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Perspective

Applications of Artificial Intelligence in Orthodontics—An Overview and Perspective Based on the Current State of the Art

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Featured Application: The aim of this article is to provide the reader with an overview of current applications of AI in orthodontics.

Abstract: Artificial intelligence (AI) has already arrived in many areas of our lives and, because of the increasing availability of computing power, can now be used for complex tasks in medicine and dentistry. This is reflected by an exponential increase in scientific publications aiming to integrate AI into everyday clinical routines. Applications of AI in orthodontics are already manifold and range from the identification of anatomical/pathological structures or reference points in imaging to the support of complex decision-making in orthodontic treatment planning. The aim of this article is to give the reader an overview of the current state of the art regarding applications of AI in orthodontics and to provide a perspective for the use of such AI solutions in clinical routine. For this purpose, we present various use cases for AI in orthodontics, for which research is already available. Considering the current scientific progress, it is not unreasonable to assume that AI will become an integral part of orthodontic diagnostics and treatment planning in the near future. Although AI will equally likely not be able to replace the knowledge and experience of human experts in the not-too-distant future, it probably will be able to support practitioners, thus serving as a quality-assuring component in orthodontic patient care.

Keywords: orthodontics; artificial intelligence; machine learning; deep learning; cephalometry; age determination by skeleton; tooth extraction; orthognathic surgery

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1. Introduction

Artificial intelligence (AI) is the technological backbone of an increasing number of applications in virtually every part of our daily lives, to which we are mostly oblivious. The term "artificial intelligence" is a very general term that is aimed at describing the imitation of human activities by computers. What is commonly associated with AI usually corresponds to so-called "machine learning": Using a variety of sample data, specialized algorithms generate mathematical models that generalize certain patterns to predict decisions without having been explicitly programmed for that individual task [1].

In recent years, the increasing availability of computing power has enabled such algorithms to be used for increasingly complex tasks. In effect, some areas of medicine have been revolutionized by this technology [2]. Some applications of AI show remarkable potential in supporting medical decisions and, in some cases, even outperform experienced clinicians in terms of diagnostic capabilities [3–6].

Accordingly, there has also been an exponential increase in scientific publications in recent years aiming to integrate AI into everyday orthodontic routines. The literature describes some promising approaches for orthodontic diagnostics, therapy planning, and the prognosis of treatment outcomes. These cover, but are not limited to, the segmentation of anatomical or pathological structures in imaging, identification of reference points, and support of decision-making. While the benefits of routinely using AI may be seen for experienced practitioners, especially in terms of time savings for certain diagnostic procedures, inexperienced practitioners may want to consider the key advantages of such algorithms, especially in terms of assisted decision-making and, thus, enhanced quality management. Nevertheless, for any kind of clinical application, it is necessary to closely look at the scientific basis of such AI solutions in order to identify and become aware of their possible limitations and their potential implications [7].

Therefore, the aim of this article is to give the reader an overview of the current state of the art regarding applications of AI in orthodontics and to provide a perspective for the use of such AI solutions in the daily clinical routine. For this purpose, this manuscript presents a selection of AI-assisted applications in orthodontics for which extended scientific research is already available and discusses the relevant scientific basis with regard to their strengths and limiting factors.

Some parts of this manuscript have already been published recently in German by Quintessenz Verlag [8]. This publisher has approved a secondary publication in English to MDPI Applied Sciences.

2. Cephalometric X-ray Analysis

Cephalometric X-ray analysis, which was introduced by Broadbent in 1931, is still a cornerstone of orthodontic treatment planning [9]. The first step in the analysis of cephalometric images is identifying landmarks. On the basis of these landmarks, geometric evaluations in the form of angles, distances, and ratios can be performed, enabling a sagittal and vertical analysis of the facial skull [10]. Prior to the use of AI, geometric constructions and measurements were merely facilitated by software solutions, but the identification of the landmarks themselves remained a manual task for the practitioner [11].

In recent years, various researchers have been able to automatize this time-consuming and error-prone process by using AI-algorithms [2,10,12–26]. The majority of studies investigating the use of AI for automated cephalometric X-ray analysis evaluate the accuracy of their AI based on the metric deviation between the landmarks set by the AI and the human gold standard. In this context, Schwendicke et al., performed a meta-analysis in which the accuracy of the automated landmark detection of different researchers was analyzed. The authors demonstrated that the majority of the included studies were able to identify landmarks within a metrical tolerance limit of 2 mm [7]. This 2 mm tolerance is generally accepted as sufficiently accurate for clinical purposes in this regard [10,11,14,17–21,27,28]. However, not only the metric deviation but also the direction of this deviation are of decisive importance to determine the actual clinically relevant accuracy of the orthodontic parameters that are measured on the basis of these landmarks. For example, in the case of angular measurements, inaccuracies of the landmarks along the angles' legs do not lead to any changes in the measured parameter [26].

To circumvent this shortcoming, another approach to assess the accuracy of automatic cephalometric analyses is to evaluate them based on the orthodontic parameters themselves [29]. However, hardly any study in the literature evaluates the quality of AI assessments on this basis. Kunz et al., (2020) analyzed the accuracy of their AI for automated cephalometric analysis based on commonly used orthodontic parameters [26]. The authors were able to show that, out of twelve different orthodontic parameters (including skeletal sagittal, skeletal vertical, and dental parameters), only one parameter was found to be significantly different compared to the human gold standard. The average deviations between the evaluations of the AI and the human gold standard were well below one degree for all parameters. It can therefore be assumed that the differences between the predictions of the AI and the human gold standard are clinically irrelevant or of marginal importance at worst.

Despite all these promising approaches, Schwendicke et al., pointed out that there was an increased risk of bias in the majority of studies investigating the use of AI for the automated analysis of cephalometric images. This fact should be viewed critically as some commercial providers already offer such software solutions for which the underlying scientific data for the AI are inadequately communicated, unclear, or lacking [7]. To date, only a few studies have examined the quality of automated cephalometric analyses from such commercial providers [30–34]. The results of these studies demonstrated that there are major differences concerning the assessment qualities of those different providers, and most authors, therefore, concluded that fully automated cephalometric analyses should only be used with human supervision by experienced clinicians [30,31,35].

3. Determination of Skeletal Age

Assessing growth potential and estimating the time of the pubertal growth spurt are of great importance for the correction of dysgnathia in children and adolescents [36]. The dynamics of growth in adolescence is highly variable from individual to individual, so the assessment of chronological age by itself is insufficient for estimating the extent of remaining growth [37,38]. Skeletal age is far more suitable for the individual assessment of growth [39–43], which can be determined radiologically using the growth-related changes in the wrist bones or the vertebral bodies, also known and abbreviated as the CVM-method (cervical vertebral maturation) [44,45]. Analyses of both methods are significantly correlated with each other [43,46,47]. In contrast to X-rays of the wrist, the assessment of skeletal age on the basis of vertebral body maturation comes with the advantage of not requiring any additional radiation exposure for the adolescent patient since the assessment of the vertebral bodies is performed on lateral cephalometric X-rays, which are part of the orthodontic diagnostic routine anyway [36,48–50].

In the CVM method, growth-related morphological changes of the vertebral bodies C2–C4 are analyzed and divided into six stages of skeletal maturity [51]. However, the correct determination of skeletal maturity using this method is difficult for inexperienced practitioners and is prone to errors due to interindividual differences [37,52–56]. In order to avoid this problem, there have been several recent approaches to automate this process using AI to objectify the determination of skeletal age [36,54,57–60]. However, previously published studies have shown quite heterogeneous results: While some authors found only moderate agreement of 58% to 71% between the predictions of the CVM stages of the AI and the humans' gold standard [36,58–60], Seo et al., were able to demonstrate accuracies of the predictions for different AI algorithms of more than 90% [54]. Furthermore, the different stages of skeletal maturity were predicted at different levels of accuracy, with the stages around the growth peak in particular showing generally lower agreement with the gold standard [36,60].

When interpreting the results, it is important to note that previous studies have usually only evaluated the precise prediction of one exact stage, whereas it is clinically irrelevant when an adjacent stage is considered for the assessment of skeletal maturity [61]. Moreover, as only one or very few experts in existing studies have defined the gold standard, differences between the gold standard and AI might also be the result of inaccuracies in the expert assessments. Based on the current state of research, it can be concluded that AI algorithms have already achieved promising results for the determination of skeletal maturity, but further studies are still required.

4. Decision Support for Orthodontic Extractions

In addition to the applications of AI in orthodontic diagnostics presented so far, modern AI algorithms can also be used to support therapeutic decision-making [62–67]. One example is the decision for or against indicated tooth extractions in orthodontic therapy. With the multitude of clinical, radiographic, and even sociocultural factors that must be considered when deciding on the indication for orthodontic extraction therapy, such decisions remain challenging even for highly experienced orthodontists [68–71]. It is difficult to make "an ideal decision" in the patient's interest [72] as it also depends on the personal training, experience, and philosophy of the practitioner [69,70,73–78]. Therefore, it is not uncommon for experts to arrive at different conclusions, therefore making different decisions, especially in borderline cases [79–81].

In recent years, there have been several approaches to automatize and objectify this complex decision-making process through the use of AI [68,69,72,82–85]. For this purpose, different algorithms have been trained on a large number of patient examples consisting of a selection of clinical factors, radiological findings, model parameters, and the corresponding expert assessment for or against orthodontic extraction therapy. The first studies show promising results with a "correct" prediction between 80 and 94% for whether an extraction is necessary [67,82,83,85]. Important orthodontic parameters, such as the extent of crowding, the position of the anterior teeth, overjet, and overbite, as well as lip closure, were identified by the AI algorithms, which significantly influenced the extraction decision [72,82,85]. Del Real et al., showed that AI algorithms could predict the decision to extract particularly reliably when radiological findings and model parameters were used together as a diagnostic basis [68].

Furthermore, some studies investigated the extent to which AI algorithms could additionally predict the ideal extraction pattern, for example, a combination of extractions of first and second premolars in the different quadrants. A correct prediction of the extraction pattern in about 84% of all cases was presented [82,83].

Despite these very promising results, the aforementioned studies have substantial limitations. Important dental findings, such as the presence of large fillings, endodontic pretreatments, periodontal damage, apical lesions, or missing teeth, were not taken into account, neither in the decision-making process for or against the orthodontically indicated extractions nor in the selection of the extraction pattern [68,69,72,82–85]. Moreover, the majority of manuscripts published at present share the same limitation that the AI algorithms were set up and trained on examples provided by only a few experts and therefore were trained largely based on the subjective treatment philosophy of these examiners [68,69,82,83,85]. To avoid this problem, sample data for training the AI would have to be provided by as many experts as possible [72].

At this point, it is important to consider that—especially in borderline cases—there is often no definite decision for or against orthodontic extraction therapy. The necessity of carefully weighing the advantages and disadvantages of both treatment options against each other continues to persist for every clinician.

5. Decision Support for Orthognathic Surgery

Another example of the use of AI in orthodontics is the field of orthognathic surgery, in which the decision for or against a necessity for surgical intervention can be made. There is a multitude of factors that plays an important role in deciding whether orthognathic surgery is indicated. In cases where it is impossible to achieve adequate occlusion with conventional means, orthognathic surgery must be considered. Moreover, such a procedure may also be indicated if the patient's chief complaints cannot be resolved by orthodontic treatment alone, for example, in terms of extraoral aesthetic improvement.

Deciding whether orthognathic surgery is needed or an orthodontic treatment aimed at a compromise is feasible is one of the most important decisions when establishing an orthodontic treatment plan, as both treatment options differ significantly in terms of anchorage and the required tooth movements. While dental compensation should be undone in a surgical approach in order to achieve an optimal surgical effect, the opposite treatment is required in the case of a non-surgical approach to achieve an adequate camouflage of the dysgnathia. Therefore, irreversible procedures, such as tooth extractions, must not be performed until orthognathic surgery can be ruled out with certainty [86,87]. The decision on whether orthognathic surgery is indicated may vary between different practitioners, owing to differences in experience and preferences [88], and clinicians with limited experience often have difficulties in making such decisions [86,89]. As no standardized criteria for decision-making regarding the need for orthognathic surgery are available, there are approaches that attempt to support clinicians through the use of AI algorithms [86,89,90].

Initial studies demonstrated promising results for this decision-making task as well. Kim et al., used different convolutional neural networks as AI algorithms that were trained to predict if orthognathic surgery was necessary on the basis of lateral X-rays and achieved correct prediction rates between 91% and 94% for a set of test images [89]. Shin et al., expanded the diagnostic basis for the training of their AI by simultaneously using both lateral and posteroanterior X-rays of each patient and were able to achieve correct predictions of 95% regarding the indication for surgery [90]. Choi et al., used other parameters in addition to the lateral X-rays as well, such as the overjet or the profile type, so that this research group was likewise able to increase the number of correct predictions regarding the indication for orthognathic surgery to 96% [86]. The remarkable feature of the latter work was that the AI could predict not only the indication for orthognathic surgery but also the indication for premolar extraction with a success rate of about 91%. In this context, it should be highlighted that the indication for extraction in class II patients worked better with a success rate of 97% than that in class III patients, where the successful decision rate dropped to 88%.

The limitations of existing studies are similar to those on the extraction decision: Important aspects influencing the practitioners' decisions on whether orthognathic surgery is indicated, e.g., mandibular asymmetries, the patient's chief complaints, as well as aesthetic aspects, were not considered and should therefore be taken into account in future studies [86,90]. In addition, with the exception of the work by Shin et al., the existing studies are based on the assessment of a single expert with its associated and previously discussed limitations herein. Considering the fact that all three studies mentioned above refer to the Korean population, the general applicability of the results to other samples is doubtful. Furthermore, details regarding the surgical procedure itself cannot be predicted at present. In summary, this leads to the conclusion that AI can provide an auxiliary reference concerning the indication for orthognathic surgery, but it cannot yet replace the expertise of experienced clinicians, and further investigations are needed to get more impeccable and generalizable results [86,91].

6. Assessment of the Present Situation and Future Perspective

The examples presented above demonstrate that, already today, there is a multitude of promising applications for AI in orthodontics. Especially inexperienced clinicians can be supported by the use of AI in diagnostics or in complex therapeutic decision-making, while for experienced clinicians, the main advantage may be the substantial time savings that AI solutions provide. Furthermore, the use of AI in daily clinical routines can be regarded as a quality-assuring procedure, as inter-individual human errors can be avoided and the clinician obtains an additional evaluation or decision at their disposal through AI.

However, the training of an AI algorithm itself is very time-consuming, as a large number of sample data sets are required, based on which the algorithm attempts to detect general patterns in order to transfer this to equivalent new situations. Especially for medical or dental purposes, the acquisition of such sample data is a great challenge, as it usually has to be provided by experts and demands a considerable amount of work [10,26]. The sample data must have a broad spectrum (e.g., patients of different ethnicities, patients with different anomalies, or X-ray images created by different devices) in order to achieve great robustness: The learned patterns must be valid for as many diverse situations as possible and should be provided by many different experts in order not to represent a subjective treatment philosophy but to ensure an objectifiable and generally valid assessment [11].

This is exactly where the limitations of currently available articles addressing the application of AI in orthodontics can often be found. The sample data and the gold standard for statistical comparisons are typically provided only by one or just a few experts, so the results, which are often very promising, bear an increased risk of bias [7]. In addition, hardly any of the studies performed an actual clinical trial for the purpose of validation. Consequently, the positive results of the AI that were demonstrated by the studies may not be applicable with equivalent quality to reality, where modified situations are to be expected. This aspect gains more importance in light of the fact that there are already several commercial vendors for AI-based software solutions for various clinical purposes that do not sufficiently disclose the scientific basis of their AI [7]. When using such commercial AI products in everyday clinical practice, it is, therefore, essential to pay attention to the scientific evidence on which these products are based [7]. In this regard, it is also necessary to verify the performance and analysis quality of such AI solutions in the context of well-conducted and preferably independent scientific studies so that the providers can put further efforts into improving their products if required.

Given the current scientific dynamics in the field of AI, it can be assumed that AI will become an integral part of orthodontic diagnostics and treatment planning in the near future. However, this requires that the vendors of commercial AI products work hand in hand with the scientific community to provide the practitioners with proper diagnostic assessments as well as reliable and valid therapeutic decision-making. Given this premise, AI will, however, probably not be ab+le to replace the medical knowledge and professional experience of human experts in the future, but it may, at some point, assist practitioners on lower levels, thus serving as a quality-management component in orthodontic patient healthcare [92].

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