RESEARCH PAPER

# The Diagnostic Frontier of Artificial Intelligence in Orthodontics: Accuracy, Clinical Pitfalls, and Interdisciplinary Boundaries in Complex Malocclusions. A narrative review

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**Abstract**
The integration of Artificial Intelligence (AI) into orthodontic practice marks a paradigm shift from a purely analogue or traditional "occlusion-driven" specialty to an objective, "face-driven," data-dense medical discipline. Encompassing machine learning (ML), artificial neural networks (ANNs), and deep learning (DL), these technologies have transitioned from theoretical laboratory frameworks into clinically validated diagnostics. Bibliometric analyses reveal that nearly 83% of the existing peer-reviewed literature on orthodontic AI has emerged since 2021, focusing heavily on automated cephalometric landmarking and three-dimensional (3D) automated segmentation.[1,8] Though AI−driven architectures optimize routine tasks, shorten processing times, and enhances the diagnostic reproducibility, a critical performance gap persists regarding absolute geometric accuracy in severe skeletal deformities, non−linear growth forecasting, and material behaviour predictions[8,9]. This narrative review considers recent high-impact literature from 2024 to evaluate the mechanical limitations, structural blind spots, and systemic pitfalls of automated tools, advocating for an ethically sound, semi-automated orthodontic workflow.
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## 1. Introduction and Foundations of AI in Dental Diagnostics

Artificial Intelligence has transformed the landscape of modern diagnostic medicine, evolving from a speculative computing paradigm into a primary pillar of clinical decision-support infrastructure. The most therapeutically revolutionary component of artificial intelligence (AI) in dental and craniofacial imaging is machine learning (ML), in which mathematical algorithms identify intricate statistical patterns in massive data sets without being specifically programmed for predetermined geometric arrangements.[1,3,8].

More precisely, image-based diagnoses have been transformed by Deep Learning (DL), which makes use of multi-layered Artificial Neural Networks (ANNs) created to replicate human cognitive frameworks. DL methods handle radiographic data at the pixel level by utilizing specialized computational architectures like Convolutional Neural Networks (CNNs). These networks automatically extract anatomical shapes, densities, and hidden details that could otherwise be difficult for human visual assessment.[1,4,6,10].

Currently, the technical objectives of AI in dental diagnostics are concentrated across three major imaging tasks: automated detection of pathologies, localized landmark identification, and volumetric 3D segmentation. [1,3,6,11,12]

Multi−modular diagnostic systems utilize the neural pathways to achieve high sensitivity and specificity in dental screenings. For example, convolutional models trained on large − scale data sets achieve diagnostic accuracy rates between 68% and 99.02% for dental caries and upto 92.5% sensitivity for periapical radiolucent lesions.[3,6]

More completely automated 3D segmentation capabilities to isolate the maxilla, mandible, mandibular canals, and individual dentition across different acquisition techniques have been made possible by recent open-access DL models like Dental Segmentator.[12]

These programs automate tooth enumeration, locate bone boundaries, and detect periapical anomalies on both two−dimensional(2D) orthopantomograms(OPGs) and cone−beam computed tomography(CBCT) volumes.[1,5,6,12]

AI creates a very dependable pre-treatment diagnostic baseline by automating these fundamental examinations. This optimization moves the diagnostic emphasis of contemporary orthodontic planning to a more thorough examination of tissue boundaries. [4,7,8]

## 2. Clinical Applications Across the Orthodontic Workflow

The clinical application of AI in orthodontics has expanded beyond simple administration into automated diagnostic systems categorized across five primary functional domains. [8] (Fig 1)

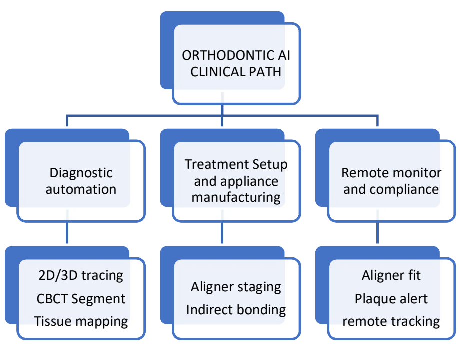



Figure 1: Clinical applications of AI across orthodontic workflow

### Diagnostic Automation and Tissue Mapping

AI pipelines transform unprocessed patient data into segmented digital models by automating the initial classification of clinical datasets. AI can segment the mandible, separate specific crowns, and map upper pharyngeal airway volumes from CBCT data in a matter of seconds using object-detection architectures like YOLO (You Only Look Once), U-Net, or nnU-Net v2. [1,4,6,11]

Such specialized deep learning frame works show high fidelity even in difficult clinical scenarios, such as the 3D localization and volumetric segmentation of impacted maxillary canines, matching expert manual accuracy while drastically reducing segmentation time. [11]

### Treatment Planning and Decision-Support Systems

Machine learning models (such as Random Forest, Support Vector Machines, and CatBoost) support clinicians in complex clinical triage. Trained on historical expert data, these models achieve diagnostic accuracy rates between 72% and 95% in recommending extraction versus non-extraction pathways or identifying candidates for orthognathic surgery. [3,6,8]

They analyse skeletal parameters (e.g., the ANB angle), inter−arch crowding, and soft−tissue draping to propose clinical interventions. [4,5,6,10]

### Growth and Skeletal Maturation Triage

When planning for functional appliances or orthognathic surgery, it is essential to estimate a patient's skeletal age. Cervical vertebral maturation (CVM) on lateral cephalograms is evaluated automatically by deep learning frameworks. In order to anticipate the remaining potential for adolescent growth, models like Cat Boost combine vertebral geometry with the mandibular second molar's dental maturation stages, age, and sex. [3,6,8]

### Appliance Design, Staging, and Simulation

AI optimizes virtual setups and creates successive tooth movements in clear aligner therapy. Reinforcement learning techniques and Generative Adversarial Networks (GANs) compute force distributions, automate case staging, and forecast structural final positions.[3,7,8]

For fixed appliances, object−detection systems calculate optimized bracket angulation and torque parameters for customized indirect bonding (IDB) trays. [3,6]

### Remote Telemonitoring and Compliance Tracking

Telemonitoring solutions enable patients to take intraoral photos from home using AI smartphone applications. Convolutional networks evaluate these images asynchronously, monitoring aligner tracking, tracking oral hygiene conditions (e.g., plaque indices, gingival inflammation), and alerting clinicians to tracking loss or emergencies. [3,7,8]

Recent clinical benchmarks demonstrate that remote vision AI models achieve upto 93.2% accuracy [8]

## 3. AI-Driven Cephalometric Landmark and Tracing Boundaries

Cephalometric analysis remains a standard diagnostic method for identifying skeletal anomalies and defining structural configurations. However, manual tracing is historically limited by inter-operator variability and a significant time investment. Modern automated cephalometric software that uses CNNs, Vision Transformers (ViTs), and multimodal deep learning models (like Deep Fuse) has been introduced to overcome these constraints and improve workflow efficiency. [2,5,7,9]

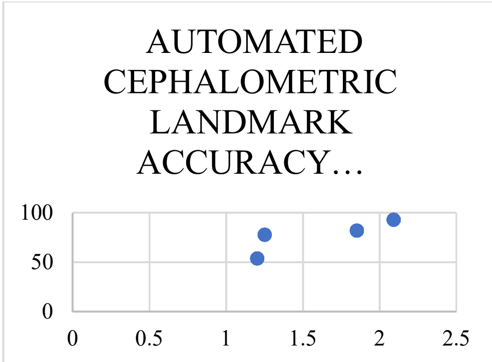


Figure 2: AUTOMATED CEPHALOMETRIC LANDMARK ACCURACY ENVELOPE

While AI systems provide excellent reproducibility (T1 to T2) by placing points consistently in identical coordinate frameworks, systematic evaluations reveal a clinical gap regarding absolute diagnostic accuracy. [2,5,8] Across Scopus and PubMed clinical studies, the overall mean radial error (MRE) of fully automated landmark detectors typically ranges from 1.04±0.89mm to 3.40±1.57mm. [2,8] with advanced multimodal networks integrating CBCT and 2D cephalometry reaching an MRE of 1.21mm and a 92.4% accuracy [9]. While well−defined landmarks on high−contrast borders fall within the clinically acceptable 2.0mm error envelope, accuracy drops significantly when evaluating complex anatomical structures or blurred skeletal boundaries. [2,5,9] (Figure 2)

Diagnostic studies underscore that automated landmark accuracy is highly site-dependent. Points located on sharp skeletal junctions (such as the Sella, Nasion, and Menton) achieve near-perfect automatic detection rates (98% to 100%)[2,9]. However, the success rate drops significantly as landmarks obscured by bilateral structures or are located on smooth, continuous curves:

- **Porion (Po) & Condylion (Co):** These landmarks exhibit considerable displacement, with errors often surpassing 2.5 mm, due to bilateral superimposition and the thick temporal bone structure. [2,5,9]
- **Gonion (Go) & Articulare (Ar):** Algorithm accuracy is compromised by overlapping mandibular ramus anatomy and varying condylar curvatures; in unguided tracking setups. Maximum errors for Gonion can reach 8.30 ± 2.98 mm.. [2,5]
- **Anterior (ANS) & Posterior Nasal Spine (PNS):** Weak contrast at the thin hard palate junction leads to frequent landmark misplacement. [2,5,9]
- **Point A & Point B:** These dental sites, which are situated on smooth, continuous curving profiles and lack clear skeletal intersections, reduce the algorithm's success rate to 52% and 26%, respectively, under small tracking margins. [2,5]

Performance is further impacted by changes in image quality and mapping of soft-tissue profiles. Significant performance trade-offs have been reported in recent studies of deep learning models (such as LSTM, RNN, and GAN architectures) for face soft-tissue profile categorization; single-modality CNNs have a high risk of overfitting when evaluating subtle soft-tissue contours.[10] Soft-tissue profile mapping is compromised by high contrast and low brightness levels, and more localization errors are correlated with higher tube voltage and smaller sensor sizes. [2,5,10] As a result, fully automatic tracing is still vulnerable to clinically significant diagnostic errors, according to current diagnostic research. The gold standard for clinical accuracy and patient safety is still a semi-automated method in which the AI system suggests an initial landmark template, which is then manually verified and edited by the orthodontist. [2,5,7,8]

**4. Growth Prediction and Setup Pitfalls in Severe Skeletal Malocclusions**

The most complex challenges for automated orthodontic software occur in growth forecasting and virtual setup generation for severe skeletal Class III deformities, craniofacial asymmetries, and congenital anomalies like cleft lip and palate. [2,4,6,9] While AI excels at identifying patterns in normative geometries, its clinical efficacy decreases when evaluating structural anomalies that diverge from standard training models. [4,6,8]

**Landmark Misplacement in Dysmorphic Anatomy**

Standard anatomical landmarks are either absent or fundamentally abnormal in people with unilateral cleft lip and palate. Highly variable skeletal architecture, which exhibits significant variations in soft-tissue characteristics and dental inclinations (such as U1-NA), is not recognized by automated algorithms. Errors at the nasolabial junctions and soft-tissue profile contours can be more than 18°. [2,4,10]

**The Non-Linear "Soft-Tissue Blindspot"**

The machine learning algorithms (such as LASSO, Random Forest, and RNNs) that are used to predict post-pubertal mandibular growth spurts rely more on pattern recognition than biological mechanics. [4,6,10] These models predict hard−tissue mandibular length with in a reasonable 2.5mm to 3.0mm margin in balanced patterns, but struggle with hyperdivergent growth or severe Class III anomalies. [2,4,6,9]

AI models frequently overlook non-linear changes in musculature and soft-tissue tension because they anticipate a linear biological response.[4,6,10] This structural blind spot may cause mandibular prognathism or vertical growth to be underestimated, which could mislead decisions about surgical vs non-surgical camouflage. [2,4,6,8]

**Tracking Loss in Clear Aligner Predictions**

In automatic clear aligner settings, there is a statistical performance cliff between standard and severe malocclusions. Clinical accuracy dramatically declines in complex skeleton instances, while automated setups achieving up to an 85% forecasting rate for mild-to-moderate crowding, according to statistical audits. [3,6,7,8]

| Setup Parameter / Component | Primary Anatomical Blindspot | Clinical Consequence of AI Error |
|---|---|---|
| **CNN Landmark Detectors** [2,5,9] | Condylion (Co), Porion (Po), Soft-Tissue Pogonion (Pg') | Errors in establishing the SN plane or true vertical references, leading to skewed ANB/Wits appraisal calculations. [2,5,9] |
| **Automated 3D Aligner Setups** [3,7,8] | Buccal-lingual crown tips & Root Torque (50% accuracy drop) | Unrealistic virtual movements that defy biological bone boundaries; leads to tracking loss and frequent mid-course corrections. [3,7,8] |
| **ML Growth Forecasters** [4,6,10] | Non-linear growth spurts in hyperdivergent Class III or asymmetric patients | Gross underestimation of mandibular prognathism or vertical growth, potentially misguiding surgical vs. non-surgical triage decisions. [2,4,6,8] |

Table 1: Primary anatomical blind spots of AI based Cephalometric landmark identification

The reason for this decline is that the program does not adequately account for intricate biological tissue responses, bone thickness limits, or patient compliance variables when planning geometric tooth movements. [3,7,8] As a result, unguided AI aligner configurations frequently produce motions that cross biological limits, leading to significant clinical tracking loss and necessitating regular mid-course adjustments. [3,7,8] (Table 1)

**5. Systemic Bottlenecks, Material Trajectories, and Future Directions**

A number of interdisciplinary constraints need to be overcome in order to transform AI from a time-saving diagnostic tool into a trustworthy clinical utility. Data dependence and a lack of adaptable learning are the main drawbacks of existing orthodontic deep learning algorithms. Training datasets are frequently tiny, substantially skewed toward local demographics and particular treatment philosophies, and sourced from single-centre archives. [1,6,7,8,12]

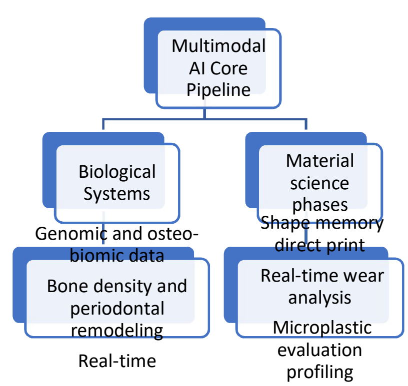
Further more, a lot of algorithms function as "black boxes" that cannot be deciphered. Clinicians are unable to assess the biomechanical reasoning behind automated judgments due to this lack of explainable logic. [6, 7, 8] Furthermore, traditional models are not flexible enough to respond to changes in clinical settings or improve predictions based on real-time physician revisions. [6,7,8]

Concurrently, a major materials science trajectory is unfolding in clear aligner fabrication. According to recent research, direct 3D-printed aligners made of sophisticated shape-memory polymers are replacing conventional vacuum thermoformed thermoplastic sheets. [3,7,8]

This direct printing method allows for variable local thickness mapping and removes print-model processing problems. By integrating unique geometric attachments straight into the aligner trays, direct printing maximizes force application and improves control over intricate actions like root torque and body intrusion. [1,3,7,8]

However, in terms of intraoral material deterioration, this shift presents difficult inter-disciplinary issues. Long-term toxicological safety must be assessed in future evaluations, with an emphasis on residual monomer elution profiles and microplastic/nanoplastic release kinetics under active, continuous orthodontic loading in the oral cavity. [3,7]

**Future interdisciplinary flow:**



The future of orthodontic AI lies in the transition from pure pattern recognition toward comprehensive biological modelling [3,6,7,9] Future architectures will likely integrate multi modal data sets— combining genomic sequence markers, individualized bone density maps, and periodontal tissue modelling with 3D soft−tissue photographs and jaw tracking data. [1,3,7,9]

**Conclusion**

By incorporating patient-specific physiological variables, AI systems can transition toward true predictive modelling. [3,6,7,9] Additionally, integrating AI engines with customized robotic wires and micro−implant guides will support the delivery of highly precise, data−driven orthodontic care [3,7,8]

**References**


1. Polizzi, A., Boato, M., Serra, S., D'Antò, V., & Leonardi, R. (2025). Applications of artificial intelligence in orthodontics: a bibliometric and visual analysis. *Clinical Oral Investigations*, 29(1), 65.
2. Ribas-Sabartés, J., Sánchez-Molins, M., & d'Oliveira, N. G. (2024). The Accuracy of Algorithms Used by Artificial Intelligence in Cephalometric Points Detection: A Systematic Review. *Bioengineering*, 11(12), 1286.
3. Olawade, D. B., Leena, N., Egbon, E., Rai, J., Mohammed, A. P. E. K., Oladapo, B. I., & Boussios, S. (2025). AI-Driven Advancements in Orthodontics for Precision and Patient Outcomes. *Dentistry Journal*, 13(5), 198.
4. Tomášik, J., Zsoldos, M., Oravcová, L., Lifková, M., Pavleová, G., Strunga, M., & Thurzo, A. (2024). AI and Face-Driven Orthodontics: A Scoping Review of Digital Advances in Diagnosis and Treatment Planning. *AI*, 5(1), 158–176.
5. Mercier, J. P., Rossi, C., Sanchez, I. N., Renovales, I. D., Sahagún, P. M., & Templier, L. (2024). Reliability and accuracy of Artificial intelligence-based software for cephalometric diagnosis. A diagnostic study. *BMC Oral Health*, 24(1), 1309.
6. Kazimierczak, N., Kazimierczak, W., Serafin, Z., Nowicki, P., Nożewski, J., & Janiszewska-Olszowska, J. (2024). AI in Orthodontics: Revolutionizing Diagnostics and Treatment Planning—A Comprehensive Review. *Journal of Clinical Medicine*, 13(2), 344.
7. Tucci, I., Gimondo, E., Jovanova, E., Angjelova, A., Isola, G., & Grippaudo, C. (2026). Present and Future of the Use of Artificial Intelligence in Orthodontics. *Bioengineering*, 13(3), 263.
8. Arab, A., & Qutieshat, A. (2026). Artificial intelligence in orthodontics: a narrative review of clinical and educational applications. *Journal of Medical Artificial Intelligence*, 9, 1282.
9. Gao, F., & Tang, Y. (2025). Multimodal deep learning for cephalometric landmark detection and treatment prediction. *Scientific Reports*, 15(1), 25205.
10. Azis, H., Salim, Y., & Puspitasari, Y. (2026). Deep Learning Approaches for Soft Tissue Classification of Cephalometric Images in Orthodontics. *JOIV: International Journal on Informatics Visualization*, 10(3), 988–995.
11. Akkaya, N., & Celik, E. (2025). Deep learning-based 3D automatic segmentation of impacted canines in CBCT scans. *BMC Oral Health*, 25(1), 114.
12. Gillot, M., Thomas, M., & Vanrenterghem, A. (2024). DentalSegmentator: robust deep learning-based CBCT image segmentation and anatomical modeling. *Computers in Biology and Medicine*, 178, 108742.