics

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Abstract

The clinical use of artificial intelligence technology in orthodontics has increased significantly in recent years. Artificial intelligence can be utilized in almost every part of orthodontic workflow. It is an important decision-making aid as well as being a tool for building more efficient treatment methods. The use of artificial intelligence reduces costs, accelerates the diagnosis and treatment process and reduces or even eliminates the need for manpower. This review article evaluates the current literature on artificial intelligence and machine learning in the field of orthodontics. The areas that the artificial intelligence is still absent have also been discussed in detail. Despite its shortcomings, artificial intelligence is considered to be a fundamental part of orthodontic practice in the near future.

Keywords: artificial intelligence, digital orthodontics, machine learning, orthodontics

1. Introduction

Digital data processing technologies in medical and dental fields have gained attention in the last two decades. Utilization of digital technology, especially artificial intelligence (AI) technology, can help to reduce the cost and duration of treatment, the need for human expertise and the number of medical error cases. This approach also has a revolutionary potential in public health scenarios in developing countries.

Artificial intelligence, which was brought forward by McCarthy in 1956, can be described as the behavior of the non-biologic beings which has the capacity to perceive complex environments, learn and react accordingly (Nilsson and Nilsson, 1998). Artificial intelligence does not necessarily mimic the human brain, it is rather a problem-solving tool which has its own set of rules. Studies have been conducted to achieve human-like behaviors with AI and it has been found that computers exceed human results in many parameters (Faber et al., 2019). Artificial intelligence technology has been used in a wide spectrum from differential diagnosis and radiographic interpretation to restorative treatment in dental field (Khanna, 2010). Dental management software, which uses AI to gather and store the patient data, is available in the market. In this point, artificial intelligence can be used to generate complete detailed virtual databases which are easily accessible. Interactive and voice recognizing interfaces help dental clinicians to easily complete some complex tasks. Software with AI technology can document the necessary data and transfer them to the clinician faster and more efficiently than its human counterparts (Kannan, 2017). With its unique learning ability, AI can be trained to perform different tasks. It can be integrated into dental imaging systems to identify even the smallest deviations which human eye cannot recognize. With this outstanding ability, it can easily be used to make accurate diagnosis of cephalometric landmarks (Tong et al., 1989).

Artificial intelligence-based software systems have significant and modificative role in the field of orthodontics and they are considered as the future of dental applications. For this reason, we aimed to review the literature on the use of AI technology in the orthodontic field (Table 1). Artificial intelligence is used in every area of orthodontics from patient communication and diagnosis to treatment processes. Orthodontic software programs which use AI technologies are based on "machine learning" technology. "The machine" uses raw data to collect information from a database in machine learning technology. These software programs can analyze diagnostic dental radiographs and photos, also they can give guidance to the dentists, during 3D intraoral scanning, to reach an ideal model easily (Kattadiyil et al., 2014). The use of AI can be divided into two main application areas in orthodontics in particular: diagnosis and treatment (Fig. 1).

2. Artificial intelligence and orthodontic diagnosis

Patient data, carefully obtained from an adequate database containing a detailed list of the patient's problems, form the basis of correct and accurate orthodontic diagnosis. The orthodontic diagnostic database can be obtained from written or verbal interview data; clinical examination and examination of patient records including dental impressions, radiographs, and diagnostic photographs (Proffit et al., 2018).

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Table 1. Current literature on the use of artificial intelligence in orthodontic

Year	Author	Article
2002	Akçam et al.	Fuzzy modelling for selecting headgear types
2006	Noroozi et al.	Orthodontic treatment planning software
2006	Zarei et al.	An intelligent system for prediction of orthodontic treatment outcome
2009	Kim et al.	Prognosis prediction for class III malocclusion treatment by feature wrapping method
2009	Tanikawa et al.	Automated cephalometry: system performance reliability using landmark-dependent criteria
2010	Khanna et al.	Artificial intelligence: contemporary applications and future compass
2010	Mario et al.	Paraconsistent artificial neural network as auxiliary in cephalometric diagnosis
2010	Tanikawa et al.	Automatic recognition of anatomic features on cephalograms of preadolescent children
2010	Xie et al.	Artificial neural network modeling for deciding if extractions are necessary prior to orthodontic treatment
2010	Yagi et al.	Decision-making system for orthodontic treatment planning based on direct implementation of expertise knowledge
2011	Auconi et al.	A network approach to orthodontic diagnosis
2011	Banumathi et al.	Diagnosis of dental deformities in cephalometry images using support vector machine
2014	Buschang et al.	Predicted and actual end-of-treatment occlusion produced with aligner therapy
2014	Yu et al.	Evaluation of facial attractiveness for patients with malocclusion: a machine-learning technique employing Procrustes
2015	Auconi et al.	Prediction of Class III treatment outcomes through orthodontic data mining.
2015	Gupta et al.	A knowledge-based algorithm for automatic detection of cephalometric landmarks on CBCT images
2016	Jung et al.	New approach for the diagnosis of extractions with neural network machine learning
2016	Nino-Sandoval et al.	An automatic method for skeletal patterns classification using craniomaxillary variables on a Colombian population
2016	Wang et al.	Objective method for evaluating orthodontic treatment from the lay perspective: An eye-tracking study
2017	Grünheid et al.	How accurate is Invisalign in nonextraction cases? Are predicted tooth positions achieved?
2017	Kannan et al.	Artificial Intelligence-Applications in Healthcare
2017	Lee et al.	Fully automated deep learning system for bone age assessment
2017	Murata et al.	Towards a fully automated diagnostic system for orthodontic treatment in dentistry
2017	Nino-Sandoval et al.	Use of automated learning techniques for predicting mandibular morphology in skeletal class I, II and III.
2017	Spampinato et al.	Deep learning for automated skeletal bone age assessment in X-ray images
2018	Iglovikov et al.	Paediatric bone age assessment using deep convolutional neural networks
2018	Larson et al.	Performance of a deep-learning neural network model in assessing skeletal maturity on pediatric hand radiographs
2018	Montúfar et al.	Automatic 3-dimensional cephalometric landmarking based on active shape models in related projections
2018	Montúfar et al.	Hybrid approach for automatic cephalometric landmark annotation on cone-beam computed tomography volumes
2019	Faber et al.	Artificial intelligence in orthodontics
2019	Kök et al.	Usage and comparison of artificial intelligence algorithms for determination of growth and development by cervical vertebrae stages in orthodontics.
2019	Patcas et al.	Applying artificial intelligence to assess the impact of orthognathic treatment on facial attractiveness and estimated age
2020	Kunz et al.	Artificial intelligence in orthodontics: Evaluation of a fully automated cephalometric analysis using a customized convolutional neural network
2020	Lee et al.	Deep Convolutional Neural Networks Based Analysis of Cephalometric Radiographs for Differential Diagnosis of Orthognathic Surgery Indications

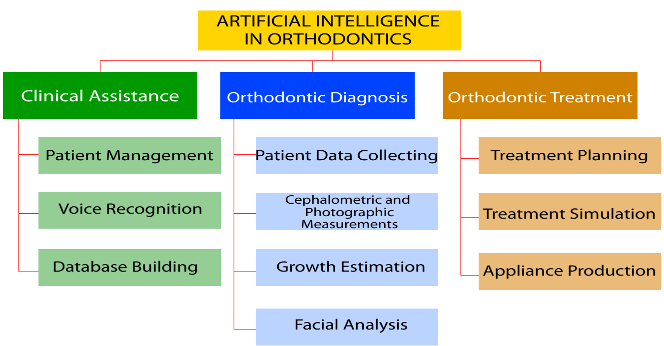

Fig. 1. The areas of orthodontics that artificial intelligence was used

Clinicians experience some time and accuracy constraints in patient evaluation process. For the reason that patient evaluation and getting patient records are time-consuming steps, automation of diagnosis and imaging is essential to increase the speed and accuracy of the evaluation (Murata et al., 2017).

The need of a thorough simultaneous evaluation of different parts of facial structures from different aspects makes orthodontic diagnosis a challenging task. Digital dentistry tools have enabled the collection of patient data on a digital platform and the creation of a digital database that can be used for diagnosis and treatment. Although digital data acquisition accelerated the speed of diagnosis and treatment phases, it still does not eliminate the need for an expert clinician for analysis and decision-making steps (Yagi et al., 2010). The automation systems which use AI and machine learning technologies remarkably have decreased the evaluation workload and prevented the diagnostic variations (Murata et al., 2017).

Different algorithms of AI systems were tested in several studies in the orthodontic field. All these algorithms needed a big database of patient examination records as input. The results showed that the use of AI during diagnosis reduced the need for an expert clinician and the number of diagnostic errors. The researchers concluded that the AI applications were promising in orthodontic field (Kim et al., 2009; Yagi et al., 2010; Auconi et al., 2011;; Niño-Sandoval et al., 2016; Wang et al., 2016; Murata et al., 2017).

Noroozi et al. (2006) described a software which used “fuzzy logic” concept. The software took graphical and numeric patient data as input and could recommend treatment plan for non-surgical orthodontic patients. Fuzzy logic enables the software work with the nominal parameters. Human brain is naturally accustomed to these “fuzzy” parameters. The authors asserted that the software program could suggest treatment options even for the specific situations like missing teeth.

3. Automated cephalometric tracing

Tracing of cephalometric radiographs can either be done manually or digitally with computer aid. Although the use of computers for cephalometric tracing aims to save time by reducing tracking errors and increasing the diagnostic value of cephalometric analysis, the inconsistency in identifying anatomical landmarks is still a major source of random error (Miller et al., 1971).

In order to overcome this problem, efforts have been made to automate cephalometric analysis with the aim of reducing errors and the time required for analysis (Hutton et al., 2000).

Levy-Mandel et al. (1985) conducted the first study on automatic extraction of anatomical landmarks on lateral cephalometric radiographs. They preprocessed the image with an edge-detector and knowledge-based line-following algorithm, involving a production system with organized sets of rules and a simple interpreter, was subsequently applied. Automated cephalometric tracing was subsequently studied by several other researchers and proved to perform as successfully as expert dentists and could be used to accelerate the cephalometric diagnostic phase (Tanikawa et al., 2009, 2010; Mario et al., 2010; Banumathi et al., 2011; Gupta et al., 2015; Montúfar et al., 2018a, 2018b; Kunz et al., 2020). Although AI systems have not been utilized for fully automated cephalometric tracing yet, they have reached the maturity to be used in some existing cephalometric software programs to suggest possible locations of anatomical structures.

Lee et al. (2020) used deep convolutional neural network-based analysis for automated cephalometric tracing. Authors asserted that the developed software had a high success rate (over 90%) in differential diagnosis of cephalometric landmarks. The automated tracing module was integrated into a recent web-based software. The web-based software can also detect soft tissue profile in profile photographs and with its orthognathic surgery planning module, it can simulate possible soft tissue changes after planned orthognathic treatment.

4. Estimation of growth and development

Timing is one of the main components of orthodontic treatment. Growth and development can be estimated by anthropometric indicators like chronologic age, menarche, vocal changes, height increase and skeletal maturation (skeletal age) (Hägg and Taranger, 1982). Radiographs are widely used for detection of skeletal maturation indicators (Hägg and Taranger, 1980). Deep learning (a machine learning algorithm that uses multiple layers to progressively extract higher level features from the raw input) and AI technologies were used by several authors to automate the age estimation by examining hand and wrist radiographs. With deep learning ability, AI systems can evaluate the radiographs after the input of a vast database consists of race, age, and gender. Results show that the AI systems can evaluate the skeletal maturity with a performance like a radiologist (Lee et al., 2017; Spampinato et al., 2017; Iglovikov et al., 2018; Larson et al., 2018).

Maturation levels of cervical vertebrae are also used for assessment of skeletal maturity. Kök et al. (2019) compared seven different, widely used AI algorithms to estimate cervical vertebrae maturation levels. Artificial Neural Networks (ANN) algorithm, which is a mathematical model of human nervous system formed by artificial nerve cells, showed better results. The authors concluded that ANN could be used in the future applications for determining cervical vertebrae stage.

5. Facial proportions

Evaluation of facial proportions includes measurement of ratios and linear lengths between facial structures. Although lateral cephalometric radiographs and profile photographs are widely used for linear assessments, it is difficult to perform sensitive measurements because of the magnification differences. Ratios and angular measurements are independent of dimensions and generally used for photographic assessment.

Measurements of “ideal” facial proportions are currently used by surgeons and orthodontists to comprehend the ideals of beauty and reproduce aesthetically “beautiful” proportions (Harrar et al., 2018). However, the classical rules of ideal facial aesthetics have some deficiencies in reflecting the beauty perception of the population because facial beauty is a very subjective concept and there is not widely used and validated set of rules for facial aesthetics, which is approved by the population. (Knight and Keith, 2005; Yin et al., 2014).

Today, AI applications do not only perform basic tasks such as optical facial recognition, but they are also matured enough to simulate much complex cognitive tasks including analysis and interpretation of facial data. Studies in this field showed that AI systems seemed to be promising tools to build a validated formula for the human perception of facial attractiveness (Patcas et al., 2019; Yu et al., 2014).

6. Artificial intelligence and orthodontic treatment planning

Extraction decision

Planning phase is the most significant and critical part of orthodontic treatment. Extractions should be carefully planned due to their irreversible nature. Clinicians come to the stage of deciding to extractions after combining the patient data derived from clinical evaluations, diagnostic photographs, dental models and radiographs with their clinical expertise. Although practitioners with less experience can learn from the decisions of their more experienced colleagues, the lack of a standard assessment method for the decision-making process requires a different approach. Neural networks were used to mimic human decision-making process for orthodontic extractions. Sagittal, vertical and molar relationships, tooth inclinations, overjet, overbite, protrusion index, soft tissue characteristics and patient complaints were given as input. Artificial intelligence system can then guide the clinician to decide the extraction, based on the analysis fed from the mentioned inputs. Studies showed that artificial intelligence systems can assist clinicians by preventing errors in decision step and can provide 80 to 90% accuracy when making an orthodontic extraction decision (Jung and Kim, 2016; Xie et al., 2010).

Appliance selection

Headgears are widely used as an extraoral anchorage device for growth modification, and they also provide force for molar distalization. Although they are typically used for the Class II patients with increased overbite and overjet and decreased mandibular plane angle, case selection is still challenging for inexperienced clinicians especially when planning the “borderline” or “marginal” cases because the decision-making process to choose an appropriate headgear type is considered more appropriate to be treated not separately, but rather in a continuous manner, that is, fuzzy logic.

Akçam and Tanaka (2002) developed a professional system based on fuzzy logic, which could infer an optimum selection of headgear type for orthodontic patients. The model in their study used overjet, overbite, and mandibular plane angle as input parameters. System used three different fuzzy logic clusters to choose from low, medium, or high pull headgear types. Eight expert orthodontists evaluated the headgear recommendation for 85 patients. Average satisfaction rate of the examiners was as high as 95,6%. Therefore, the usefulness of the proposed inference logic system was confirmed.

Estimation of treatment results and appliance production

Multi-regression models are used in the dental and medical field to assess the relationship between a range of features and the outcomes. This technique has the potential to identify the best predictors and it also offers a model that expresses the dependent variables in terms of correlated independent variables. On the other hand, it has some shortcomings, such as limitations in identifying all possible outcomes and establishing a linear relationship between variables and their outcomes (Zarei et al., 2006).

Artificial neural networks were cited as good candidates to develop a predictive model for orthodontic therapy, thanks to their ability to detect complex non-linear relationships between inputs and outputs. Artificial neural networks were shown to have the ability to learn and generalize beyond the situations they were faced with (Zarei et al., 2006).

There are studies in the literature which showed that the treatment results of Class II and Class III patients could be simulated by utilizing artificial neural networks technique. The researchers conclude that the neural networks technique is a promising tool which can be used for simulation of different malocclusion models (Zarei et al., 2006; Auconi et al., 2015).

Simulation of orthodontic treatment has gained popularity by clear aligner systems produced by a digital process.

Moving the teeth with “tooth positioning appliances” through sequential stages which are formed by “set-ups” on plaster models was a concept introduced by Kesling (1945). The major drawback of this technique was that there was a need to manually subdivide the movement into small increments by different plaster set-ups for each increment (Faltin et al., 2003).

The introduction of the Invisalign system in 1997, which was the first treatment technique in the field of orthodontics using digital 3D technology, made Kesling's idea much more practical. Instead of requiring a new model for each step of the treatment, Invisalign used a set of algorithms to generate altered digital 3D models to produce a set of aligners. The system digitally simulated incremental movements of the teeth. Based on input data and statistical analysis, AI software helps to estimate tooth movement and the outcome of orthodontic treatment. Similar software programs are used for production of different orthodontic appliances (Vecsei et al., 2017). To have a valid and effective aligner treatment, it is essential to have comparable predicted and actual outcomes (Buschang et al., 2014). The tooth control capability and outcome prediction of this AI-based digital system have been discussed extensively in the previous literature.

A case report by Faltin et al. (2003) compared the estimated end results provided by the ClinCheck software, the software for planning Invisalign treatments, to actual clinical results and concluded that the similarities between virtual and clinical results seemed to be satisfying. As a result, treatment and the treatment plan with the system were proved to have a reliable estimation capability.

In two more recent papers Buschang et al. (2014) and Grünheid et al. (2017) again compared ClinCheck treatment results to clinical results with the aim of testing the simulation capacity of the software. They found that although the software was successful in simulating simpler treatment plans, there were significant differences between the simulation and clinical results in more complex treatments. The ClinCheck software showed extremely limited reliability when it came to simulation of extraction therapy. ClinCheck models failed to accurately reflect patients' final occlusion in complex treatments.

7. Conclusion

It is quite clear that AI technology has a significant impact on the dental field, and so far, there have been major investments in this field. Although early attempts showed apparent deficiency, improvement in AI area is accelerating. Artificial intelligence can be a useful and practical tool for minimizing errors and improving patient care.

One of the most common criticisms against AI technology stems from the fear that corporate initiatives will exclude expert clinicians from the healthcare system and reduce treatment costs by using AI systems. Furthermore, it is difficult to say that this is an unnecessary fear because recent developments show that attempts in this direction have already started. Although it is still clear that AI is not likely to replace clinicians in the near future, the increasing use of digital 3D technologies in orthodontics shows that AI technology, which helps in interpretation of complex data, will also keep attracting increasing attention.

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