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Review Article

Orthodontics 2.0: The Transformative Role of Artificial Intelligence in Shaping the Future of Orthodontics Care - A Review

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Abstract

AI has been grown remarkably in the field of dentistry as well and now in one of the most leading branch orthodontics. Studies have shown that AI can be a potent tool for clinical care decision-making in dentistry. AI is now being used for diagnostic imaging. Currently, it is concentrating on a variety of topics, including the diagnosis of osteoporosis, categorization and segmentation of maxillofacial cysts and tumours, a description of periapical disease, the identification of cephalometric landmarks, etc.

Keywords: Artificial Intelligence; Machine Learning; AI in Orthodontics

Introduction

The digital transformation in dentistry has enabled the integration of multi-source data, including clinical records, remote monitoring systems, photographic documentation, lateral cephalograms, panoramic radiographs, and three-dimensional (3D) imaging modalities such as cone-beam computed tomography (CBCT), digital dental models, and 3D photogrammetry [27,31]. Artificial intelligence (AI) has emerged as a fundamental technological framework supporting a wide range of applications that increasingly permeate everyday life, often functioning seamlessly in the background [39].

In the contemporary era, orthodontics is undergoing a significant paradigm shift driven by the integration of advanced digital technologies and AI-based methodologies [9]. AI is now considered a cornerstone of modern healthcare innovation and plays a pivotal role in the advancement of digital orthodontics, enhancing diagnostic accuracy, treatment planning, and clinical decision-making [7,8].

Machine learning and AI

A comprehensive understanding of AI in orthodontics necessitates familiarity with key foundational concepts. The primary objective of AI is to simulate human intelligence in machines, enabling them to learn from data and perform tasks autonomously [39]. Machine learning (ML), a critical subset of AI, utilizes computational algorithms to identify patterns within datasets and generate predictive models without explicit programming [5].

ML techniques commonly applied in orthodontics include support vector machines (SVM), logistic regression (LR), naïve Bayes classifiers, decision trees (DT), random forests (RF), extreme learning machines (ELM), fuzzy k-nearest neighbors (FKNN), and convolutional neural networks (CNN) [6]. These approaches allow systems to analyze complex datasets and support clinical decision-making processes.

Neural networks are computational models inspired by biological neural systems, consisting of interconnected artificial neurons that process information through weighted connections. Deep learning, an advanced subset of ML, employs multi-layered neural networks to extract hierarchical features from data, enabling automated pattern recognition and improved analytical performance [3,38].

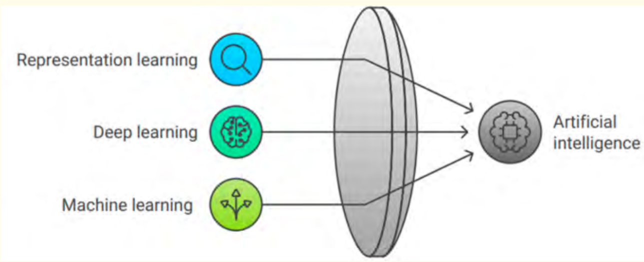

Figure 1: Principles of artificial intelligence.

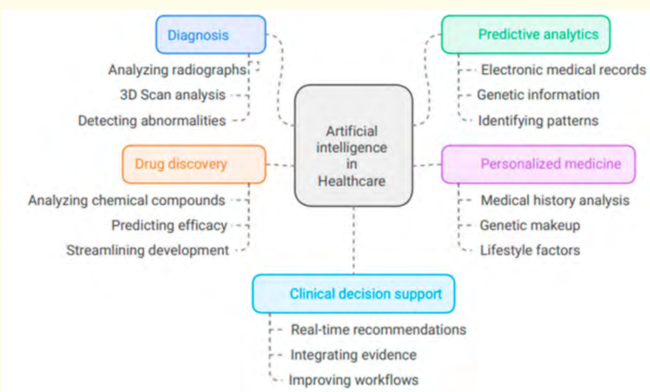

Figure 2: Illustrates the uses of artificial intelligence in health care.

Levels and types of artificial intelligence used in orthodontics:

Level 1: Basic AI applications in orthodontics

Type: Rule-Based Systems

- Subtype: Pre-programmed algorithms for specific tasks in treatment planning.
- Example: Automated cephalometric analysis based on predefined rules.

Level 2: Machine Learning in Orthodontics

Type: Supervised Learning

- Subtype: Training algorithms on labeled datasets for predictive modeling.
- Example: Predicting treatment outcomes based on historical patient data.

Type: Unsupervised Learning

- Subtype: Identifying patterns and relationships in data without predefined labels.
- Example: Clustering similar patient cases for personalized treatment plans.

Level 3: Advanced AI in orthodontics

Type: Deep Learning

- Subtype: Neural networks with multiple layers for complex pattern recognition.
- Example: Automated detection of cephalometric landmarks for treatment planning.

Type: Natural Language Processing (NLP)

- Subtype: Processing and understanding human language for improved patient communication.
- Example: Extracting information from patient records for treatment history analysis.

Level 4: Integration and Decision Support

Type: Expert Systems

- Subtype: Integrating AI knowledge with clinical expertise for decision support.
- Example: Providing treatment recommendations based on AI analysis and clinician expertise.

Type: Augmented Intelligence

- Subtype: Collaborative systems where AI enhances human decision-making.
- Example: AI tools assisting orthodontists in treatment planning and case assessments.

Level 5: AI-Driven Patient Care

Type: Personalized Treatment Plans

- Subtype: AI-generated treatment plans tailored to individual patient needs.
- Example: Recommending specific orthodontic interventions based on patient characteristics and historical data.

Type: Continuous Learning Systems

- Subtype: Systems that continuously update and improve based on real-world outcomes.
- Example: Adaptive AI algorithms refining treatment strategies based on patient responses over time.

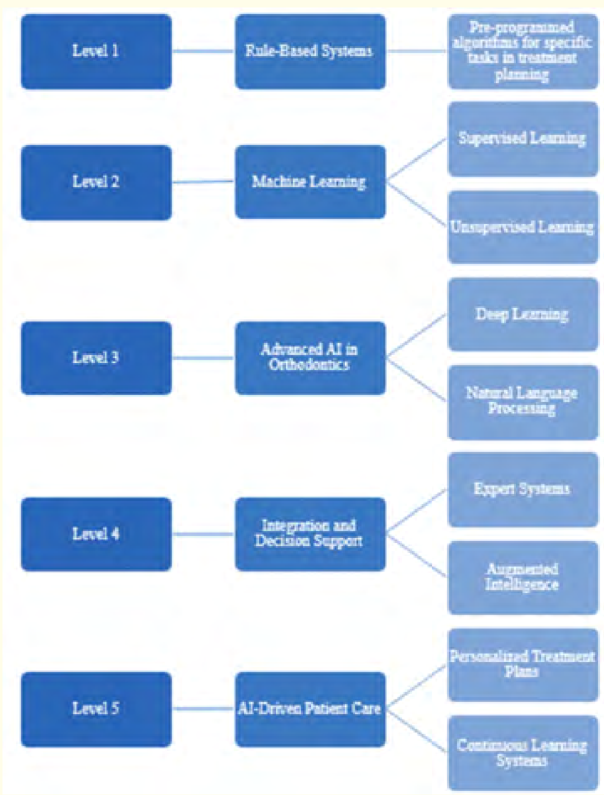

Figure 3: Levels of artificial intelligence.

History of AI transformation in orthodontics

In 1955, the term artificial intelligence was introduced by John McCarthy, who is widely regarded as the father of AI. He conceptualized it as the capability of machines to perform tasks that typically require human intelligence, thereby laying the foundation for modern AI research [3].

Over time, orthodontics has evolved from conventional mechanical approaches into a technologically advanced specialty driven by digital innovation [21]. Early orthodontic treatment primarily relied on fixed appliances and manual adjustments to correct malocclusions. However, with the advent of digital technologies such as computer-aided design and manufacturing (CAD/CAM), intraoral scanners, cone-beam computed tomography (CBCT), and 3D printing, there has been a substantial enhancement in diagnostic precision and treatment planning efficiency [27,30].

More recently, the incorporation of digital workflows, three-dimensional imaging, and virtual treatment simulations has further revolutionized orthodontic practice. These advancements have facilitated the development of more aesthetic and patient-friendly treatment options, including clear aligner therapy, which offers improved comfort and convenience compared to traditional appliances [32].

The integration of AI into orthodontics represents a transformative shift in clinical practice. AI-driven systems contribute to increased efficiency, improved diagnostic accuracy, and enhanced treatment predictability. As technological advancements continue, the synergy between AI and orthodontics is expected to redefine dental healthcare by enabling more personalized and evidence-based treatment approaches [4,8].

AI is increasingly influencing routine orthodontic practice and is currently applied in several key domains, including:

- **Accelerated diagnosis:** AI enables rapid analysis of facial images, radiographs, photographs, and intraoral scans, facilitating early and accurate detection of malocclusions [19,22].
- **Treatment planning and outcome prediction:** Machine learning models assist in surgical decision-making and forecasting treatment outcomes, improving clinical reliability [14,16].
- **Treatment monitoring and progression:** AI-powered remote monitoring systems allow continuous assessment of treatment progress, enhancing patient compliance and reducing the need for frequent clinical visits [32,35].

Period	Technological developments	Treatment modalities	Imaging*
1	ca 1907		Cephalometrics, 1931 Panoramic, ca 1960
	- Brackets/wires (Begg interlude)	- Non Extraction - Extraction	
	"Latest and best" edgewise spill-over	The debate	
2	ca 1975		
	- Bonding/"smart" brackets - Lingual appliances - Smart wires	- Non Extraction - Gnathology - Orthognathic surgery *(Relapse interlude, then rigid fixation)*	
	Space age spill-over	Pushing the envelope	
3	ca 1990/95		Imaging programs (simulation), ca1990 CBCT Mouth scanner
	- Invisalign - Temporary anchorage devices - Microvibrations	- Non Extraction - Shifting borderlines between orthodontics/ orthognathic surgery - Less invasive surgery: decortication, microperforations	
	Information technology spill-over	Toward personalized treatment	
GOALS	More controlled, faster movement; Less noticeable appliances	Occlusion/Function; Balance of facial esthetics; Stability	Precise anatomic representation

Table 1: 3 Key orthodontic developments in the past 100 years organized into 3 defined periods. Timeline in technology and treatment modalities is shown along with the goals sought by orthodontists in each area. Although imaging belongs in technology, it is listed separately because it impacted treatment in all periods. *Impact on diagnosis, treatment planning, and conduct [21].

Artificial neural network

Artificial neural networks (ANNs), a sub-domain of machine learning, are inspired by the biological neural architecture of the human brain [40]. ANNs have been extensively utilized to analyze complex relationships within large datasets [38,40]. A typical ANN consists of at least three layers: an input layer, one or more hidden layers, and an output layer [13]. Neurons within these layers are interconnected, forming a network capable of processing information efficiently. ANNs with multiple hidden layers are referred to as deep learning models, which have demonstrated superior performance in tasks such as classification and segmentation, particularly in computer vision applications [12,37]. The growing popularity of deep learning can be attributed to advancements in computational power and the development of sophisticated training algorithms [38,40]. Furthermore, a key advantage of deep learning over traditional machine learning lies in its ability to perform automatic feature extraction, thereby eliminating the need for manual intervention and enabling more effective utilization of data [38].

Convolutional neural networks (CNNs), one of the most widely used deep learning architectures, have shown exceptional performance in processing high-resolution images [37,38]. In CNNs, the conventional hidden layers are replaced by three primary types of layers: convolutional layers, pooling layers, and fully connected layers. Convolutional layers use filters (kernels) to extract relevant features and generate feature maps, thereby reducing the complexity of input images. Pooling layers are typically applied after convolutional layers to reduce the spatial dimensions of feature maps while preserving essential information. After multiple iterations of convolution and pooling, the extracted features are integrated within fully connected layers for final decision-making. Owing to this hierarchical structure, CNNs demonstrate superior performance compared to traditional ANNs in image-based tasks [37,38].

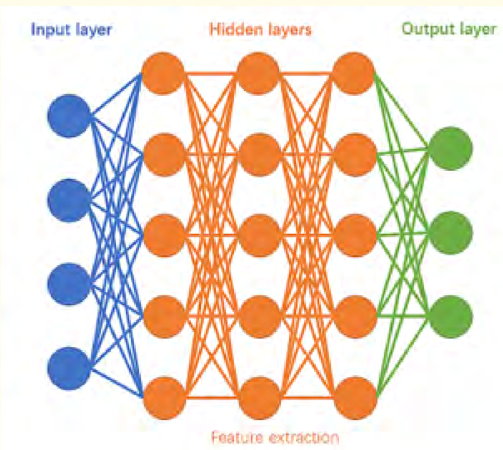

Figure 4: Schematic diagram of deep learning.

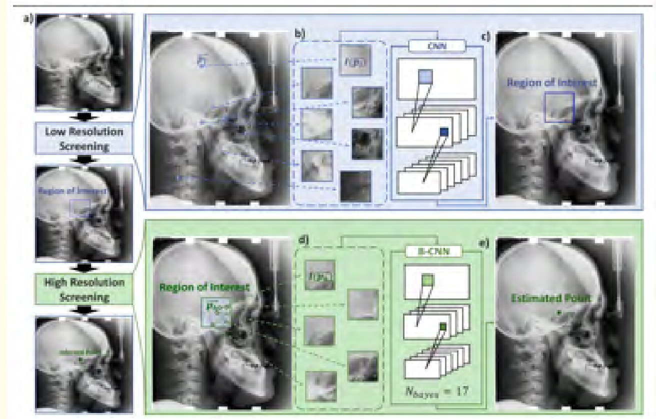

Figure 5: Schematic representation of the overall detection framework. (a) The original lateral cephalogram is downsampled by a factor of three. (b) From the downsampled image, batches are sampled with a stride of 3 mm along both width and height. (c) Based on low-resolution screening (LRS), a convolutional neural network (CNN) identifies a region of interest (ROI) for the target landmark. (d) Each pixel within the ROI is further sampled as an image batch and processed using a Bayesian CNN (B-CNN) for iterative refinement. (e) High-resolution screening (HRS) yields the final predicted position of the target landmark [20].

Accuracy of orthodontic diagnosis

Artificial intelligence (AI) is increasingly being utilized as an assistive tool in clinical orthodontics, enabling the analysis of diverse diagnostic datasets to support accurate identification and decision-making [1,4]. For instance, automated cephalometric analysis for the identification of anatomical landmarks on radiographic images has demonstrated high levels of accuracy, with some studies reporting performance approaching 92% [19,20].

Additionally, automated tooth detection and identification using artificial intelligence have demonstrated high accuracy, often exceeding 88% [21,22]. Automated digital labeling further facilitates rapid assessment and enhances diagnostic efficiency. AI-based dental age estimation using radiographic indicators has also shown high accuracy, reaching up to 94% in certain studies [25,26]. Furthermore, AI-driven decision support systems have been explored for early detection of temporomandibular joint osteoarthritis using multimodal data, including CBCT, clinical, and biological parameters [42,43]. Although AI has also been applied for the assessment of facial midline and asymmetry, current evidence suggests that it does not consistently outperform conventional diagnostic methods [45].

Treatment planning

Treatment planning in orthodontics can be significantly enhanced through the application of artificial intelligence (AI), particularly in areas such as extraction decisions, orthognathic surgery recommendations, prediction of dentofacial outcomes, and evaluation of patient experience in aligner therapy. Well-designed AI systems can improve decision-making confidence among early-stage orthodontists, reduce treatment duration, enhance esthetic outcomes, and ultimately improve patient satisfaction [1,5,9]. For example, machine learning models have been developed using clinical, radiographic, and patient data to predict extraction decisions and anchorage requirements [11,14]. Additionally, predictive algorithms have demonstrated the ability to estimate post-treatment facial changes and assess patient experience during clear aligner therapy, including factors such as pain and anxiety [30,44]. Other applications include appliance selection and optimization of treatment modalities based on individual patient characteristics [6,10].

AI is also increasingly utilized during and after orthodontic treatment. Remote monitoring systems enable tracking of tooth movement and reconstruction of three-dimensional (3D) digital models throughout treatment [32–34]. These systems, often integrated with smartphone-based applications, improve patient compliance and allow continuous monitoring without frequent in-office visits [35,36]. Furthermore, treatment outcomes can be evaluated using AI-based facial attractiveness and esthetic assessment models [30,45].

Recent studies have explored the use of AI and machine learning (ML) for predicting orthodontic diagnoses and treatment plans. One such study analyzed clinical, cephalometric, and photographic data from a large patient cohort and developed multiple ML models to determine jaw relationships, extraction needs, and treatment strategies, achieving an overall accuracy of approximately 84% [13,18]. These findings highlight the strong correlation between diagnostic parameters and key factors in orthodontic treatment planning.

Several studies have specifically focused on extraction decision-making. Machine learning approaches have demonstrated effectiveness in predicting the need for tooth extractions, improving consistency in clinical decisions [14,11]. Similarly, artificial neural network (ANN)-based models have been successfully trained using clinical and radiographic data to support extraction planning, including decisions regarding extraction patterns and space management [12,13].

In summary, these studies highlight the significant potential of AI in orthodontic treatment planning. AI can reduce inter-clinician variability, enhance diagnostic precision, and improve the consistency and effectiveness of treatment decisions. However, it is important to emphasize that AI should function as an adjunct to, rather than a replacement for, clinical expertise and professional judgment [41].

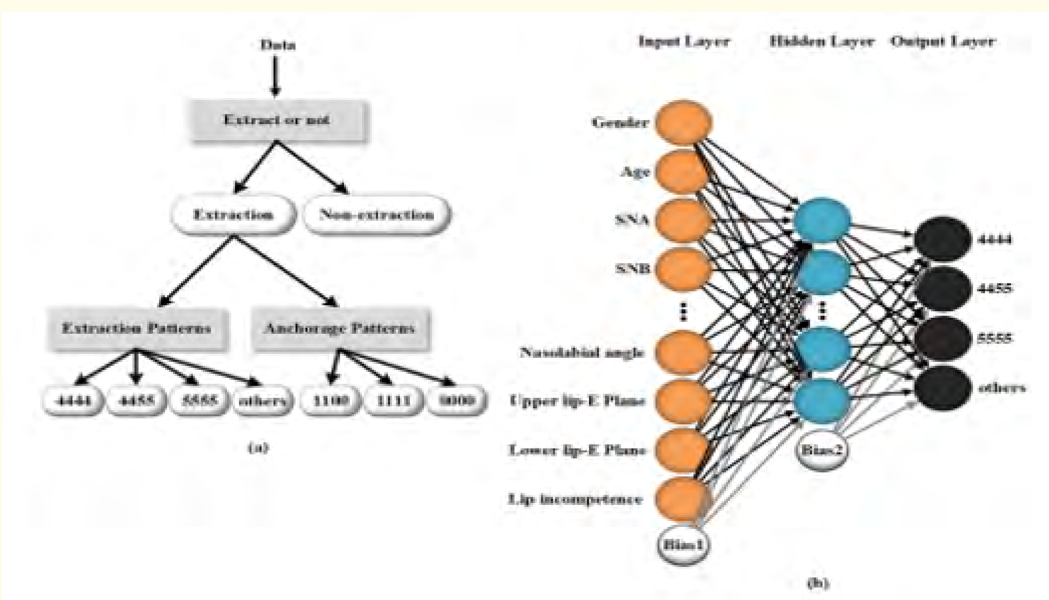

Figure 6: Data processing flowchart and structure of the neural network used to predict extraction patterns. The network architecture consists of a three-layer fully connected multilayer perceptron [13].

Implementation of AI systems

As manufacturers continue to develop and refine AI-integrated technologies, dental professionals must understand how these systems function and their potential impact on patient care. Many clinicians may already be using AI-enabled tools without explicit awareness, as these technologies are often embedded within software designed to optimize clinical workflows and decision-making processes [2,10].

Successful implementation of AI in dental practice requires consideration of technology acceptance and continuous quality assurance. Key determinants of adoption include perceived usefulness and ease of use, both of which influence clinician trust and integration into routine workflows. Training in controlled environments can enhance user confidence and facilitate smoother adoption. Additionally, continuous monitoring and validation of AI systems are essential to ensure patient safety, particularly as some models evolve through updates or continuous learning. Establishing standardized performance metrics and conducting periodic evaluations are critical for maintaining system reliability [3,40].

Regulatory frameworks also play an important role in ensuring the safe implementation of AI technologies. Agencies such as the U.S. Food and Drug Administration oversee the approval of software as a medical device, ensuring that AI systems used in healthcare meet stringent safety and efficacy standards. As AI adoption expands, maintaining a balance between regulatory compliance and technological innovation remains essential [2,39].

Dental analysis

In orthodontic clinical practice, intraoral photographs and study models are fundamental tools for dental analysis, providing critical information on molar relationships, crowding, arch width, overjet, overbite, and overall oral health. However, manual analysis is often time-consuming and labor-intensive, highlighting the potential role of AI in automating these processes [4,27].

Deep learning algorithms have demonstrated promising results in detecting malocclusion traits from intraoral images. AI systems can accurately identify features such as crowding, spacing, and abnormal overjet or overbite, thereby enhancing diagnostic efficiency [21,23]. Similarly, convolutional neural network (CNN)-based models have been applied to quantify tooth crowding with high precision, reducing measurement errors and improving reproducibility [23,24].

Advances in digital technology have further facilitated the integration of three-dimensional (3D) intraoral scans and digital dental models into orthodontic practice. These technologies enable automated measurements and comprehensive analysis of dental structures. Deep learning approaches, including graph-based neural networks, have shown high accuracy in automated tooth segmentation and reduced computational time compared to conventional methods [23,24,29]. Continuous improvements in tooth segmentation and landmark recognition are expected to further enhance automated dental analysis and expand its clinical applications [22,24].

Facial analysis

Facial photographs are essential for evaluating facial symmetry, proportions, and overall esthetics in orthodontics. AI-based facial analysis systems have been developed to automate landmark detection and morphological assessment; however, this field is still evolving.

Early approaches using machine learning algorithms demonstrated moderate accuracy in landmark identification, with a significant proportion of measurements showing deviations from manual analysis [45]. More recent AI models, including deep learning-based systems, have shown improved precision in assessing facial dimensions and proportions, with results comparable to manual methods in certain parameters [30,45].

Despite these advancements, automated facial analysis remains in its early stages, and current evidence suggests that AI does not yet consistently outperform conventional clinical assessment. Further research is required to enhance accuracy, validate clinical applicability, and expand its role in orthodontic diagnosis and treatment planning [45].

Cephalometry

For decades, manual identification of anatomical landmarks was the primary method for cephalometric tracing. However,

Figure 7: Facial landmark points identified and located on the subject's image.

recent advancements in artificial intelligence (AI) have provided a reliable and efficient alternative. Modern AI-based software can process digital or scanned lateral cephalometric images to automatically identify cephalometric points (CPs) and perform tracing and measurements with high precision [19,20].

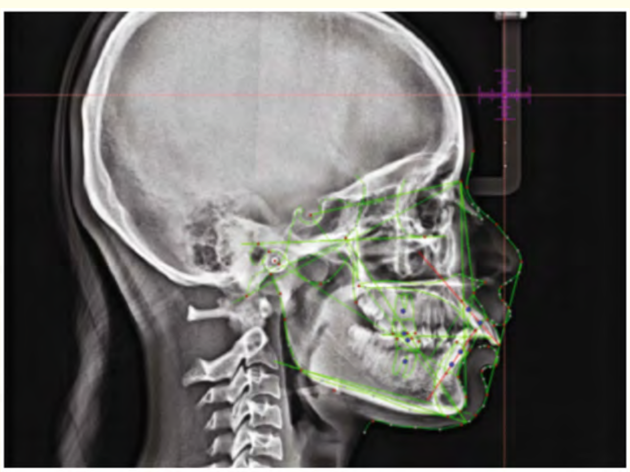

Figure 8: Prediction of cephalometric landmarks using artificial intelligence.

The accuracy of AI in identifying cephalometric landmarks has been evaluated in multiple studies. Analyses conducted on large datasets of lateral cephalograms have demonstrated encouraging results, with accuracy levels typically ranging from approximately 88% to 92%, supporting the clinical applicability of AI in both two-dimensional and three-dimensional CBCT-based orthodontic evaluations [19,20].

With the rapid advancement of machine learning (ML) techniques, particularly deep learning, there has been significant progress in the classification of skeletal relationships using cephalometric images. Deep convolutional neural network (DCNN)-based models have been developed to classify sagittal skeletal patterns based on cephalometric parameters such as A-point, Nasion (Na), B-point, and ANB angle, demonstrating performance comparable to conventional methods [19,37].

In addition, deep learning models trained on large datasets of lateral cephalograms have shown accuracy levels comparable to experienced orthodontists in cephalometric landmark detection, highlighting their potential as reliable clinical support tools [19,20].

Various digital platforms have also been introduced for cephalometric analysis, including software-assisted and fully automated web-based tracing systems. These systems have demonstrated comparable performance to manual and semi-automated methods while significantly reducing analysis time, indicating their potential for routine clinical use [20,22].

Skeletal maturity

Assessment of skeletal maturity is essential in determining the optimal timing and modality of orthodontic treatment. Recent advancements in artificial intelligence (AI) have enabled the development of automated systems for evaluating skeletal maturity indicators (SMIs), offering improvements over traditional methods such as the Greulich and Pyle and Tanner–Whitehouse techniques [25,26]. These AI-based systems typically involve automated detection of regions of interest (ROIs), evaluation of skeletal maturity stages, and mapping of these stages to standardized indices, thereby enhancing diagnostic efficiency and consistency in clinical practice [25,26].

Craniofacial growth is commonly described in terms of magnitude, direction, and velocity, with the mandible exhibiting significant growth potential within the craniofacial complex. Machine learning (ML) techniques have been applied to analyze longitudinal cephalometric data for predicting craniofacial growth patterns, including mandibular length and growth direction [45].

Furthermore, ML-based predictive models utilizing cephalometric datasets have demonstrated promising accuracy in forecasting postpubertal mandibular development, highlighting their potential role in improving treatment planning and timing decisions in orthodontics [45].

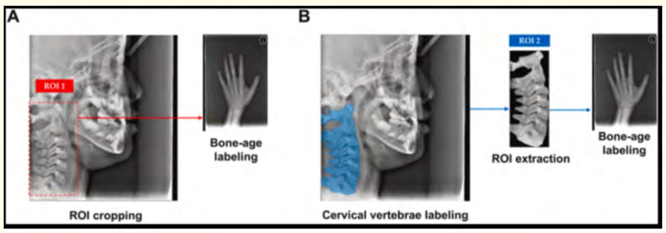

Figure 9: DeepLabv3+ architecture for the semantic segmentation network.

Bone age assessment

Bone age assessment is a critical diagnostic tool in orthodontics and related fields for evaluating skeletal development relative to chronological age. Recent advances in deep learning (DL) have significantly improved the accuracy and efficiency of bone age estimation using radiographic images. Convolutional neural networks (CNNs), in particular, have demonstrated strong performance in medical image analysis, enabling automated and reliable assessment while reducing interobserver variability associated with traditional methods [25,37,38].

AI-based approaches for skeletal maturity assessment using lateral cephalograms and other radiographic modalities have shown promising results, enhancing both diagnostic consistency and clinical efficiency. These systems automate key steps such as feature extraction and classification, thereby improving reproducibility and reducing the time required for evaluation [25,26].

Recent studies utilizing CNN-based models for cervical vertebral maturation (CVM) staging have demonstrated moderate to high accuracy, highlighting the potential of AI in assessing skeletal maturity and supporting clinical decision-making in orthodontics [25,26].

CBCT

Cone-beam computed tomography (CBCT) provides comprehensive three-dimensional visualization of craniofacial structures, offering significant advantages over conventional two-dimensional imaging. However, manual analysis of CBCT data is often complex and time-consuming. AI-based tools have been introduced to streamline this process by enabling automated landmark identification, segmentation of skeletal structures and teeth, and enhanced diagnostic capabilities [28,29,31].

AI-driven 3D cephalometric analysis facilitates accurate assessment of skeletal relationships and supports growth prediction and treatment planning, particularly in complex orthodontic and surgical cases [28,31]. These advancements contribute to improved precision and efficiency in clinical workflows, making AI an essential component of modern digital orthodontics.

Orthognathic surgery

Artificial intelligence (AI) and machine learning (ML) are increasingly integrated into software systems for orthognathic surgery planning. These technologies enable automated segmentation of craniofacial structures, real-time modification of cephalometric parameters, and enhanced visualization for surgical simulation [41].

AI-based image processing tools are also widely used in airway analysis, allowing accurate assessment of airway volume changes before and after orthodontic or orthognathic interventions. This is particularly important, as soft tissue dynamics and airway adaptations play a crucial role in treatment stability and functional outcomes [41,45]. Automated segmentation significantly reduces analysis time and minimizes operator-dependent variability, improving consistency in clinical practice [23,24].

Furthermore, predictive AI models have been developed to assist in orthognathic treatment planning, particularly in patients with skeletal Class III malocclusion. Machine learning algorithms such as random forest and logistic regression have demonstrated high accuracy in predicting surgical needs and treatment outcomes, supporting clinical decision-making [16]. Similarly, artificial neural network (ANN)-based models have shown strong agreement with clinical decisions regarding the need for orthognathic surgery, highlighting their potential as reliable adjunctive tools in treatment planning [16,41].

Figure 10: Flow chart representing the group allocation, training and testing processes.

Orthodontic treatment monitoring

Artificial intelligence (AI) has significantly enhanced orthodontic treatment monitoring by enabling continuous, precise, and automated assessment of treatment progress. AI-driven remote monitoring systems integrate image analysis, machine learning algorithms, and patient-generated data to track tooth movement and treatment outcomes in real time [32,33]. These systems improve clinical efficiency by reducing the need for frequent in-office visits while maintaining high standards of care.

AI-based platforms for monitoring orthodontic treatment, particularly in clear aligner therapy, have demonstrated high effectiveness in evaluating treatment progress and patient compliance. Such systems utilize intraoral images and advanced algorithms to assess tooth movement and detect deviations from planned treatment, thereby allowing timely clinical interventions [33,34].

The integration of intraoral scans with three-dimensional imaging modalities such as CBCT has further improved the accuracy of digital dental models, enabling more precise tracking of treatment progression over time [28]. These advancements contribute to improved treatment outcomes by facilitating data-driven decision-making throughout the course of orthodontic therapy.

In addition to monitoring tooth movement, AI has also been applied to evaluate treatment outcomes in terms of facial esthetics. Machine learning models can analyze facial features to assess changes in attractiveness and estimated age following orthodontic treatment, providing an objective and standardized approach to outcome evaluation [41,45]. This integration of functional and esthetic assessment represents a significant advancement in comprehensive orthodontic care.

Force system prediction

Orthodontic tooth movement is governed by the interaction between applied forces and biological tissue response. Traditionally, force systems have been analyzed using simplified mechanical models; however, AI has introduced new possibilities for understanding complex biomechanical interactions.

Artificial neural networks (ANNs) have been employed to model and predict orthodontic force systems, demonstrating effectiveness in mapping input-output relationships in systems such as orthodontic springs. These models provide valuable insights into force distribution and tooth movement patterns, contributing to improved appliance design and treatment planning [40].

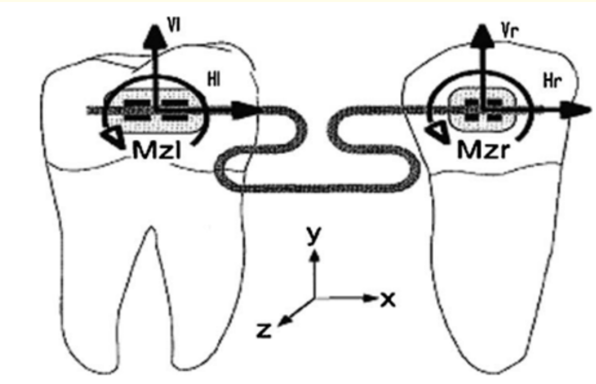

Figure 11: The general two-dimensional x-y plane model.

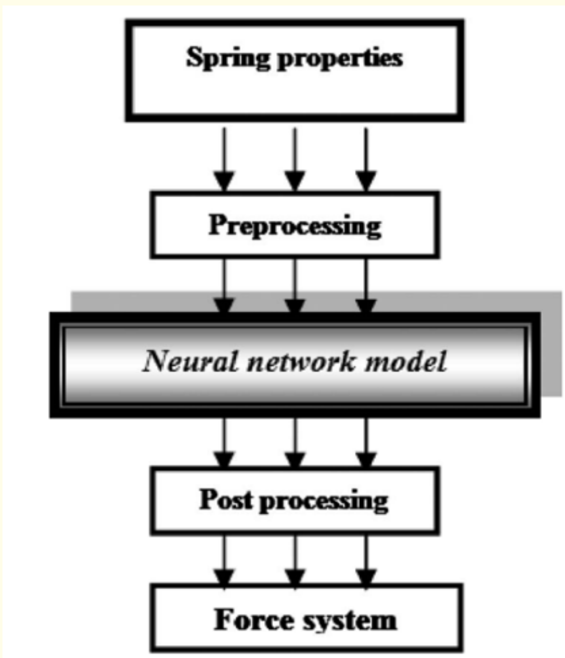

Figure 12: NN T-spring force system prediction model.

In treatment outcome

Management of impacted canines

Management of impacted canines requires careful diagnosis and treatment planning to achieve optimal orthodontic and periodontal outcomes. The complexity of treatment is influenced by the position and degree of displacement of the impacted tooth. Artificial intelligence (AI) techniques, including probabilistic models such as Bayesian approaches, have been explored to improve diagnostic accuracy and treatment prediction [4].

Radiographic assessments using panoramic and lateral cephalometric images play a crucial role in predicting maxillary canine impaction. Machine learning algorithms, including random forest models, have demonstrated good predictive performance in determining eruption outcomes. Additionally, AI-based frameworks utilizing cone-beam computed tomography (CBCT) have been applied to analyze maxillary structures and quantify variations associated with impacted canines, improving diagnostic precision [24].

Headgear selection

Headgear is an orthopedic appliance used to modify maxillary growth through extraoral force application. Selection of the appropriate type—high-pull, medium-pull, or low-pull—depends on the patient's clinical presentation. AI-based decision support systems have been developed to assist clinicians in selecting the most suitable headgear type, thereby improving decision-making, particularly for less experienced practitioners [18].

Soft tissue outcomes

Evaluation of the soft tissue profile is a critical component of orthodontic diagnosis and treatment planning. Changes in the relationship between the nose, lips, and chin significantly influence facial esthetics. Artificial neural network (ANN)-based models have demonstrated effectiveness in predicting soft tissue changes following orthodontic treatment, including differences between extraction and non-extraction cases, thereby enhancing treatment outcome prediction [44].

Temporomandibular joint disorders

Orthopantomograms (OPGs) and CBCT imaging are commonly used to evaluate temporomandibular joint (TMJ) conditions. However, interpretation may be challenging in the absence of expert evaluation. AI-based diagnostic systems have been developed to detect TMJ osteoarthritis and related bony changes from radiographic images, improving diagnostic accuracy and reducing observer variability [42,43].

Clinical practice

Practice guidance

AI applications in orthodontics extend to clinical decision support and treatment guidance. Machine learning-based systems have been developed to assist in the management of complex conditions such as deep overbite by providing detailed, multi-parameter treatment protocols. These systems can guide clinical decisions related to tooth movement strategies and treatment mechanics, improving overall treatment outcomes [17].

Advanced deep learning models, such as three-dimensional U-Net architectures, are widely used for segmentation tasks in CBCT imaging. These models enable automated analysis of anatomical structures, including bone and soft tissue thickness, which is essential for procedures such as miniscrew placement and treatment planning [24,28].

Remote care

Remote monitoring technologies allow orthodontists to track treatment progress using patient-submitted images or digital scans, reducing the need for frequent in-office visits. AI-enhanced remote monitoring systems improve treatment efficiency, patient compliance, and early detection of issues such as appliance failure or relapse [32–34]. These systems can be applied to both fixed appliance therapy and clear aligner treatments, providing accurate and continuous evaluation of treatment progress [33,35].

Limitations of AI

Despite its significant advantages, AI in orthodontics has several limitations. One of the most common challenges is overfitting, where models perform well on training data but poorly on new, unseen data [2,38]. Contributing factors include limited dataset size, lack of data diversity, and excessive model complexity. Strategies such as data augmentation, cross-validation, and regularization techniques are essential to improve model generalizability [3,9].

Although AI has shown substantial progress in orthodontic diagnosis, its role in guiding treatment execution remains limited. Further research is needed in areas such as automated assessment of orthodontic treatment need and real-time clinical decision support. As data availability and computational capabilities continue to improve, AI is expected to play an increasingly significant role in advancing orthodontic practice [7,40].

Conclusion

Artificial intelligence has significantly transformed the field of orthodontics, with applications ranging from diagnosis and treatment planning to treatment monitoring and outcome assessment. Numerous studies have demonstrated that AI-based systems can achieve accuracy comparable to experienced clinicians in tasks such as cephalometric analysis, treatment prediction, and facial assessment.

The integration of AI with digital technologies, including intraoral scanning and CBCT imaging, has enabled comprehensive three-dimensional evaluation of craniofacial structures and treatment outcomes. AI-driven remote monitoring systems further enhance treatment efficiency, patient compliance, and clinical decision-making. Additionally, AI offers the ability to objectively evaluate treatment outcomes, including facial esthetics and predicted age changes, providing a more holistic assessment of orthodontic success.

Despite these advancements, AI should be considered an adjunct to clinical expertise rather than a replacement. The orthodontist's role remains central in interpreting AI outputs and making informed clinical decisions. As AI technologies continue to evolve, they are expected to contribute to more precise, efficient, and personalized orthodontic care.

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Conflict of Interest

No conflict of interest.

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