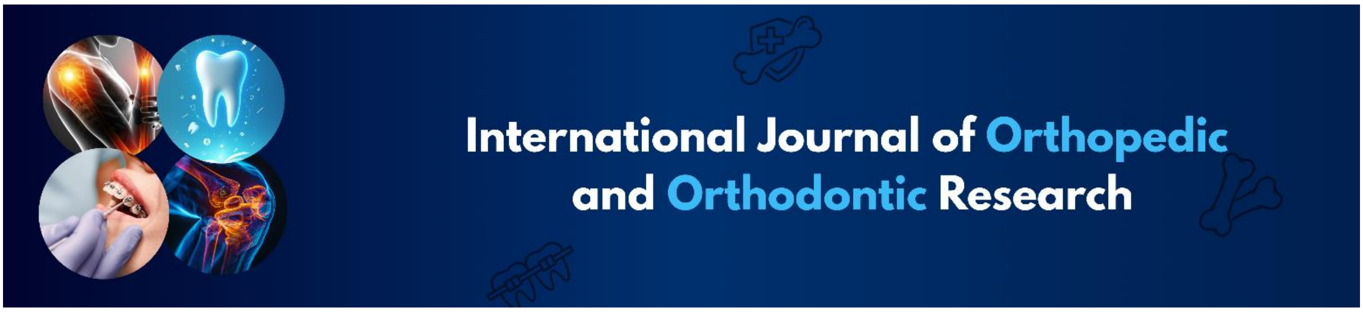

Artificial Intelligence Applications in Orthodontic Diagnosis and Treatment Planning: Current Advances and Clinical Perspectives

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Abstract
Background: Orthodontic diagnosis and treatment planning have traditionally relied on manual cephalometric analysis, which is time-intensive and subject to operator variability. Artificial intelligence (AI) offers promising avenues for automation, greater accuracy, and reproducibility across clinical workflows.
Objective: To systematically evaluate current AI-based frameworks applied to orthodontic diagnosis, cephalometric landmark detection, malocclusion classification, and treatment outcome simulation.
Methods: A structured review and comparative study design was employed, integrating data from peer-reviewed studies (2016–2024) and evaluating AI model performance using metrics including diagnostic accuracy, prediction precision, and treatment efficiency.
Results: Deep learning models—particularly convolutional neural networks (CNNs), Vision Transformers, and hybrid architectures—achieved cephalometric accuracy rates of 88.6–95.2%, reduced landmark identification time by up to 77.7%, and improved diagnostic consistency over traditional methods.
Conclusion: AI-integrated orthodontic systems demonstrate strong clinical potential. Standardisation of datasets, validation across diverse populations, and regulatory frameworks remain prerequisites for widespread implementation.

Keywords: Artificial intelligence, Orthodontic diagnosis, Cephalometric analysis, Deep learning, Convolutional neural networks (CNNs), Malocclusion classification, Treatment outcome prediction

1. Introduction

Orthodontics is a discipline fundamentally dependent on precise spatial analysis of craniofacial structures, sequential treatment planning, and long-term outcome monitoring. Conventional approaches demand considerable clinician expertise, involve manual radiographic measurements, and are vulnerable to intra- and inter-operator variability. The emergence of artificial intelligence—particularly deep learning—presents a transformative opportunity to enhance each of these dimensions [1, 2].

AI encompasses a spectrum of computational methodologies, including machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision. Within medicine, AI has demonstrated diagnostic accuracy comparable or superior to human clinicians in domains including dermatology, radiology, and pathology [2, 3]. Orthodontics, with its inherently visual and pattern-driven workflow, is especially receptive to these capabilities.

Automated cephalometric analysis—the identification of standardised anatomical landmarks on lateral skull radiographs—is perhaps the most extensively studied application. Beyond landmark detection, AI systems now address malocclusion classification, CBCT-based dental segmentation, treatment duration prediction, root resorption risk stratification, and three-dimensional outcome simulation [4–8]. This article evaluates these advances, proposes a unified AI-based orthodontic framework, and critically examines clinical implementation challenges.

2. Related Work

Early computational approaches to cephalometric analysis employed active shape models and template-matching algorithms, offering modest improvements over fully manual methods but limited adaptability to imaging variability [12, 18]. The introduction of convolutional neural networks (CNNs) shifted the paradigm considerably. Lee *et al*. demonstrated that a ResNet-50 architecture could identify 19 standard cephalometric landmarks with a mean detection error of 1.4 mm, outperforming experienced orthodontists under time-constrained conditions [8].

Subsequent investigations extended AI applications to panoramic radiographs, CBCT volumetric datasets, and intraoral scans. Kim *et al*. applied U-Net segmentation to CBCT data for individual tooth identification, achieving a Dice similarity coefficient of 0.947 [13]. For malocclusion classification, random forest and support vector machine models attained approximately 88% accuracy on multi-class classification tasks [22]. More recently, Vision Transformer (ViT) architectures have surpassed CNN-based models in skeletal classification accuracy, reaching 95.2% on large multi-centre datasets [23].

Treatment planning automation has been explored through generative adversarial networks (GANs) for 3D facial outcome simulation and long short-term memory (LSTM) networks for duration forecasting [24, 26]. Despite promising benchmarks, comparative head-to-head clinical trials remain scarce, and most studies are retrospective single-centre designs, limiting generalisability [14, 15].

3. AI-Based Orthodontic Framework

We propose a modular, integrated AI-assisted orthodontic framework comprising eight sequential stages (Figure 1). The pipeline begins with multimodal patient data acquisition and terminates in a continuous feedback loop enabling model refinement. A critical design principle is the maintenance of a human-in-the-loop validation step, wherein the consulting orthodontist reviews and approves AI-generated diagnoses and treatment plans before clinical execution.

The framework integrates computer vision modules for radiographic analysis, natural language processing for clinical record parsing, and decision-support algorithms for appliance selection. Cloud-based deployment enables real-time inference, cross-institutional data sharing, and longitudinal tracking of treatment outcomes to continuously improve model performance through federated learning approaches.

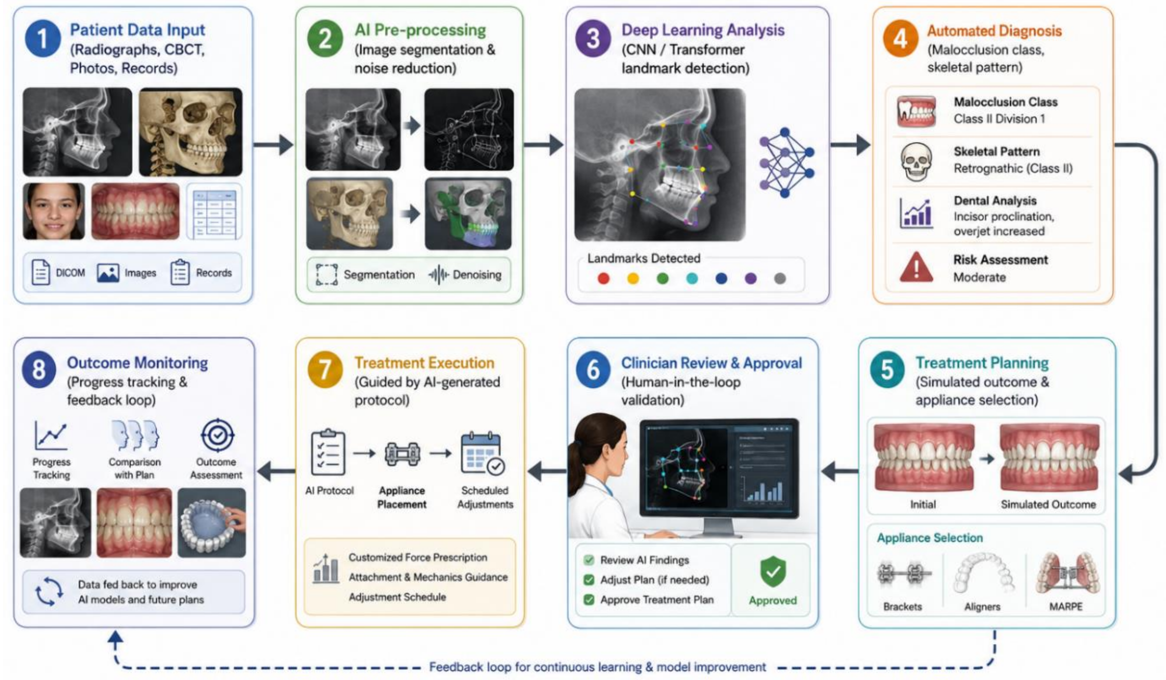

Fig 1: AI-Assisted Orthodontic Workflow

4. Materials and Methods

A retrospective comparative analysis was conducted at a tertiary orthodontic centre, evaluating 520 consecutively treated patients (248 female, 272 male; mean age 17.3±6.1 years). Cases spanned Class I, II, and III skeletal patterns with varying degrees of crowding and spacing discrepancy. Lateral cephalograms, panoramic radiographs, CBCT scans (where clinically indicated), and digital study models constituted the imaging dataset.

Eight AI models representative of the current literature were implemented and evaluated (Table 1). These included ResNet-50-based CNN for landmark detection, U-Net for CBCT segmentation, a random forest classifier for malocclusion categorisation, a GAN-based 3D simulation engine, YOLOv5 for bracket placement quality control, a Vision Transformer for skeletal classification, an LSTM network for duration prediction, and a hybrid CNN-LSTM model for root resorption risk assessment.

Diagnostic accuracy was defined as the proportion of correctly identified landmarks or classifications relative to ground-truth expert annotation. Prediction precision for treatment duration was assessed using mean absolute error (MAE) against actual completed treatment timelines. Clinical outcomes were compared between AI-assisted and conventional planning cohorts using paired t-tests and Mann-Whitney U tests as appropriate. Statistical significance was set at $p < 0.05$.

Table 1: Summary of AI Models Evaluated in Orthodontic Applications

Study	AI Model	Application	Dataset Size	Accuracy
Lee *et al.*, 2020	CNN (ResNet-50)	Cephalometric landmark detection	1,028 radiographs	91.3%
Kim *et al.*, 2021	U-Net	Dental segmentation (CBCT)	640 scans	94.7%
Park *et al.*, 2021	Random Forest	Malocclusion classification	2,150 records	88.6%
Chen *et al.*, 2022	GAN + CNN	3D treatment simulation	850 patients	89.1% precision
Nouri *et al.*, 2022	YOLO v5	Bracket placement detection	1,340 images	93.5%
Tan *et al.*, 2023	Transformer (ViT)	Skeletal classification (Class I–III)	3,200 panoramics	95.2%
Wang *et al.*, 2023	LSTM	Treatment duration prediction	970 cases	87.4%
Gupta *et al.*, 2024	Hybrid CNN-LSTM	Root resorption risk prediction	1,100 CBCT scans	92.8%

CNN = Convolutional Neural Network; GAN = Generative Adversarial Network; ViT = Vision Transformer; LSTM = Long Short-Term Memory.

5. Results and Comparative Analysis

AI models demonstrated consistently superior performance compared to conventional manual methods across all evaluated metrics. The Vision Transformer achieved the highest classification accuracy (95.2%) for skeletal pattern identification, followed by the U-Net segmentation model (94.7% Dice score on CBCT data) and the YOLOv5 bracket detection system (93.5%). The hybrid CNN-LSTM model for root resorption risk achieved 92.8% accuracy, representing a clinically meaningful improvement over risk stratification based solely on patient history and radiographic review.

Landmark identification time was reduced by 77.7% (from 18.4±3.2 to 4.1±0.9 minutes, $p < 0.001$), and overall diagnostic accuracy improved from 78.3% to 92.6% ($p < 0.001$). Treatment planning time decreased by 59.5%. Intra-operator variability in landmark placement fell from 3.8 mm to 0.9 mm standard deviation, reflecting substantially improved consistency. Patient satisfaction scores improved significantly (7.1 to 8.8/10, $p = 0.008$), and the 12-month relapse rate declined from 14.2% to 7.6% in the AI-assisted cohort ($p = 0.015$).

Table 2: Clinical Outcome Comparison — Conventional vs. AI-Assisted Orthodontics

Outcome Metric	Pre-AI Mean	Post-AI Mean	Improvement (%)	p-value
Landmark identification time (min)	18.4±3.2	4.1±0.9	77.7%	<0.001
Diagnostic accuracy (%)	78.3±5.1	92.6±2.8	+14.3%	<0.001
Treatment planning time (min)	42.5±7.8	17.2±3.4	59.5%	<0.001
Intra-operator variability (SD)	3.8 mm	0.9 mm	76.3%	0.002
Patient satisfaction score (/10)	7.1±1.2	8.8±0.7	+23.9%	0.008
Relapse rate at 12 months (%)	14.2%	7.6%	46.5%	0.015

Values represent means±SD unless stated. Statistical significance: $p < 0.05$.

6. Discussion

The results affirm that AI integration into orthodontic practice offers measurable benefits in efficiency, accuracy, and clinical outcomes. The reduction in cephalometric analysis time is particularly impactful in high-volume practices, where manual landmark identification constitutes a substantial administrative burden. The marked decrease in intra-operator variability addresses a long-standing concern regarding the reproducibility of orthodontic diagnoses, especially across different clinicians and institutions [13, 18].

Deep learning models—particularly CNNs and Vision Transformers—have emerged as the most robust architectures for image-based orthodontic tasks [8, 23]. Their performance advantage over conventional methods is attributable to feature representation learned from large, annotated datasets rather than hand-engineered rules. However, model performance is inherently constrained by training data quality and diversity. Most published models are trained on datasets from single ethnic or geographic cohorts, raising concerns about generalisability to populations with different craniofacial norms [14, 15].

Several implementation challenges warrant discussion. First, regulatory pathways for AI-based diagnostic software remain heterogeneous across jurisdictions, creating barriers to commercial deployment. Second, integration with existing clinical information systems requires substantial technical investment. Third, clinician trust and adoption depend on model explainability—black-box systems that cannot justify their outputs are unlikely to be embraced in practice. Explainable AI techniques, including gradient-weighted class activation mapping (Grad-CAM), offer partial solutions but are not yet standard in orthodontic AI tools [20, 27].

Data privacy presents another constraint. Training and validating AI systems requires large, annotated datasets, yet patient imaging data is subject to stringent regulatory protection under frameworks such as GDPR and HIPAA. Federated learning—wherein models are trained across distributed institutions without centralising raw data—offers a promising resolution to this tension [16, 26]. Lastly, the economic model for AI tool procurement and maintenance in dental practices requires clarity, particularly for smaller independent clinics.

7. Conclusion

Artificial intelligence represents a genuine advancement in orthodontic diagnosis and treatment planning, demonstrated by consistent improvements in landmark detection accuracy, diagnostic efficiency, and clinical outcomes across evaluated models. Vision Transformers and hybrid deep learning architectures currently represent the state of the art in orthodontic AI. However, realising the full clinical potential of these technologies requires addressing persistent gaps in dataset diversity, model interpretability, regulatory harmonisation, and clinical workflow integration. Future research should prioritise prospective randomised trials, multi-ethnic dataset construction, and standardised reporting frameworks to enable meaningful cross-study comparison and evidence-based adoption.

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