



Precision, Prediction, Perfection: The AI Takeover in Orthodontics.

Deepika Yadav¹, Namrata Dogra², Khushal Sharma³

¹Assistant Professor, Department of Orthodontics, Faculty of Dental Sciences, SGT University, India

²Professor, Department of Orthodontics, Faculty of Dental Sciences, SGT University, India

³Consultant, Swasthya Hospital, India

Received Date: 11/08/2025

Revised Date: 10/09/2025

Accepted Date: 06/10/2025

KEYWORDS

artificial intelligence; personalized orthodontics; tooth movement prediction; aligner fabrication; remote monitoring; dental care.

ABSTRACT:

Recent years, artificial intelligence technology has been a revolutionary tool in health care system, an increase in application of the technology noted significantly in Orthodontics as well. AI is an outstanding tool to help orthodontists as it can be utilized from the beginning to diagnose till the planning of the treatment. Along with speeding up the diagnosis and treatment processes, automation can cut labour expenses to zero.

AI has shown promising results in enhancing the accuracy of diagnoses, treatment planning, and predicting treatment outcomes. Its usage in orthodontic practices worldwide has increased with the availability of various AI applications and tools.

We have witness the broadening of the application of AI in orthodontics, accompanied by advancements in its performance. Additionally, this review outlines the existing limitations within the field and offers future perspectives.

INTRODUCTION

The practice of dentistry has undergone significant transformation in recent years. It has become possible to create more recent technologies that imitate the way the human brain works¹. The concept of Turing machine was introduced in 1936 by Alan Turing, in order to simulate human calculation. The theory of computation and the Turing machine concept served as the fundamental building blocks for the creation of artificial intelligence (AI). John McCarthy first used the term "artificial intelligence" in 1956^{2,3}.

In recent years, technological advancements have paved the way for digitalization in orthodontics, which has largely improved and simplified diagnostic and treatment planning workflows. The main highlights towards achieving a computer-based digital workflow in orthodontics have been the incorporation of three-dimensional (3D) imaging devices, computer-aided design and manufacturing platforms (CAD/CAM) and 3D printing. Such technologies offer faster, more precise and predictable treatment with less patient discomfort.

The expert system and machine learning are two important branches of AI. Unlike the knowledge-based expert system, which is established based on predetermined rules and knowledge, machine learning focuses on "learning" from training data to improve its capability^{4,5}. In addition to its strong adaptability and generalization capabilities, machine learning is capable of processing large-scale data and has more open-source algorithms, which makes it one of the most promising technologies in AI.

Artificial neural networks (ANNs), a sub-domain of machine learning, draw inspiration from the biological neural system of the human brain⁶. ANNs have been notably employed to analyze intricate connections between massive data⁷. An ANN typically has a minimum of three layers, namely, an input layer, an output layer, and at least one hidden layer⁸. Neurons within each layer are interconnected to establish a network of processors. ANNs encompassing multiple hidden layers are commonly referred to as deep learning, which has demonstrated exceptional performance in computer vision tasks such



as classification and segmentation⁹. Deep learning is becoming increasingly popular due to its high feasibility and growing computing performance, as well as advanced model training algorithms¹⁰. In addition, one notable advantage of deep learning over traditional machine learning is that it allows automated feature extraction without manual intervention, enabling the better harnessing of the information within the data¹¹. Convolutional neural networks (CNNs), one of the most widely used deep learning algorithms,

exhibit particularly remarkable performance in handling high-resolution images¹²⁻¹⁴.

In CNN, the hidden layers are substituted with three distinct functional layers, namely, convolution layers, pooling layers, and fully connected layers. The convolution layers employ convolution kernels as filters to generate feature maps. The convolution process effectively reduces image complexity, making CNNs highly suitable for tasks like recognizing objects, shapes, and patterns. The pooling layers are commonly employed after convolutional layers to decrease the dimension of feature maps while retaining essential information. Following several iterations of convolutional and pooling layers, the outputs are integrated in the fully connected layers for further decision making. Consequently, thanks to the above-mentioned three layers, CNNs outperform algorithms such as ANNs in image-related tasks^{8,13}. (Fig. 1)

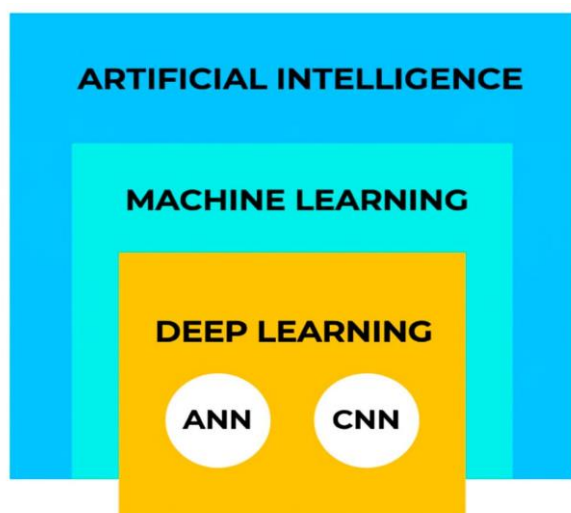


Figure 1. Simplified AI diagram.

This shift toward personalized orthodontic care powered by AI is a game-changer. AI-driven systems can optimize the design of orthodontic devices (like braces and aligners) for each patient, factoring in the unique characteristics of their teeth and jaw alignment. As a result, patients can experience faster, more efficient treatments with fewer complications or adjustments^{15,16}. The predictive capabilities of AI also offer the potential to forecast how long the treatment will take, making the process more transparent and reducing the uncertainty that patients often face during orthodontic care. Furthermore, AI enables continuous monitoring of a patient's progress throughout the treatment journey^{17,18}. Using advanced image recognition and predictive modeling, AI systems can assess whether tooth movement is proceeding as expected and provide real-time recommendations to adjust the treatment plan if needed.

This level of precision and adaptability is difficult to achieve through traditional methods, making AI-powered solutions an exciting development in orthodontics¹⁹.

1. AI IN ORTHODONTICS

The AI improves the landmark identification process especially in regards of the time required for this procedure, however clinicians still need to refine or manually correct the landmark positions before rigorous assessments. Although efforts are being made to improve the robustness of the automatic landmark identification tools, the precision and accuracy of landmark identification still requires extensive training and tests before a fully precise automated landmark identification can be achieved with AI (Fig. 2).

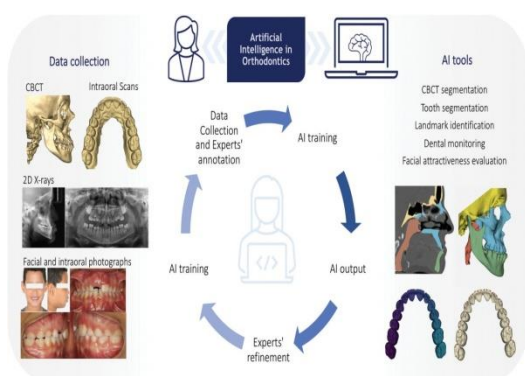


Figure 2. Sequence of development of AI tools in orthodontics.

A series of studies have shown that AI can significantly enhance the efficiency of clinical orthodontic practice^{20,21}. Several commercially available AI-driven software (3Shape Dental System 2.22.0.0, Uceph 4.2.1, Mastro 3D V6.0 etc.) programs have found widespread applications in orthodontic care. With the ongoing advancement of AI algorithms, computing capabilities and the growing availability datasets, the scope of AI applications in orthodontics is expanding, accompanied by continuous performance improvement. Staying updated on the latest developments of AI applications in orthodontics through timely summaries helps researchers gain a rapid and accurate understanding of this field. In addition, despite obtaining encouraging results, there is still significant room for progress in the application of AI in orthodontics.

Therefore, this review provides a comprehensive summary of the current state of AI applications in orthodontics, encompassing diagnosis, treatment planning, and clinical practice. Additionally, the review discusses the current limitations of AI and offers future perspectives, aiming to offer valuable insights for the integration of AI into orthodontic practice.

2.1 Diagnosis and treatment planning

Orthodontic diagnosis is a difficult undertaking since it necessitates a complete simultaneous evaluation of various facial components from various angles. With the use of digital dentistry tools, patient information can now be gathered on a digital platform and turned into a database that can be utilized for both diagnosis and treatment. The evaluation burden has been significantly reduced and diagnostic variations have

been avoided thanks to automation solutions that use AI and machine learning technology^{22,23}.

One such AI-based system, developed by Diagnocat Ltd. (San Francisco, CA, USA), utilizes CNNs and provides precise and comprehensive dental diagnostics. The system enables tooth segmentation and enumeration, oral pathology diagnosis (including periapical lesions and caries), and volumetric assessment. Several scientific papers have validated the diagnostic performance of this program, demonstrating its high efficacy and accuracy²⁴⁻²⁸.

2.2 Cephalometric Analysis

Currently AI-based cephalogram are replacing manual tracing and identification of landmarks by saving time and minimizing errors. The AI is largely used to recognize and analyze cephalometric landmarks, make extraction decisions, analyze faces, segment teeth and the mandible, determine bone ages, forecast orthognathic surgery and segment the temporomandibular joint. Automated cephalometric tracing was subsequently investigated by a number of other researchers and found to be effective.

A deep convolutional neural network-based analysis for automated cephalometric tracing was used by Lee et al.²⁹ The program developed has a high success rate (over 90%), according to the authors in the differential diagnosis of cephalometric landmarks.

Accurate and repeatable landmark identification is crucial for reliable CA outcomes. Several studies have demonstrated the effectiveness of AI in identifying cephalometric landmarks. Although lateral radiography remains the most commonly used method in CA, recent AI advancements have sparked renewed interest in the use of cone-beam computed tomography (CBCT)³⁰.

2.3 Estimation of Growth and Development

The determination of patient's growth spurt is critical for orthodontic treatment, especially for those who need functional and orthopedic treatment. Hand-wrist X-rays have been regarded as the most conventional and accurate way to determine skeletal age. In recent years, several studies have reported combining AI with hand-wrist radiographs to predict skeletal age³¹⁻³³. A



number of research studies have revealed that the cervical vertebral maturation (CVM) method is also effective for growth estimation and highly correlates with the hand–wrist radiograph method³⁴⁻³⁹.

Caution is advised when interpreting AI-assisted CVM assessment studies due to the limited number of expert readers used to establish the gold standard for evaluation. Errors made by these readers may have influenced the study results and subsequently impacted the performance of the AI algorithm⁴⁰. The lack of scientific evidence in meta-analyses highlights the need for a broader examination of the role of AI in CMR. A recent systematic review by The Angle Orthodontist reported that the model accuracy for test data ranged from 50% to more than 90%. The authors emphasized the importance of conducting new studies to develop robust models and reference standards that can be applied to external datasets. While these findings are encouraging, we anticipate that future advancements in AI technology will enhance the diagnostic accuracy of CMR tools, potentially making them comparable to wrist X-ray assessments for skeletal maturity.

2.4 TMJ examination & disorders

Osteoarthritis (OA) is a condition that affects joints and is characterized by the gradual deterioration of joint cartilage, bone remodelling, and the formation of osteoproliferative bodies⁴¹. Temporomandibular joint osteoarthritis (TMJ OA) is a specific type of temporomandibular disorder that can cause significant joint pain, dysfunction, and dental malocclusion and a decrease in overall quality of life⁴¹. The examination of TMJ function and morphology is crucial in orthodontic and dental treatments⁴². TMJ OA is one of the causes of malocclusion and facial asymmetry^{43,44}. Radiographic examination, such as OPG/CBCT, confirms the presence of TMJ OA by revealing bony changes⁴⁵, while MRI is the preferred modality for evaluating joint discs⁴².

Recent studies have demonstrated the high diagnostic performance of AI in detecting and staging TMJ OA⁴⁵⁻⁴⁹. These studies have shown the potential for automated, detailed assessment of joint morphology using various imaging techniques,

including OPG, CBCT and MRI. Therefore, the authors anticipate that the use of AI systems for TMJ diagnostic imaging will contribute to future research on early detection and personalized treatments for OA.

2.5 Extraction decision making

One of the most challenging issues during orthodontic treatment is deciding whether extraction is mandatory in a particular case. A wrong decision about extraction could cause a series of irreversible problems like an unfavourable profile, improper occlusion and extraction-space closure difficulties. AI can contribute to reducing the likelihood of incorrect tooth extraction protocols. Several AI tools have been introduced in recent years to support therapeutic decision making in orthodontics.

ANNs are the most utilized method to predict extraction diagnosis and patterns⁵⁰⁻⁵⁵. Jun et al. Built an AI expert system with neural-network machine learning based on 12 cephalometric variables and 6 additional indices, reaching a success rate of 93% and 84% in deciding extraction/non-extraction and detailed extraction patterns, respectively. In this study, one-third of the learning dataset was chosen as the validation set to prevent overfitting⁵¹. Li et al. adopted a multilayer perceptron ANN and obtained similar results, with an accuracy of 94% and 84.2% in the determination of extraction diagnosis and patterns.

2.6 Orthognathic decision making & planning

Despite significant developments in orthodontics and surgery, there is a lack of clearly established criteria for qualifying patients for surgical procedures. This issue becomes particularly problematic in borderline cases, where the orthodontist faces the decision of whether to refer the patient for surgical treatment or a mouflage treatment^{56,57}.

Lateral cephalograms are the most used method in clinical practice to assess sagittal skeletal deformities. Several studies have used lateral cephalograms as the input data, whether using an ANN or CNN, and all achieved accuracy rates exceeding 90%^{58,59}. Shin et al. adopted both lateral cephalograms and posteroanterior cephalograms as their training data to take both the sagittal



nd lateral relationship of the jaws into consideration⁶⁰. The proposed CNN model reached an accuracy of 95.4% in predicting orthognathic surgery diagnosis.

A systematic review by Salzar et al.⁶¹ further highlighted the significant heterogeneity among current studies and the difficulty in generalizing their results. The authors cautiously concluded that AI could be a valuable tool in orthognathic surgery planning, but further research is necessary.

2.7 Management of Impacted Canines

In order to achieve the best orthodontic and periodontal results, impacted canines require extensive therapeutic care. The length of the therapy depends on the difficulty level and how much the canine is displaced from the surrounding teeth. An intermediary stance between statistics and artificial intelligence is taken by the Bayesian Network (BN)⁶².

Based on the angular and linear measurements, panoramic and lateral cephalometric radiographs are helpful in predicting an impacted maxillary canine. The random forest method had the best degree of accuracy and correctly predicted the canine eruption condition (83%). In cases with unilateral canine impaction, Wang et al. used CBCT and a machine learning technique called Learning-based multi-source Integration framework for Segmentation (LINKS) to quantify the variance in the maxilla.

2.8 Upper airway obstruction management

Skeletal deformity and airway obstruction mutually influence each other. Upper-airway obstruction can alter breathing, which can affect the normal development of craniofacial structures and potentially lead to malocclusion and other craniofacial abnormalities. Screening the presence of upper-airway obstruction, especially adenoid hypertrophy, is critical for orthodontic diagnosis and treatment planning.

Dong et al. proposed two deep learning algorithms, the hierarchical masks self-attention U-net (HMSAU-Net) and 3D-ResNet, to automatically segment upper airways and dia-

gnose adenoid hypertrophy, respectively, from CBCT. Of note, a high accuracy of 0.912 was achieved by the adenoid hypertrophy diagnosis model⁶³. In addition to adenoid hypertrophy, the morphology and volume of the upper airway are also important indicators for assessing upper-airway obstruction. By using a CNN model, Jeong et al. obtained promising results in automated upper-airway obstruction evaluation based on lateral cephalograms, with a positive predictive value of 0.90 and negative predictive value of 0.85⁶⁴. The segmentation of the airway from CBCT can provide a 3D view, enabling the more accurate detection of airway obstruction. Recent studies have shown continuous progress in airway segmentation, with deep learning, especially CNN algorithms, being the most commonly used.

2.9 In Treatment Outcome

Orthodontists face the challenge of selecting the most appropriate treatment strategy for each patient based on their individual expectations, socioeconomic conditions, cultural background, and skills. Currently, AI can aid in predicting dental, skeletal and facial changes, as well as patient's experience of clear aligners, thereby guiding the treatment planning. Orthodontic tooth setup, initially proposed by Kesling, enables the visualization of the treatment progress and final occlusion, but manual tasks like tooth segmentation and reposition are labour intensive. With the continuous advancement of digital orthodontics and artificial intelligence, automated virtual setups have been widely applied, especially in the field of clear aligners. Woo et al. compared the accuracy of three pieces of automated digital-setup software with that of a manual setup regarding six directions of tooth movement⁶⁵.

In a recent study by Tanikawa et al.⁶⁶, a DL model was used to predict the 3D outcomes of orthodontic and orthognathic treatment in Japanese patients, resulting in mean errors of 0.69 ± 0.28 mm and 0.94 ± 0.43 mm for the orthodontic and surgical patient groups, respectively. Similarly, Park et al.⁶⁷ evaluated a DL algorithm that accurately predicted treatment outcomes in terms of 3D facial changes, with a mean prediction error of 1.2 ± 1.01 mm. A recent



scoping review⁶⁸ revealed that AI models are not only efficient but also perform conventional methods in orthognathic treatment planning and outcome prediction. This review highlighted the reliability and reproducibility of these models, suggesting their potential to improve clinical outcomes, especially for less experienced practitioners.

2.10 Miscellaneous

The COVID-19 pandemic has brought attention to the importance of social distancing, remote work, and telemedicine. Orthodontic treatment typically lasts approximately 20 months and requires regular progress monitoring and potential complications. Traditional methods of monitoring can be time-consuming and repetitive. However, recent advancements in orthodontics, such as self-ligating systems and aligners, along with the implementation of telemedicine, have led to the development of dental monitoring (DM)⁶⁹. During the orthodontic treatment, orthodontists often come across various challenges, including clinical expertise in orthodontics and patient communication and management. The application of AI can help facilitate efficient and effective orthodontic treatment regarding practice guidance, remote care and clinical documentation.

Remote monitoring allows orthodontists to remotely track treatment progress and provide timely feedback based on photos or oral scans of the dentition, avoiding unnecessary visits, and bringing flexibility and convenience to patients. AI has enhanced the applications and effectiveness of remote monitoring software⁷⁰. Clinical photos and radiographs are routinely taken for diagnosis and treatment monitoring. AI can aid in classifying and categorizing these images, thereby enhancing the efficiency of clinical practice. Ryu et al. applied CNNs to automatically classify facial and intraoral photographs, including four facial photos and five intraoral photos. The CNN model obtained an overall valid prediction rate of 98%⁷¹.

2. Future Challenges

Orthodontic data sets represent a considerable privacy

and security risk due to the sensitive nature of the data they contain—among others, clinical photographs that can make patients identifiable. Furthermore, different data modalities are usually stored in isolated repositories, referred to as “data silos” (Rischke et al. 2022); accessing them and fusing them remains challenging.

Explainability refers to the black box phenomenon of AI. Deep learning algorithms inherently lack the ability to explain model predictions. Thus, efforts have been undertaken that provide insight into this “black box.” AI-based end-to-end classification of lateral cephalograms (eg. growth pattern, cervical vertebrae maturation stages) is not inherently explainable.

Interoperability lays the foundation to a frictionless integration of AI into the clinical workflow. It simplifies the development of AI in orthodontics and streamlines the application in the clinical workflow. Interoperability becomes more crucial for the development and deployment of multimodal AI. Currently, however, the majority of clinical note taking in orthodontics lacks standardization. This poses a significant challenge in consolidating these valuable data into datasets for model training.

Potential errors in automated diagnosis are a major challenge, as AI systems depend on the quality and comprehensiveness of their training data⁷². If an AI model has been trained on a dataset that lacks certain dental conditions, it may fail to recognize or accurately diagnose remalocclusions, leading to incorrect or suboptimal treatment recommendations. This highlights the need for continuous model improvement, where AI systems are regularly updated with diverse and high-quality datasets to enhance diagnostic accuracy.

Another challenge in AI-driven orthodontics is the high cost of implementation. AI-powered systems, including advanced imaging tools, treatment planning software, and cloud-based AI services, requires substantial financial investment⁷³. Many orthodontic practices, particularly smaller clinics, may find the cost of integrating AI prohibitive. To promote widespread adoption, AI technologies must be



come more affordable and accessible, with flexible pricing models that allow clinics to adopt AI tools without significant financial strain.

Additionally, over-reliance on AI without orthodontist verification can lead to significant risks. AI-generated treatment plans should always be reviewed by a qualified orthodontist to validate their feasibility. Blindly following AI recommendations without critical assessment could result in suboptimal patient care, particularly if an AI model fails to consider certain biomechanical or patient-specific factors. AI should function as a complementary tool, providing recommendations that orthodontists can refine based on their clinical expertise.

3. Limitations

Despite its many benefits, AI-based orthodontic tools are not without limitations. Overfitting is a common issue in the whole field of AI. This means the model performs excessively well in the training datasets but shows unsatisfactory performance in the testing dataset. Factors like data insufficiency, low data heterogeneity and excessive variables could all lead to overfitting. Methods like improving data samples, data augmentation, regularization, cross-validation and specific algorithms have all been reported to prevent overfitting.

Although AI has been extensively explored in orthodontic treatment, there are still several other areas where it could be further investigated, for example, the automated detection of orthodontic treatment needs like the index of orthodontic treatment need (IOTN) and index of orthognathic functional treatment need (IOFTN). Currently, AI excels mostly in orthodontics diagnosis, yet it has limited guidance on the treatment process⁷³. Orthodontists may encounter various challenges throughout the entire orthodontic treatment, including correcting deep overbites and voiding bone dehiscence or fenestration. Using AI to aid in preventing or addressing these issues could also be a potential area for future development. As clinical data continue to grow and AI computing power improves, there is no doubt that AI will significantly advance the field of orthodontics.

4. Conclusion

Undoubtedly, AI has the potential to revolutionize medicine, particularly in the field of diagnostic imaging, including orthodontics. The continuous advancement of AI algorithms that support pretreatment diagnostic processes allows the visualization of outcomes and facilitates decision making during treatment, placing orthodontics among the disciplines benefiting the most from the introduction of AI technology.

By leveraging AI's sophisticated predictive capabilities, orthodontists are able to develop highly individualized treatment plans that not only improve patient outcomes but also significantly reduce treatment times. AI's ability to predict tooth movement, optimize aligner and brace design, and continuously monitor treatment progress allows for a more effective and streamlined approach to orthodontic care. Despite the many benefits, challenges such as data security, algorithmic bias, and the need for widespread adoption remain. These obstacles must be addressed to ensure that AI technologies are applied ethically and equitably across diverse patient populations.

As AI continues to evolve and integrate with other advanced technologies like robotics and 3D printing, the future of orthodontics will likely become more accessible, cost-effective, and patient-centered. The ongoing development of AI holds the promise of transforming not only the patient experience but also the overall landscape of orthodontic care, leading to better dental health outcomes on a global scale.

REFERENCES

1. Khanagar SB, Al-Ehaideb A, Vishwanathaiah S, Maganur PC, Patil S, Naik S, et al (2021). Scope and performance of artificial intelligence technology in orthodontic diagnosis, treatment planning, and clinical decision-making- A systematic review. *JDentSci*. 16(1):482-92. doi:10.1016/j.jds.2020.05.022.
2. Hung HC, Wang YC, Yu-Chih W (2020). Applications of Artificial Intelligence in Orthodontics. *Taiwanese J Orthod*. 32(2):3-3. doi:10.38209/2708-2636.1005.



3. Subramanian AK, Chen Y, Almalki A, Sivamurthy G, Kafle D (2022). Cephalometric Analysis in Orthodontics Using Artificial Intelligence—A Comprehensive Review. *BioMed Res Int*. doi:10.1155/2022/1880113.
4. Moravčík, M.; Schmid, M.; Burch, N.; Lisý, V.; Morrill, D.; Bard, N.; Davis, T.; Waugh, K.; Johanson, M.; Bowling (2017). DeepStack: Expert-level artificial intelligence in heads-up no-limit poker. *Science*, 356, 508–513.
5. Wang, X.L.; Liu, J.; Li, Z.Q.; Luan, Z.L. (2021). Application of physical examination data on health analysis and intelligent diagnosis. *BioMed Res. Int.* 8828677.
6. Sharif, M.S.; Abbod, M.; Amira, A.; Zaidi, H. (2010). Artificial Neural Network Based System for PET Volume Segmentation. *Int. J. Biomed. Imaging*, 10, 5610.
7. Wang, D.; Yang, J.S. (2021). Analysis of Sports Injury Estimation Model Based on Mutation Fuzzy Neural Network. *Comput. Intell. Neurosci.* 3056428.
8. Ding, H.; Wu, J.; Zhao, W.; Matinlinna, J.P.; Burrow, M.F.; Tsoi, J.K. (2023). Artificial intelligence in dentistry—A review. *Front. Dent. Med.* 4, 1085251.
9. Chiu, Y.C.; Chen, H.H.; Gorthi, A.; Mostavi, M.; Zheng, S.; Huang, Y.; Chen, Y. (2020). Deep learning of pharmacogenomics resources: Moving towards precision oncology. *Brief. Bioinform.* 21, 2066–2083.
10. Taye, M.M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers* 12, 91.
11. Mohammad-Rahimi, H.; Nadimi, M.; Rohban, M.H.; Shamsoddin, E.; Lee, V.Y.; Motamedian, S.R. (2021). Machine learning and orthodontics, current trends and the future opportunities: A scoping review. *Am. J. Orthod. Dentofac. Orthop.* 160, 170–192. e174.
12. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. (2017). ImageNet classification with deep convolutional neural networks. *Commun. ACM*, 60, 84–90.
13. Li, Z.; Liu, F.; Yang, W.; Peng, S.; Zhou, J. (2022). A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. *IEEE Trans. Neural Netw. Learn. Syst.*, 33, 6999–7019.
14. Tomè, D.; Monti, F.; Baroffio, L.; Bondi, L.; Tagliasacchi, M.; Tubaro, S. (2016). Deep convolutional neural networks for pedestrian detection. *Signal Process. Image Commun.* 47, 482–489.
15. Strunga, M.; Urban, R.; Surovková, J.; Thurzo, A. (2023). Artificial Intelligence Systems Assisting in the Assessment of the Course and Retention of Orthodontic Treatment. *Healthcare*, 11, 683.
16. Dipalma, G.; Inchingolo, A.D.; Inchingolo, A.M.; Piras, F.; Carpentiere, V.; Garofoli, G.; Azzollini, D.; Campanelli, M.; Paduanelli, G.; Palermo, A.; et al (2023). Artificial Intelligence and Its Clinical Applications in Orthodontics: A Systematic Review. *Diagnostics*, 13, 3677.
17. Gurgel, M.; Alvarez, M.A.; Aristizabal, J.F.; Baquero, B.; Gillot, M.; Al Turkestani, N.; Miranda, F.; Castillo, A.A.; Bianchi, J.; de Oliveira Ruellas, A.C.; et al (2024). Automated artificial intelligence-based three-dimensional comparison of orthodontic treatment outcomes with and without piezosurgery. *Orthod. Craniofac. Res.* 27, 321–331.
18. Kondody, R.T.; Patil, A.; Devika, G.; Jose, A.; Kumar, A.; Nair, S. (2022). Introduction to artificial intelligence and machine learning into orthodontics: A review. *APOS Trends Orthod*, 12, 214–220.
19. Hung, K.; Yeung, A.W.K.; Tanaka, R.; Bornstein, M.M. (2020). Current Applications, Opportunities, and Limitations of AI for 3D Imaging in Dental Research and Practice. *Int. J. Environ. Res. Public Health*, 17, 4424.
20. Monill-González, A.; Rovira-Calatayud, L.; d'Oliveira, N.G.; Ustrell-Torrent, J.M. (2021). Artificial intelligence in orthodontics: Where are we now? A scoping review. *Orthod. Craniofacial Res.* 24, 6–15.
21. Albalawi, F.; Alamoud, K.A. (2022). Trends and Application of Artificial Intelligence Technology in Orthodontic Diagnosis and Treatment Planning—A Review. *Appl. Sci.* 12, 11864.
22. Faber J, Faber C, Faber P (2019). Artificial intelligence



- northodontics. *APOSTrends Orthod*, 9(4):201–5.
23. Hägg U, Taranger J(1980). Menarche and voice change as indicators of the pubertal growth spurt. *Acta Odontol Scand*. 38(3):179–86. doi:10.3109/00016358009004718.
 24. Orhan, K.; Bayrakdar, I.S.; Ezhov, M.; Kravtsov, A.; Özyürek, T(2020). Evaluation of Artificial Intelligence for Detecting Periapical Pathosis on Cone-Beam Computed Tomography Scans. *Int. Endod. J.* 53, 680–689.
 25. Issa, J.; Jaber, M.; Rifai, I.; Mozdziak, P.; Kempisty, B.; Dyszkiewicz-Konwińska, M (2023). Diagnostic Test Accuracy of Artificial Intelligence in Detecting Periapical Periodontitis on Two-Dimensional Radiographs: A Retrospective Study and Literature Review. *Medicina*. 59, 768.
 26. Orhan, K.; Shamshiev, M.; Ezhov, M.; Plaksin, A.; Kurbanova, A.; Ünsal, G.; Gusarev, M.; Golitsyna, M.; Aksoy, S.; Mısırlı, M.; et al (2022). AI-Based Automatic Segmentation of Craniomaxillofacial Anatomy from CBCT Scans for Automatic Detection of Pharyngeal Airway Evaluations in OSA Patients. *Sci. Rep.* 12, 11863.
 27. Vujanovic, T.; Jagtap, R(2023). Evaluation of Artificial Intelligence for Automatic Tooth and Periapical Pathosis Detection on Panoramic Radiography. *Oral. Surg. Oral. Med. Oral. Pathol. Oral. Radiol.* 135, e51.
 28. Brignardello-Petersen, R(2020). Artificial Intelligence System Seems to Be Able to Detect a High Proportion of Periapical Lesions in Cone-Beam Computed Tomographic Images. *J. Am. Dent. Assoc.* 151, e83.
 29. Lee H, Tajmir S, Lee J, Zissen M, Yeshiwas BA, Alkasab TK, et al (2017). Fully automated deep learning system for bone age assessment. *J Digit Imaging*. 30(4):427–41. doi:10.1007/s10278-017-9955-8.
 30. Chung, E.J.; Yang, B.E.; Park, I.Y.; Yi, S.; On, S.W.; Kim, Y.H.; Kang, S.H.; Byun, S.H(2022). Effectiveness of Cone-Beam Computed Tomography-Generated Cephalograms Using Artificial Intelligence Cephalometric Analysis. *Sci. Rep.* 12, 20585.
 31. Kim, H.; Kim, C.S.; Lee, J.M.; Lee, J.J.; Lee, J.; Kim, J.S.; Choi, S.H(2023). Prediction of Fishman's skeletal maturity indicators using artificial intelligence. *Sci. Rep.* 13, 5870.
 32. Lee, H.; Tajmir, S.; Lee, J.; Zissen, M.; Yeshiwas, B.A.; Alkasab, T.K.; Choy, G.; Do, S(2017). Fully Automated Deep Learning System for Bone Age Assessment. *J. Digit. Imaging*. 30, 427–441.
 33. Kim, J.R.; Shim, W.H.; Yoon, H.M.; Hong, S.H.; Lee, J.S.; Cho, Y.A.; Kim, S(2017). Computerized Bone Age Estimation Using Deep Learning Based Program: Evaluation of the Accuracy and Efficiency. *AJR Am. J. Roentgenol.* 209, 1374–1380.
 34. Kök, H.; Izgi, M.S.; Acilar, A.M(2021). Determination of growth and development periods in orthodontics with artificial neural network. *Orthod. Craniofacial Res.* 24(Suppl. S2), 76–83.
 35. Franchi, L.; Baccetti, T.; McNamara, J.A., Jr(2000). Mandibular growth as related to cervical vertebral maturation and body height. *Am. J. Orthod. Dentofac. Orthop.* 118, 335–340.
 36. Flores-Mir, C.; Burgess, C.A.; Champney, M.; Jensen, R.J.; Pitcher, M.R.; Major, P.W(2006). Correlation of skeletal maturation stages determined by cervical vertebrae and hand-wrist evaluations. *Angle Orthod.* 76, 1–5.
 37. Kucukkeles, N.; Acar, A.; Biren, S.; Arun, T(1999). Comparisons between cervical vertebrae and hand-wrist maturation for the assessment of skeletal maturity. *J. Clin. Pediatr. Dent.* 24, 47–52.
 38. McNamara, J.A., Jr.; Franchi, L(2018). The cervical vertebral maturation method: A user's guide. *Angle Orthod.* 88, 133–143.
 39. Kim, D.W.; Kim, J.; Kim, T.; Kim, T.; Kim, Y.J.; Song, I.S.; Ahn, B.; Choo, J.; Lee, D.Y(2021). Prediction of hand-wrist maturation stages based on cervical vertebrae images using artificial intelligence. *Orthod. Craniofacial Res.* 24 (Suppl. S2), 68–75.
 40. Mathew, R.; Palatinus, S.; Padala, S.; Alshehri, A.; Awadh, W.; Bhandi, S.; Thomas, J.; Patil, S(2022).



- Neural Networks for Classification of Cervical Vertebrae Maturation: A Systematic Review. *Angle Orthod.* 92, 796–804.
41. Wang, X.D.; Zhang, J.N.; Gan, Y.H.; Zhou, Y.H. (2015). Current Understanding of Pathogenesis and Treatment of TMJ Osteoarthritis. *J. Dent. Res.* 94, 666–673.
 42. Derwich, M.; Mitus-Kenig, M.; Pawlowska, E. (2020). Interdisciplinary Approach to the Temporomandibular Joint Osteoarthritis—Review of the Literature. *Medicina.* 56, 225.
 43. Crincoli, V.; Cortelazzi, R.; De Biase, C.; Cazzolla, A.P.; Campobasso, A.; Dioguardi, M.; Piancino, M.G.; Mattia, L.; Di Comite, M. (2022). The Loss of Symmetry in Unilateral Bony Synostosis: A Case Report and Literature Review. *Symmetry* 14, 2008.
 44. Andrade, N.N.; Mathai, P.; Aggarwal, N. (2021). Facial Asymmetry. In *Oral and Maxillofacial Surgery for the Clinician*; Springer Nature: Singapore. pp. 1549–1576.
 45. Choi, E.; Kim, D.; Lee, J.Y.; Park, H.K. (2021). Artificial Intelligence in Detecting Temporomandibular Joint Osteoarthritis on Orthopantomogram. *Sci. Rep.* 11, 10246.
 46. de Dumast, P.; Mirabel, C.; Cevidane, L.; Ruellas, A.; Yatabe, M.; Ioshida, M.; Ribera, N.T.; Michoud, L.; Gomes, L.; Huang, C.; et al. (2018). A Web-Based System for Neural Network Based Classification in Temporomandibular Joint Osteoarthritis. *Comput. Med. Imaging Graph.* 67, 45–54.
 47. Bianchi, J.; de Oliveira Ruellas, A.C.; Gonçalves, J.R.; Paniagua, B.; Prieto, J.C.; Styner, M.; Li, T.; Zhu, H.; Sugai, J.; Giannobile, W.; et al. (2020). Osteoarthritis of the Temporomandibular Joint Can Be Diagnosed Earlier Using Biomarkers and Machine Learning. *Sci. Rep.* 10, 8012.
 48. Shoukri, B.; Prieto, J.C.; Ruellas, A.; Yatabe, M.; Sugai, J.; Styner, M.; Zhu, H.; Huang, C.; Paniagua, B.; Aronovich, S.; et al. (2019). Minimally Invasive Approach for Diagnosing TMJ Osteoarthritis. *J. Dent. Res.* 98, 1103–1111.
 49. Ito, S.; Mine, Y.; Yoshimi, Y.; Takeda, S.; Tanaka, A.; Onishi, A.; Peng, T.Y.; Nakamoto, T.; Nagasaki, T.; Kakimoto, N.; et al. (2022). Automated Segmentation of Articular Disc of the Temporomandibular Joint on Magnetic Resonance Images Using Deep Learning. *Sci. Rep.* 12, 221.
 50. Xie, X.; Wang, L.; Wang, A. (2010). Artificial neural network modeling for deciding if extractions are necessary prior to orthodontic treatment. *Angle Orthod.* 80, 262–266.
 51. Jung, S.K.; Kim, T.W. (2016). New approach for the diagnosis of extractions with neural network machine learning. *Am. J. Orthod. Dentofac. Orthop.* 149, 127–133.
 52. Li, P.; Kong, D.; Tang, T.; Su, D.; Yang, P.; Wang, H.; Zhao, Z.; Liu, Y. (2019). Orthodontic treatment planning based on artificial neural networks. *Sci. Rep.* 9, 2037.
 53. Suhail, Y.; Upadhyay, M.; Chhibber, A.; Kshitiz (2020). Machine learning for the diagnosis of orthodontic extractions: A computational analysis using ensemble learning. *Bioengineering.* 7, 55.
 54. Etemad, L.; Wu, T.H.; Heiner, P.; Liu, J.; Lee, S.; Chao, W.L.; Zaytoun, M.L.; Guez, C.; Lin, F.C.; Jackson, C.B.; et al. (2021). Machine learning from clinical dataset of a contemporary decision for orthodontic tooth extraction. *Orthod Craniofacial Res.* 24 (Suppl. S2), 193–200.
 55. Shojaei, H.; Augusto, V. (2022). Constructing Machine Learning models for Orthodontic Treatment Planning: A comparison of different methods. In *Proceedings of the IEEE International Conference on Big Data (Big Data)*, Osaka, Japan.
 56. Georgalis, K.; Woods, M.G. (2015). A Study of Class III Treatment: Orthodontic Camouflage vs Orthognathic Surgery. *Aust. Orthod. J.* 31, 138–148.
 57. Raposo, R.; Peleteiro, B.; Paço, M.; Pinho, T. (2018). Orthodontic Camouflage versus Orthodontic-Orthognathic Surgical Treatment in Class II Malocclusion: A Systematic Review and Meta-Analysis. *Int. J. Oral. Maxillofac. Surg.* 47, 445–455.
 58. Choi, H.-I.; Jung, S.-K.; Baek, S.-H.; Lim, W.H.; Ahn, S.-J.; Yang, I.-H.; Kim, T.-



- W(2019). Artificial intelligent model with neural network machine learning for the diagnosis of orthognathic surgery. *J. Craniofacial Surg.* 30, 1986–1989.
59. Lee, K.-S.; Ryu, J.-J.; Jang, H.S.; Lee, D.-Y.; Jung, S.-K(2020). Deep convolutional neural networks based analysis of cephalometric radiographs for differential diagnosis of orthognathic surgery indications. *Appl. Sci.* 10, 21–24.
60. Shin, W.; Yeom, H.G.; Lee, G.H.; Yun, J.P.; Jeong, S.H.; Lee, J.H.; Kim, H.K.; Kim, B.C(2021). Deep learning based prediction of necessity for orthognathic surgery of skeletal malocclusion using cephalogram in Korean individuals. *BMC Oral Health.* 21, 130.
61. Salazar, D.; Rossouw, P.E.; Javed, F.; Michelogiannakis, D(2023). Artificial Intelligence for Treatment Planning and Soft Tissue Outcome Prediction of Orthognathic Treatment: A Systematic Review. *J. Orthod.*
62. Bahaa K, Noor G, Yousif Y(2011). The artificial intelligence approach for diagnosis, treatment and modelling in orthodontic. *Principles Contemp Orthod.* 451.
63. Dong, W.; Chen, Y.; Li, A.; Mei, X.; Yang, Y(2023). Automatic detection of adenoid hypertrophy on cone-beam computed tomography based on deep learning. *Am. J. Orthod. Dentofac. Orthop.* 163, 553–560. e553.
64. Jeong, Y.; Nang, Y.; Zhao, Z(2023). Automated Evaluation of Upper Airway Obstruction Based on Deep Learning. *BioMed Res. Int.* 8231425.
65. Woo, H.; Jha, N.; Kim, Y.-J.; Sung, S.-J(2023). Evaluating the accuracy of automated orthodontic digital setup models. *Semin. Orthod.* 29, 60–67.
66. Tanikawa, C.; Yamashiro, T(2021). Development of Novel Artificial Intelligence Systems to Predict Facial Morphology after Orthognathic Surgery and Orthodontic Treatment in Japanese Patients. *Sci. Rep.* 11, 15853.
67. Park, Y.S.; Choi, J.H.; Kim, Y.; Choi, S.H.; Lee, J.H.; Kim, K.H.; Chung, C.J(2022). Deep Learning–Based Prediction of the 3D Post orthodontic Facial Changes. *J. Dent. Res* 101, 1372–1379.
68. Khanagar, S.B.; Alfouzan, K.; Awawdeh, M.; Alkadi, L.; Albalawi, F.; Alghilan, M.A (2022). Performance of Artificial Intelligence Models Designed for Diagnosis, Treatment Planning and Predicting Prognosis of Orthognathic Surgery (OGS)—A Scoping Review. *Appl. Sci.* 12, 5581.
69. Caruso, S.; Caruso, S.; Pellegrino, M.; Skafi, R.; Nota, A.; Tecco, S(2021). A Knowledge-Based Algorithm for Automatic Monitoring of Orthodontic Treatment: The Dental Monitoring System. Two Cases. *Sensors.* 21, 1856.
70. Hansa, I.; Semaan, S.J.; Vaid, N.R(2020). Clinical outcomes and patient perspectives of Dental Monitoring® GoLive® with Invisalign®—a retrospective cohort study. *Prog. Orthod.* 21, 16.
71. Ryu, J.; Lee, Y.S.; Mo, S.P.; Lim, K.; Jung, S.K.; Kim, T.W(2022). Application of deep learning artificial intelligence technique to the classification of clinical orthodontic photos. *BMC Oral Health.* 22, 454.
72. Shang, Z.; Chauhan, V.; Devi, K.; Patil, S(2024). Artificial Intelligence, the Digital Surgeon: Unravelling Its Emerging Footprint in Healthcare—The Narrative Review. *J. Multidiscip. Healthc.* 17, 4011–4022.
73. Lee, J.M.; Moon, J.H.; Park, J.A.; Kim, J.H.; Lee, S.J(2024). Factors influencing the development of artificial intelligence in orthodontics. *Orthod. Craniofac. Res.* 27, 6–12.