International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2025: 7.089

Emerging Trends of Artificial Intelligence in Orthodontic Practice

Dr. Sarita[1], Dr. Sunil Sharma[2], Dr. Deepak Kumar Sharma[3], Dr. Chiranjeev Saini[4], Dr. Ashish Kumar[5]

Abstract: ***The integration of artificial intelligence (AI) into orthodontics represents a significant technological advancement with the potential to reshape diagnostic, planning, and clinical practices. This review systematically examines current AI applications within orthodontics, focusing on three core areas: diagnostic assistance, treatment planning, and clinical workflow enhancement. Diagnostic applications include automated cephalometric landmarking, dental and facial analysis, skeletal maturation staging, and airway assessment. In treatment planning, AI supports extraction and orthognathic surgery decisions, along with outcome prediction. Clinically, AI aids in practice guidance, remote monitoring, and documentation management. While performance continues to improve, challenges such as data availability, model interpretability, and standardization persist. This paper also discusses ongoing limitations and proposes future directions for research and implementation, aiming to guide the responsible integration of AI into orthodontic care.***

Keywords: artificial intelligence; orthodontics; machine learning; deep learning; digital dentistry

1. Introduction

Artificial intelligence (AI) refers to computational systems designed to perform tasks typically requiring human cognitive functions [1]. In recent years, AI has transitioned from theoretical research to practical applications across various medical specialties, including dentistry and orthodontics [2]. Unlike earlier rule-based expert systems, modern machine learning approaches- particularly deep learning- enable systems to learn patterns directly from data, improving their performance with exposure to larger datasets [3].

Within orthodontics, AI is positioned to address several long-standing challenges. Malocclusion, a prevalent condition affecting dental alignment and craniofacial relationships, requires extensive analysis for accurate diagnosis and treatment planning [4]. Traditional methods are often time-intensive, subjective, and dependent on clinician experience [5]. AI-driven tools offer the promise of increased efficiency, consistency, and accessibility, potentially supporting both specialists and general practitioners [6].

This review provides a structured overview of the current state of AI applications in orthodontics, categorized by their role in diagnosis, treatment planning, and clinical practice. It also highlights persisting limitations and suggests pathways for future development, with the goal of informing clinicians, researchers, and developers engaged in the digital transformation of orthodontic care.

2. AI in Diagnostic Processes

2.1 Automated Cephalometric Analysis

Cephalometric tracing is a foundational step in orthodontic assessment. Manual landmark identification is prone to intra- and inter-examiner variability [7]. Recent advances in convolutional neural networks (CNNs), such as YOLOv3, U-Net, and cascade CNN architectures, have demonstrated high accuracy in automating landmark detection on lateral and posteroanterior cephalograms, often achieving mean errors below 2 mm [8-10]. Three-dimensional landmarking using cone-beam computed tomography (CBCT) data is also progressing, though further validation is needed for widespread clinical adoption [11].

2.2 Dental Arch and Occlusal Analysis

AI models have been developed to assess tooth crowding, arch dimensions, overjet, and overbite from intraoral photographs and 3D digital models [12]. Some systems automate tooth segmentation and landmark identification on intraoral scans, facilitating digital model analysis and treatment simulation [13-15].

2.3 Facial Analysis

Though less developed than cephalometric applications, AI-based facial analysis aims to evaluate symmetry, vertical proportions, and soft tissue contours from 2D or 3D facial images [16]. Early studies show potential for automated assessment but require further refinement for clinical reliability [17,18].

2.4 Skeletal Maturation Assessment

Determining skeletal age is crucial for growth modification timing. AI models using lateral cephalograms can classify cervical vertebral maturation (CVM) stages, offering a radiation-free alternative to hand-wrist radiographs [19]. Deep learning approaches, including ResNet and Inception architectures, have shown promising classification accuracy [20,21].

2.5 Upper Airway Evaluation

AI assists in detecting adenoid hypertrophy and segmenting pharyngeal airways from lateral radiographs or CBCT scans [22]. CNNs can calculate adenoid–nasopharyngeal ratios or perform 3D airway reconstructions, supporting the diagnosis of obstructive conditions relevant to orthodontic treatment planning [23,24].

3. AI in Treatment Planning and Prediction

3.1 Extraction Decision Support

Multiple machine learning models, including artificial neural networks (ANNs), random forests, and support vector machines, have been trained to recommend extraction versus non-extraction treatment plans [25]. Input variables typically include cephalometric, dental, and demographic data. Recent studies also use intraoral photos directly as input to CNN models, achieving high prediction accuracy [26].

3.2 Orthognathic Surgery Planning

AI can help identify patients who may benefit from combined orthodontic-surgical treatment [27]. Models trained on cephalometric parameters, facial photographs, or 3D facial scans can distinguish between surgical and non-surgical cases with high sensitivity and specificity, aiding in borderline case decision-making [28,29].

3.3 Treatment Outcome Prediction

Predictive AI models simulate post-treatment dental, skeletal, and soft tissue changes [30]. Applications include virtual setup accuracy for clear aligners, prediction of cephalometric changes following orthopedic intervention, and estimation of 3D facial changes after orthognathic surgery [31,32]. Conditional generative adversarial networks (cGANs) have been used for realistic facial outcome visualization [33].

3.4 Patient Experience Forecasting

Emerging research uses ANN models to predict patient-reported outcomes such as pain, anxiety, and quality of life during clear aligner therapy, potentially aiding in patient preparation and management [34].

4. AI in Clinical Workflow and Practice Management

4.1 Clinical Decision Support

AI systems provide step-by-step guidance for specific clinical challenges, such as deep overbite correction or optimal mini-implant placement sites based on CBCT-derived bone thickness maps [35,36].

4.2 Remote Monitoring and Tele-Orthodontics

AI-powered platforms enable remote tracking of treatment progress via smartphone photographs or scans [37]. These systems can detect issues such as poor aligner fit, attachment loss, or bracket failure, facilitating timely intervention and reducing in-person visits [38].

4.3 Automated Documentation

Deep learning models can classify and organize clinical photographs (e.g., facial, intraoral) and radiographs into predefined categories, streamlining digital record management and retrieval [39,40].

5. Challenges and Future Outlook

5.1 Data Limitations

The performance of AI models depends on large, diverse, and well-annotated datasets [41]. Data scarcity, heterogeneity, and privacy regulations currently limit model generalizability. Federated learning and synthetic data generation may help overcome these barriers [42,43].

5.2 Model Interpretability and Trust

Many deep learning models operate as "black boxes," making it difficult to understand their decision-making process [44]. Explainable AI (XAI) techniques, such as gradient-weighted class activation mapping (Grad-CAM), are needed to build clinician trust and facilitate oversight [45].

5.3 Standardization and Validation

Variability in study designs, performance metrics, and clinical endpoints complicates cross-study comparisons [46]. Adoption of reporting standards such as MI-CLAIM could improve transparency and reproducibility [47].

5.4 Integration into Clinical Workflows

Successful implementation requires seamless integration with existing digital infrastructure, user-friendly interfaces, and alignment with clinical protocols [48]. Ethical, legal, and training considerations must also be addressed [49].

6. Conclusion

Artificial intelligence holds considerable promise for augmenting orthodontic practice by enhancing diagnostic precision, supporting complex decision-making, and optimizing clinical workflows [50]. Current applications demonstrate encouraging performance, particularly in image-based tasks such as cephalometric landmarking and airway analysis [51]. However, AI is not yet positioned to replace clinical judgment [52]. Rather, it serves as a complementary tool that can increase efficiency, reduce subjectivity, and improve accessibility to high-quality orthodontic care [53]. Ongoing advancements in data science, model transparency, and interdisciplinary collaboration will be essential to realize the full potential of AI in orthodontics [54].

References

[1] Kulikowski CA. An Opening Chapter of the First Generation of Artificial Intelligence in Medicine: The First Rutgers AIM Workshop, June 1975. Yearb Med Inform. 2015; 10: 227-233.
[2] Schwendicke F, Samek W, Krois J. Artificial Intelligence in Dentistry: Chances and Challenges. J Dent Res. 2020;99(7):769-774.
[3] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-444.
[4] Proffit WR, Fields HW, Sarver DM. Contemporary Orthodontics. 6th ed. St. Louis: Mosby; 2018.
[5] Baumrind S, Frantz RC. The reliability of head film measurements: 1. Landmark identification. Am J Orthod. 1971;60(2):111-127.
[6] Mohammed-Rahimi H, et al. Machine learning and orthodontics, current trends and the future opportunities: A scoping review. Am J Orthod Dentofacial Orthop. 2021;160(1):170-192.e4.
[7] Durao AR, et al. Cephalometric landmark variability among orthodontists and dentomaxillofacial radiologists: A comparative study. Imaging Sci Dent. 2015;45(4):213-220.
[8] Hwang HW, et al. Automated identification of cephalometric landmarks: Part 2-Might it be better than human? Angle Orthod. 2020;90(1):69-76.
[9] Yao J, et al. Automatic localization of cephalometric landmarks based on convolutional neural network. Am J Orthod Dentofacial Orthop. 2022; 161(2): e250-e259.
[10] Kim J, et al. Accuracy of automated identification of lateral cephalometric landmarks using cascade convolutional neural networks on lateral cephalograms from nationwide multi-centres. Orthod Craniofac Res. 2021;24(Suppl 2):59-67.
[11] Dot G, et al. Automatic 3-dimensional cephalometric landmarking based on artificial intelligence: A systematic review. J Stomatol Oral Maxillofac Surg. 2022; 123(5): e600-e608.
[12] Talaat S, et al. The validity of an artificial intelligence application for assessment of orthodontic treatment need from clinical images. Semin Orthod. 2021;27(3):164-171.
[13] Im J, et al. Accuracy and efficiency of automatic tooth segmentation in digital dental models using deep learning. Sci Rep. 2022;12(1):9429.
[14] Zhao Y, et al. Two-Stream Graph Convolutional Network for Intra-Oral Scanner Image Segmentation. IEEE Trans Med Imaging. 2022;41(4):826-835.
[15] Wu TH, et al. Two-Stage Mesh Deep Learning for Automated Tooth Segmentation and Landmark Localization on 3D Intraoral Scans. IEEE Trans Med Imaging. 2022;41(12):3158-3166.
[16] Rao GKL, et al. Identification and analysis of photometric points on 2D facial images: A machine learning approach in orthodontics. Health Technol. 2019;9(5):715-724.
[17] Yurdakurban E, et al. Evaluation of an automated approach for facial midline detection and asymmetry assessment: A preliminary study. Orthod Craniofac Res. 2021;24(Suppl 2):84-91.
[18] Rousseau M, Retrouvey JM. Machine learning in orthodontics: Automated facial analysis of vertical dimension for increased precision and efficiency. Am J Orthod Dentofacial Orthop. 2022;161(4):445-450.
[19] Kok H, et al. Usage and comparison of artificial intelligence algorithms for determination of growth and development by cervical vertebrae stages in orthodontics. Prog Orthod. 2019;20(1):41.
[20] Seo H, et al. Comparison of Deep Learning Models for Cervical Vertebral Maturation Stage Classification on Lateral Cephalometric Radiographs. J Clin Med. 2021;10(16):3591.
[21] Radwan MT, et al. Artificial intelligence-based algorithm for cervical vertebrae maturation stage assessment. Orthod Craniofac Res. 2023;26(3):349-355.
[22] Shen Y, et al. A deep-learning-based approach for adenoid hypertrophy diagnosis. Med Phys. 2020;47(5):2171-2181.
[23] Zhao T, et al. Automated Adenoid Hypertrophy Assessment with Lateral Cephalometry in Children Based on Artificial Intelligence. Diagnostics. 2021;11(8):1386.
[24] Dong W, et al. Automatic detection of adenoid hypertrophy on cone-beam computed tomography based on deep learning. Am J Orthod Dentofacial Orthop. 2023;163(5):553-560.e1.
[25] Li P, et al. Orthodontic treatment planning based on artificial neural networks. Sci Rep. 2019;9(1):2037.
[26] Ryu J, et al. Evaluation of artificial intelligence model for crowding categorization and extraction diagnosis using intraoral photographs. Sci Rep. 2023;13(1):5177.
[27] Choi HI, et al. Artificial intelligent model with neural network machine learning for the diagnosis of orthognathic surgery. J Craniofac Surg. 2019;30(7):1986-1989.
[28] Shin W, et al. Deep learning based prediction of necessity for orthognathic surgery of skeletal malocclusion using cephalogram in Korean individuals. BMC Oral Health. 2021;21(1):130.
[29] Lee H, et al. A novel machine learning model for class III surgery decision. J Orofac Orthop. 2023;84(1):1-10.
[30] Park JH, et al. Use of artificial intelligence to predict outcomes of nonextraction treatment of Class II malocclusions. Semin Orthod. 2021;27(2):87-95.
[31] Woo H, et al. Evaluating the accuracy of automated orthodontic digital setup models. Semin Orthod. 2023;29(1):60-67.
[32] Tanikawa C, Yamashiro T. Development of novel artificial intelligence systems to predict facial morphology after orthognathic surgery and orthodontic treatment in Japanese patients. Sci Rep. 2021;11(1):15853.
[33] Park YS, et al. Deep Learning-Based Prediction of the 3D Postorthodontic Facial Changes. J Dent Res. 2022;101(12):1372-1379.
[34] Xu L, et al. Predicting patient experience of Invisalign treatment: An analysis using artificial neural network. Korean J Orthod. 2022;52(4):268-277.
[35] El-Dawlatly MM, et al. Evaluation of the efficiency of computerized algorithms to formulate a decision support

system for deepbite treatment planning. Am J Orthod Dentofacial Orthop. 2021;159(4):512-521.
[36] Tao T, et al. Artificial intelligence-assisted determination of available sites for palatal orthodontic mini implants based on palatal thickness through CBCT. Orthod Craniofac Res. 2023;26(4):491-499.
[37] Dalessandri D, et al. Attitude towards Telemonitoring in Orthodontists and Orthodontic Patients. Dent J. 2021;9(5):47.
[38] Hansa I, et al. Clinical outcomes and patient perspectives of Dental Monitoring® GoLive® with Invisalign®: a retrospective cohort study. Prog Orthod. 2020;21(1):16.
[39] Ryu J, et al. Application of deep learning artificial intelligence technique to the classification of clinical orthodontic photos. BMC Oral Health. 2022;22(1):454.
[40] Li S, et al. Artificial Intelligence for Classifying and Archiving Orthodontic Images. Biomed Res Int. 2022; 2022: 1473977.
[41] Candemir S, et al. Training Strategies for Radiology Deep Learning Models in Data-limited Scenarios. Radiol Artif Intell. 2021; 3(6): e210014.
[42] Rieke N, et al. The future of digital health with federated learning. NPJ Digit Med. 2020;3(1):119.
[43] Frid-Adar M, et al. GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing. 2018; 321: 321-331.
[44] Singh A, et al. Explainable deep learning models in medical image analysis. J Imaging. 2020;6(6):52.
[45] Selvaraju RR, et al. Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. Int J Comput Vis. 2020;128(2):336-359.
[46] Schwendicke F, et al. Deep learning for cephalometric landmark detection: Systematic review and meta-analysis. Clin Oral Investig. 2021;25(7):4299-4309.
[47] Norgeot B, et al. Minimum information about clinical artificial intelligence modeling: The MI-CLAIM checklist. Nat Med. 2020;26(9):1320-1324.
[48] Strunga M, et al. Artificial Intelligence Systems Assisting in the Assessment of the Course and Retention of Orthodontic Treatment. Healthcare. 2023;11(5):683.
[49] Attaran M. Blockchain technology in healthcare: Challenges and opportunities. Int J Healthc Manag. 2022;15(1):70-83.
[50] Albalawi F, Alamoud KA. Trends and Application of Artificial Intelligence Technology in Orthodontic Diagnosis and Treatment Planning- A Review. Appl Sci. 2022;12(22):11864.
[51] Cao L, He H, Hua F. Deep Learning Algorithms Have High Accuracy for Automated Landmark Detection on 2D Lateral Cephalograms. J Evid Based Dent Pract. 2022;22(3):101798.
[52] Monill-González A, et al. Artificial intelligence in orthodontics: Where are we now? A scoping review. Orthod Craniofac Res. 2021;24(Suppl 1):6-15.
[53] Allareddy V, et al. Blockchain technology and federated machine learning for collaborative initiatives in orthodontics and craniofacial health. Orthod Craniofac Res. 2023;26(4):385-394.
[54] Taye MM. Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. Computers. 2023;12(5):91.