Review

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AI in Orthodontics: Revolutionizing Diagnostics and Treatment Planning

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Review

AI in Orthodontics: Revolutionizing Diagnostics and Treatment Planning

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Abstract: The advent of AI in medicine has transformed various medical specialties, including orthodontics. AI has shown promising results in enhancing the accuracy of diagnoses, treatment planning, and predicting treatment outcomes. With the growing number of AI applications and commercially available tools, there is an increase in their usage in orthodontic practices worldwide. This review aims to explore the principles of artificial intelligence (AI), its applications in the diagnostic process of modern orthodontic practices, and concerns associated with the implementation of AI algorithms in clinical practice. A comprehensive review of the literature was conducted, focusing on five categories where AI has been applied in orthodontics: dental diagnostics, cephalometric evaluation, skeletal age determination, temporomandibular joint (TMJ) evaluation, and extraction decision making. AI has demonstrated high efficacy in all those fields. However, variations in performance and the necessity of manual supervision indicate that AI should be used cautiously in clinical settings. Nevertheless, the high complexity and potential unpredictability of AI algorithms call for cautious implementation and regular manual validation of results. Continuous AI learning, proper governance, and addressing privacy and ethical concerns are crucial for the successful integration of AI into orthodontic practice.

Keywords: orthodontics; artificial intelligence; deep learning; cephalometric analysis; radiology; CBCT; skeletal age; treatment planning

1. Introduction

Artificial intelligence (AI), a term first introduced in 1955 by John McCarthy, describes the ability of machines to perform tasks classified as intelligent [1]. Over the past nearly 70 years since the coining of the term AI, there have been cycles of significant optimism associated with the development of AI, interspersed with periods of failures, reductions in research funding, and pessimism [2]. The breakthrough that sparked renewed widespread interest in AI and heralded the current boom in this technology was a victory of AlphaGo, a Deep Learning (DL)-based program developed by Google over the world champion in the board game Go in 2015 [2]. This event, accompanied by the introduction of Chat-GPT in 2022, foreshadowed the incredible growth of numerous AI applications in everyday life and medicine, which we are familiar with today.

AI algorithms have already proven their effectiveness in a variety of tasks across different medical specialties, even demonstrating the potential to outperform experienced clinicians [3–6]. Currently, AI enables the analysis, arrangement, depiction, and classification of healthcare data. The development of AI algorithms in medicine has especially occurred in recent years, particularly in radiology; medical imaging currently constitutes approximately 85% of FDA-approved AI programs (data for 2023) [7]. There are three main domains of AI in diagnostic imaging: operational AI improves healthcare delivery, diagnostic AI assists in interpreting clinical images, and predictive AI

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forecasts future outcomes [8]. Currently, the primary objectives of AI are to detect and segment structures, and classify pathologies [9]. The AI tools can analyze images acquired in all radiological modalities from X-ray to MRI [10–14]. The specific nature of orthodontics, associated with cephalometric analysis and pretreatment imaging, predisposes orthodontics to the field where AI is being implemented most rapidly. However, AI is being utilized in orthodontics in many other applications beyond cephalometric analysis. The current body of literature regarding the use of AI in orthodontics can be divided into five categories: diagnosis and treatment planning, automated landmark detection and cephalometric analysis, assessment of growth and development, treatment outcome evaluation, and a miscellaneous category [15].

The number of AI companies in the healthcare industry has increased exponentially, indicating a significant growth in commercial prospects for AI [8]. Currently, AI tools, in addition to being available to a specific group of researchers and scientists involved in particular research and development projects, are now accessible through commercially available web-based products. The adoption of AI in orthodontics has led to the development of several AI-based programs, such as WeDoCeph (Audax, Ljubljana, Slovenia), WebCeph (Assemble Circle, Gyeonggi-do, Korea), and CephX (ORCA Dental AI, Las Vegas, NV). These systems automatically identify cephalometric landmarks, compute angles and distances, and generate cephalometric reports with significant findings. This enables access to AI programs even from mobile devices and promotes the "democratization" of access to AI tools and their widespread availability to all those interested in implementing them. This, in turn, leads to a significant increase in the number of orthodontic practices and the number of scientific researchers globally who are engaged in AI applications. It also raises growing concerns related to patient safety, where AI is involved in diagnosis and treatment.

The main objectives of this article are: to elucidate the principles of AI, outline its applications in diagnostic process of modern orthodontic practices, and discuss the concerns associated with implementation of the AI algorithms in clinical practice.

2. AI categories

AI can be classified into two main categories: symbolic AI and machine learning. Symbolic AI involves structuring the algorithm in a human-readable symbolic manner. This approach was dominant in AI research until the late 1980s and is known as GOFAI (Good Old-Fashioned AI) [16]. Symbolic AI is still useful for solving problems with limited outcomes, limited computational power, or when human explainability is important. However, the efficiency of GOFAI in healthcare is low, mainly due to the complexity of problems, multiple variables, and limited sets of rules [17]. Therefore, with advancements in technology and computer sciences, the new powerful iterations of AI are becoming more prevalent, replacing GOFAI in medical applications. The schematic representation of AI in Figure 1.

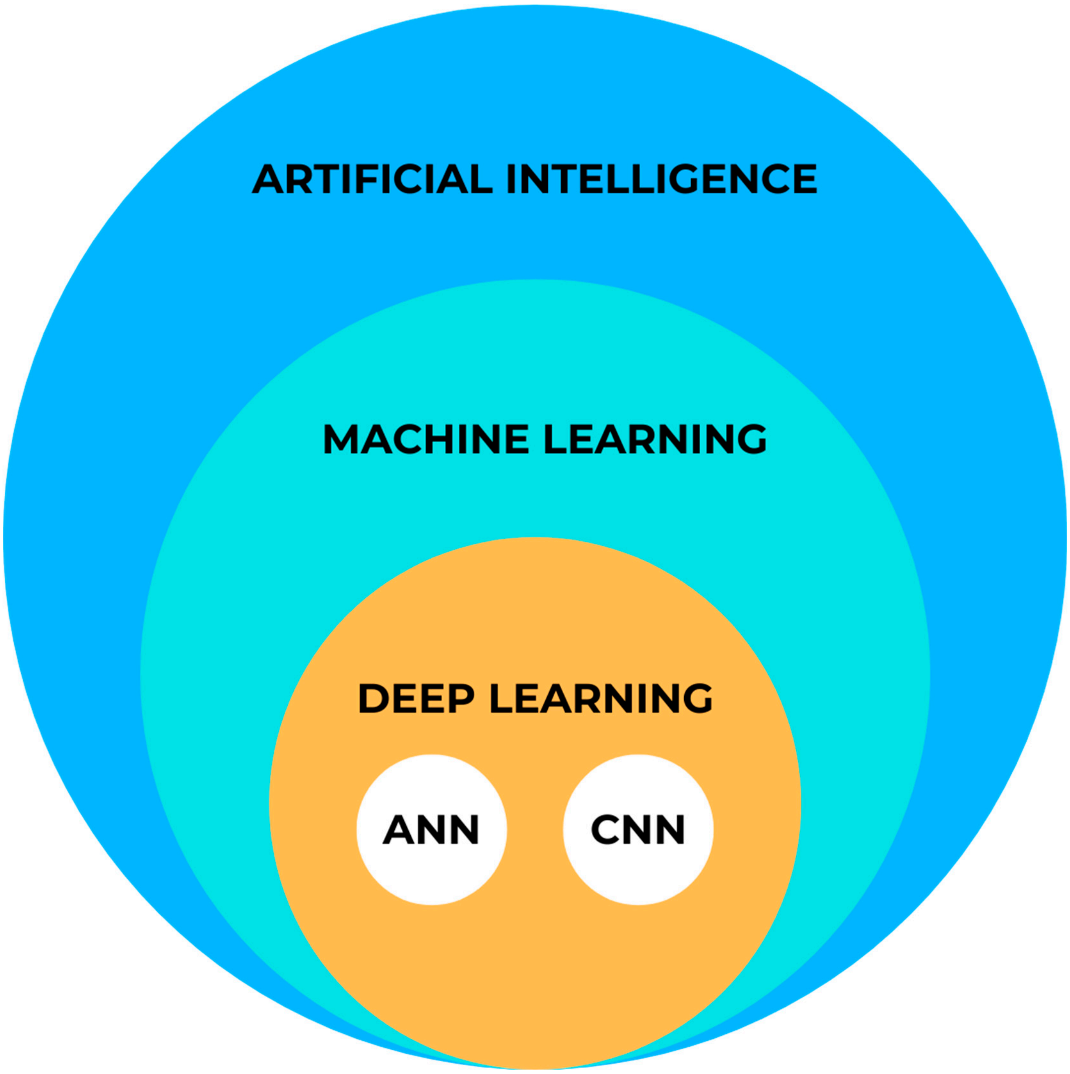

Figure 1. Simplified AI diagram.

2.1. Machine Learning

Machine learning (ML) is the predominant paradigm in the field of artificial intelligence. Coined by Arthur Samuel in 1952, ML differs from symbolic AI in that it relies on models learning from examples rather than predefined rules set by humans [18]. By leveraging statistical and probabilistic techniques, machines can improve their performance by learning from previous models and adapting their actions when new data is introduced. This can involve making predictions, identifying new patterns, or classifying new data.

ML can be categorized into three types based on the algorithm's learning approach and the desired outcome. The first type is supervised learning, which is used for classification or prediction tasks where the outcome is already known. Here, the algorithm learns from a labeled dataset and generalizes its knowledge to make accurate predictions on unseen data. The second type is unsupervised learning, which aims to discover hidden patterns and structures in data without any prior knowledge of the outcome. This type of learning is useful for tasks such as clustering and anomaly detection. Lastly, reinforcement learning involves the machine developing an algorithm that maximizes a predefined reward based on previous versions of itself. This type of learning is often used in scenarios where an agent interacts with an environment and learns through trial and error [19].

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2.2. Deep Learning

Deep learning (DL) refers to a subset of machine learning (ML) in which the machine is capable of independently computing the specific characteristics of an input. The foundation of DL can be traced back to artificial neural networks (ANN), which were developed in the 1990s. However, with advancements in computational technology and increased computing power, researchers have been able to construct more intricate and "deeper" neural networks to tackle increasingly complex tasks. Currently, in the field of medical imaging, DL algorithms predominantly employ convolutional neural networks (CNNs) with high diagnostic accuracy [20–22]. DL differs from traditional ML approaches in that it allows the machine to automatically extract relevant features from input data. Instead of relying on human engineers to manually engineer these features, DL models have the ability to learn and recognize patterns directly from the raw data. Moreover, DL algorithms do not require time consuming feature dentification and extraction [22]. This has proven to be particularly useful in imaging, where DL tools are starting to surpass experienced readers in diagnostic accuracy [20,23,24]. However, the DL is not limited only to image analysis tasks, it has shown promise in tasks such as medical disease diagnosis, and personalized treatment recommendation [25–28].

3. AI applications in Orthodontics

3.1. Dental Diagnostics

The use of radiological diagnostic methods is fundamental in dental patient care. Recently, these methods have served as a basic tool aiding the clinical diagnosis of pathologies associated with teeth and their surrounding structures. They have also been a valuable tool in the assessment of treatment outcomes [29–31]. Besides the standard pre-orthodontic treatment evaluation in lateral cephalograms, orthopantomograms (OPG) remain valuable tools for orthodontic diagnosis, treatment planning, and monitoring [32]. Although its role and indications are still being discussed, CBCT plays an important role in decision making for orthodontic patients, where conventional radiography fails to provide an accurate diagnosis of the pathology [32,33]. However, due to the increasing number of examinations performed [34], there is a need for a tool that would comprehensively support the process of radiological diagnosis. The response to such a market demand was the emergence of multi-modular diagnostic systems based on AI. These systems are used for the analysis of both CBCT and OPG, as well as periapical radiographs (PR). The tool created by Diagnocat Ltd. (San Francisco, CA, USA), based on CNN, would ideally serve for precise, comprehensive dental diagnostics, allowing for teeth segmentation and enumeration, oral pathologies diagnosis (for example, periapical lesions, caries), and volumetric assessment. Scientific papers validating the diagnostic performance of the program have proved its high efficacy and accuracy [35–39]. The study by Orhan et al [35], found that the AI system achieved 92.8% accuracy in periapical lesions detection in CBCT images, and no statistically significant difference in volumetric measurements compared to manual methods. Comparable results were achieved in a study assessing the program's diagnostic accuracy in periapical lesion detection on PRs [36]. However, there are also studies revealing conflicting results, showing unacceptable accuracy of AI in OPG assessment of periapical lesions [40]. The study by Ezhov (2021) [41], compared the overall diagnostic performance of two groups of AI-aided and unaided clinicians in oral CBCT evaluation. The AI system was equipped with teeth and jaw segmentation, tooth-localization and enumeration, periodontitis, caries, and periapical lesion-detection modules. The results of the study showed that the AI system significantly improved the diagnostic capabilities of dentists (AI-aided vs unaided group sensitivity values were 0.8537 and 0.7672, specificity values were 0.9672 and 0.9616 respectively). These results suggest that such multimodal AI programs may serve as first-line diagnostic aids and decision support systems, improving patient care on many levels. Sample Diagnocat report in Figure 2.

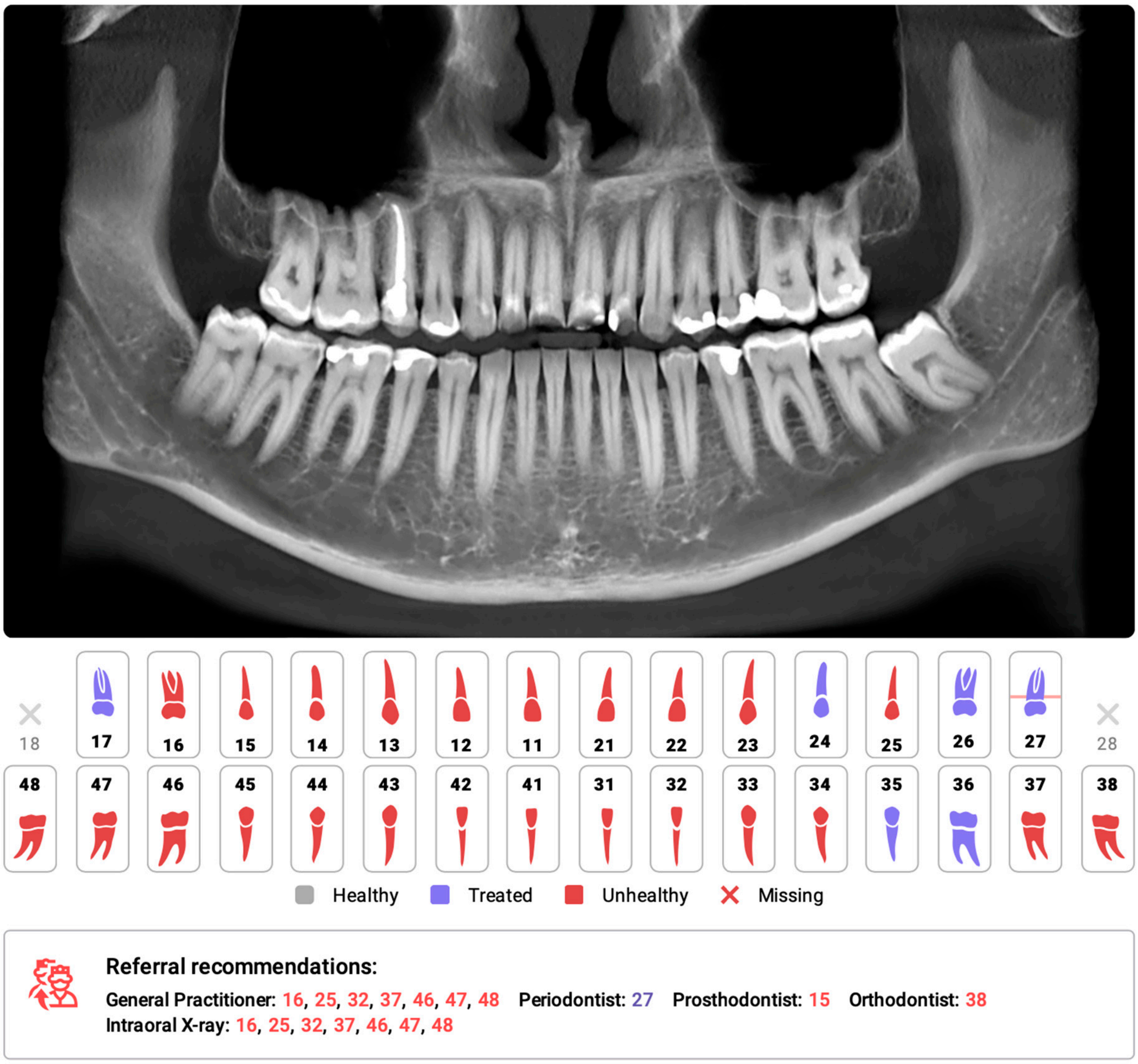

Figure 2. Part of automatic diagnostic report from a CBCT scan, conducted prior to orthodontic treatment on a 24-year-old male. The software has automatically identified the absence of teeth 18 and 28, as well as changes in the remaining teeth, primarily consisting of attrition and the presence of dental fillings. The program has recommended further consultations as necessary.

3.2. Cephalometric Analysis

Cephalometric analysis (CA), first introduced in 1931, has evolved into a key diagnostic instrument for cranial examination in orthodontics [42]. Advancements in technology have led to the substitution of time-consuming manual assessments with digital CA software, simplifying the measurement process and automatically displaying the results of the analysis. The results of automated CA have proven to be relatively stable and repeatable compared with the highly operator-dependent manual analysis with significant variability in landmark identification [43–46]. The accuracy and repeatability of landmark identification are crucial for determining CA outcomes. Numerous studies have been conducted to demonstrate the effectiveness of AI in identifying cephalometric landmarks. Despite lateral radiography being the most widely used method in CA, recent advancements in AI have brought the utilization of cone-beam computed tomography (CBCT) back into discussion [47].

Initial attempts to evaluate the effectiveness of AI in identifying cephalometric landmarks can be traced back to 1998 [48]. The authors found no statistical differences in the mean landmark identification errors between the manual and automated methods. These results were supported by multiple other studies using different automated methods of cephalometric landmark identification, with high levels of accuracy [45,46,48–63]. In a recent study conducted by Hwang et al. (2020) [46], the authors concluded that automated cephalometric landmark identification can be as reliable as an experienced human reader. Similar results, with accuracy in landmark definition between 88% and 92%, were achieved by Kim et al [53], Lee et al [62], and Dobratulin et al [49]. These authors concluded that AI demonstrated greater accuracy in landmark detection and reduced the time and human labor spent on anatomic landmark identification compared to manual methods. In other studies by be Hwang et al [45], and Yu et al [60], the authors showed that the results of automated CA were not statistically different from those calculated from manually identified landmarks. Moreover, AI can significantly improve the workflow of the practices, reducing the analysis time by up to 80 times compared to manual analysis [63]. Figure 3 presents sample cephalometric landmark definition.

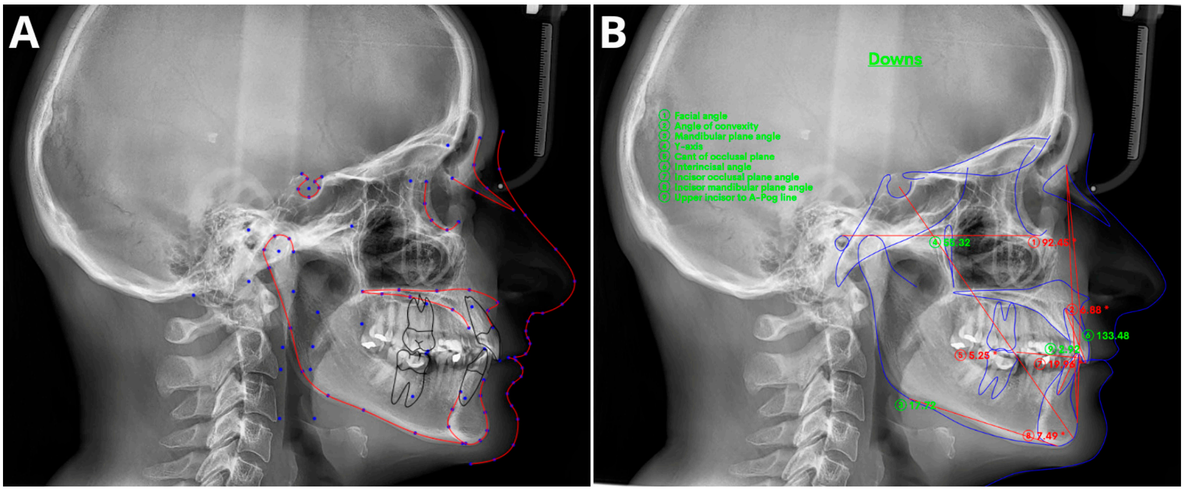

Figure 3. Sample of automatic cephalometric landmarks tracings performed by Cephx (A) and WebCeph (B) on 18-year-old male. Results of Downs cephalometric analysis superimposed on tracings (B).

The first reports regarding the utilization of Cone Beam Computed Tomography (CBCT) in CA can be traced back to the 2000s. However, due to the ineffective and time-consuming nature of this method, it did not spread widely [64]. Recent advancements in the AI field, with the possibility of automated assessment of the cranium in three dimensions, have revived the idea of CBCT-based CA. Numerous studies [65–72] leveraging AI for automatic landmark identification and analysis have demonstrated the accuracy and efficiency of these techniques compared to traditional, manual analysis. The study by Kim et al [71] showed higher repeatability of the results than those achieved by human readers. Muraev et al [72] found that ANNs could achieve accuracy in landmark identification comparable to humans and even outperform inexperienced readers in this task. However, a recent study by Bao et al (2023) [73] revealed that AI-automated analysis cannot completely replace manual tracing, and manual supervision is crucial to increase the accuracy of the results.

3.3. Determination of Skeletal Age

Growth and maturation are critical factors in the field of orthodontics, as they are closely linked to the effectiveness of orthodontic devices, which are often timed to coincide with periods of rapid growth and natural changes in facial structure. As previous studies have shown, the effectiveness of treatment can be increased by tailoring treatments to align with the patient's growth phases [74,75]. The rate of growth and the stage of facial development are crucial elements for achieving lasting results in orthodontic treatment, and precise assessment of these factors is necessary to minimize the risk of post-treatment changes resulting from ongoing facial growth [76]. The dynamics of growth in adolescence vary significantly among individuals, making chronological age alone insufficient for estimating the extent of remaining growth [77,78]. Skeletal age is a more suitable and well-established parameter for individual growth assessment with the two leading methods: cervical vertebral maturation (CVM) and wrist X-rays [74,79–82]. Since CVM can be assessed on lateral cephalometric x-rays, wrist X-rays are contraindicated in standard diagnostic orthodontic routine [32].

The last few years have seen a rise in scientific evidence supporting the diagnostic accuracy and effectiveness of AI in skeletal age assessment, based on both wrist X-rays [83,84] and CVM [85–88]. Although AI has already proven its diagnostic accuracy in skeletal age assessment, exceeding that of experienced readers in wrist X-rays [83,84] and even index finger X-rays [89], the accuracy of CVM-based models remains a concern [90,91]. Studies published on this topic have shown heterogeneous results, with agreement rates with human observers ranging from 58% to over 90% [90,92–95]. In the recent study by Seo et al. (2021) [92], the authors achieved over 90% accuracy with each of the tested CNN-based models in CVM assessment. They concluded that automatic diagnosis using lateral cephalometric radiographs can provide clinicians with accurate information on skeletal maturity. However, the results of the other above-mentioned studies call for caution when evaluating the outcomes of AI in CVM assessment and indicate significant discrepancies, especially during the critical for orthodontic treatment stages around the growth peak, which generally show lower accuracy [78,93].

We advise considering the results of AI CVM assessment studies with caution, as the gold standard was established by evaluations from a few expert readers. Therefore, the results of the studies might partially stem from errors made by the readers and their influence on AI algorithms. However, consider those results as highly encouraging, and believe that future advancements in AI technology will lead to an increase in the diagnostic accuracy of CVM tools, comparable to that of wrist X-ray skeletal maturity assessments.

3.4. TMJ Evaluation

Osteoarthritis (OA) is a condition that affects joints and is characterized by the gradual deterioration of joint cartilage associated with bone remodeling and the formation of osteoproliferative bodies. Temporomandibular joint osteoarthritis (TMJOA) is a specific type of temporomandibular disorder that can cause significant joint pain, dysfunction, dental malocclusion, and a decrease in overall quality of life [96]. The examination of TMJ function and morphology is an important part of every orthodontic or dental treatment [97], as the presence of TMJOA is one of the causes of malocclusion and facial asymmetries [98,99]. The presence of TMJOA is confirmed by bony changes observed on radiographic (OPG/CBCT) examination [100], whereas MRI remains the modality of choice in joint disc evaluation [97].

There is growing scientific evidence proving that AI applications demonstrate high diagnostic performance in the detection and staging of TMJOA [100–104]. The studies have shown the potential for automated, detailed assessment of joint morphology using various imaging techniques such as OPG, CBCT, and MRI. The authors anticipate that the utilization of AI systems for diagnostic imaging of the TMJ will enhance future research on early detection and personalized treatments for OA. They believe that the development of these AI systems, along with the proposed algorithms, will contribute to the establishment of a comprehensive diagnostic system for the maxillofacial region.

3.5. Extraction Decision Making

One of the most challenging issues during orthodontic treatment is deciding whether extraction is mandatory in a particular case. A variety of factors associated with the identified orthodontic defect, patient preferences, expected outcomes, sociocultural factors, and the professional position of the orthodontist, influence the patient's attitude towards the proposed orthodontic extraction therapy [105–107]. Additionally, on the other hand, decisions related to extractions are influenced by the experience, training, and philosophy of the orthodontist [108–111]. All these factors make the extraction decision during the orthodontic treatment very challenging, even for an experienced practitioner. Furthermore, conclusions regarding the treatment undertaken can greatly vary among experts, especially in borderline cases [112–115].

In recent years, several AI tools have been introduced, designed to support therapeutic decision-making in orthodontics [77,116,117]. Initial studies evaluating the assistance of extraction decision aids have shown promising results, with AI algorithms achieving more than 80% agreement with decisions made by experts [118–122]. The study by Xie (2010) [122] demonstrated an 80% concurrence in decisions related to extractions between AI and experts; however, the study only analyzed a mere 20 cases. The ANN system evaluated by Jung & King [120] showed a 93% success rate for diagnosing extraction versus non-extraction cases based on 12 cephalometric variables and 84% for the detailed diagnosis of specific extraction patterns. Similar results were achieved by Li et al. (2019) [121] with a 94% accuracy rate for extraction versus non-extraction predictions, 84.2% for extraction patterns, and 92.8% for anchorage patterns. The studies identified several features for predicting treatment, among which crowding of the upper arch, the position of anterior teeth, lower incisors inclination, overjet, overbite, and capability for lip closure were most important for the extraction decision. However, significant limitations that substantially affect the risk of bias of the selected AI models in the mentioned studies were pointed out [59]. In the majority of the manuscripts, the AI systems were trained on the examples provided by limited number of experts, therefore they were based on treatment philosophies of the examiners. Correctness of these approaches were not established. Moreover, the occurrence of important dental findings such as the large dental fillings, periapical lesions, periodontal damage, previous endodontic treatment and missing teeths were not considered [107,119–122].

Considering the aforementioned limitations, it is crucial to acknowledge that, particularly in borderline scenarios, a clear-cut decision regarding the implementation or avoidance of orthodontic extraction therapy is often elusive. Clinicians must meticulously evaluate the pros and cons of each treatment approach, considering `the entire clinical scenario. Moreover, the incorporation of extraction decision-making tools into clinical practice carries the risk of a specific treatment philosophy influencing patient care. Practitioners should strive to develop individualized treatment plans for their patients and not be influenced by rigid treatment 'philosophies' [106].

4. Implementation Considerations

While the potential of AI to improve patient management in orthodontics is vast, its impact has only been proven in a limited number of cases. Most of the literature on this subject consists of retrospective studies, without support from large randomized controlled trials. However, we might expect such studies in the coming years due to the exciting nature of this topic and the increasing supply of AI solutions. Financial investments and the number of introduced AI technologies are rapidly growing - in 2022, there were 69 new FDA-approved products associated with $4.8 billion in funding. By 2035, product-year funding is projected to reach $30.8 billion, resulting in 350 new AI products [7].

Despite many optimistic studies demonstrating the high performance of AI algorithms in a variety of tasks, the further incorporation of AI algorithms into everyday clinical practice remains a matter for the future. Most of the programs described above were launched in the last 2-3 years, and as studies have shown, the average time for the introduction of innovation in medicine to application in clinical practice is 17 years [123,124]. The process of implementing AI in workflows and clinical practice requires meeting a number of requirements to ensure sufficient clinical quality and patient safety. As indicated by Pianykh [8], here are still important issues to overcome. The first issue is the lack of reproducibility, as AI models are typically developed using a limited number of specific datasets and struggle to perform well on a wide range of data. The second issue is the lack of adaptivity, as existing AI models are not designed to constantly adjust to changes in their environment. The third issue is the absence of robust quality control mechanisms for AI, making it more susceptible to data errors, outliers, and sudden shifts in trends. Lastly, there is a lack of integration between AI algorithms and the workflow, preventing them from effectively adapting to changes in the data environment. The solution to these issues is the creation of continuous learning AI, enabling the AI tool to adapt continuously to changes in the data [8]. This would allow for live adjustments of the AI algorithms, preventing performance deterioration.

Like any technology used in medicine, there is a need for a sufficient AI governance process to maintain the quality of results and ensure patients' safety [125]. The need for continuous evaluation of algorithm quality should be kept in mind to prevent degradation in performance and allow for appropriate early intervention. Moreover, privacy issues, safety concerns, and health inequities (such as AI algorithms exacerbating racial or income disparities) are a few more general issues related to the application of AI in medicine, which have recently been highlighted in The Lancet [126].

Despite the availability of a wide range of products, there is still limited scientific evidence regarding the validation and effectiveness of AI products in general medicine and in a narrow field such as orthodontics [127]. Despite generally optimistic test results of various AI tools, the issues highlighted above underscore the necessity of exercising considerable caution when introducing AI into daily practice.

5. Conclusions

Undoubtedly, AI has the potential to revolutionize medicine, particularly in the field of diagnostic imaging, including orthodontics. The continuous advancement of AI algorithms supporting pre-treatment diagnostic processes, allowing visualization of outcomes, and facilitating decision-making during treatment, places orthodontics among the disciplines benefiting the most from the introduction of AI technology. However, due to the high complexity and associated unpredictability of AI, these tools should be treated with caution and their results should be regularly manually validated.

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