

ARTIFICIAL INTELLIGENCE IN CEPHALOMETRIC LANDMARK DETECTION: CURRENT APPLICATIONS, ACCURACY, AND FUTURE DIRECTIONS IN ORTHODONTICS

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ABSTRACT

Artificial intelligence (AI) is becoming increasingly significant in orthodontic diagnosis, especially in automated cephalometric landmark detection. Deep learning methods have shown promising accuracy for identifying skeletal landmarks and can assist clinicians in reducing tracing time and improving consistency. However, variations in datasets, soft tissue complexity and the lack of standardised evaluation criteria still influence reliability across different studies. This review summarises the evolution of cephalometric landmark identification, commonly used AI model types, accuracy outcomes reported in literature, currently available commercial platforms, limitations and future directions. While AI cannot fully replace experienced clinical judgement at present, it has strong potential to support routine cephalometric analysis as technology, datasets and model refinement continue to advance.

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INTRODUCTION

Rapid digitalization in orthodontics, through systems like cone beam computed tomography (CBCT), intraoral scanners, and advanced imaging software, has significantly reshaped diagnostic workflows and treatment planning¹. Artificial Intelligence (AI), a term introduced in the mid-20th century, refers to computational systems capable of extracting patterns from large datasets and generating predictions or decisions based on learned information². Among different AI frameworks, deep learning models have shown exceptional ability in complex image-based recognition tasks, making them particularly suitable for orthodontic diagnosis³. In orthodontic practice, AI-assisted tools may enhance diagnostic precision, reduce inter-operator variation, improve standardization, shorten analysis time, and support objective clinical decision-making⁴. For many clinicians, this translates into greater consistency during case discussions, especially in postgraduate training settings where manual tracing differences are commonly observed. Cephalometric radiography was formally introduced into orthodontics in 1931 by Broadbent and Hofrath⁵, and since then, it has remained a cornerstone for evaluating craniofacial relationships and treatment outcomes. Accurate localization of cephalometric landmarks is fundamental for skeletal and dental assessment⁶. Manual landmark tracing, however, is labour intensive, time-consuming,

operator dependent, and prone to variability between and within clinicians⁷. With expanding digital imaging repositories and rapid algorithmic development, AI-based landmark detection is emerging as a promising alternative capable of automating cephalometric tracing with improved reliability and efficiency⁸.

This review focuses on the present status of AI-driven cephalometric landmark detection, current levels of accuracy, identified limitations, and future research directions that may influence routine orthodontic use in the coming years.

MATERIALS AND METHODS

A literature search was performed across PubMed, Scopus, and Web of Science databases up to October 2025. The search terms included: “artificial intelligence”, “deep learning”, “machine learning”, “cephalometric analysis”, and “landmark detection”. Relevant articles were also identified through cross-referencing the bibliographies of eligible publications. Studies were included if they evaluated AI-based cephalometric landmark detection on 2D lateral cephalograms or CBCT-derived cephalometric data. Non-cephalometric AI orthodontic studies, case reports, abstracts, non-English articles, and studies lacking accuracy evaluation outcomes were excluded. Due to heterogeneity in datasets, algorithms, and outcome metrics, quantitative pooling of results or meta-analysis was not performed.

Historical Evolution of Cephalometric Landmark Detection

Cephalometric radiography has been a fundamental diagnostic modality in orthodontics since Broadbent and Hofrath introduced lateral cephalograms in 1931⁵. Initially, landmark identification was performed manually on acetate tracing films which, although widely practiced, was highly operator dependent and associated with significant inter-examiner and intra-examiner variability⁷. Following advances in computer technology, digital cephalometric systems and semi-automated tracing platforms began to replace manual tracing, which improved reproducibility and measurement consistency^{1,6}. In the early 2000s, conventional machine learning based approaches were explored for landmark identification; however, these methods depended heavily on handcrafted features and demonstrated limited generalizability across population datasets¹. A major advancement occurred with the introduction of deep learning, particularly convolutional neural networks (CNNs), enabling automatic hierarchical feature extraction directly from cephalometric images and improving detection accuracy³. Recent developments have incorporated more complex architectures, including region-based models, generative adversarial networks, hybrid attention-based techniques, and transformer models, which have demonstrated further improvements in detecting anatomically challenging landmarks⁸. Conventional vs ai-based cephalometric landmark detection

Parameter	Conventional Manual Tracing	AI-Based Landmark Detection
Time required	Slow (10–20 min per tracing)	Fast (seconds to 1 min)
Operator dependence	High – varies with skill/experience	Minimal – consistent output
Intra-/Inter-examiner variation	Significant	Greatly reduced
Accuracy for hard-tissue landmarks	Good but variable	High and consistent
Accuracy for soft-tissue landmarks	Often variable	Improving but still slightly lower
Reproducibility	Moderate	High
Learning curve	Requires training & experience	User-friendly once set up
Error sources	Fatigue, judgement, tracing differences	Dataset quality, annotation errors

Clinical use	Gold standard historically	Assistive tool with growing reliability
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Types of Ai Models Used in Cephalometric Landmark Detection

Deep learning models are currently the most widely used AI approaches for cephalometric landmark identification and have shown the most reliable accuracy in literature³. Convolutional Neural Networks (CNNs) are the basic framework used in most studies, as they automatically learn spatial patterns from radiographic pixels without requiring manual feature selection³. Region-based networks such as Faster R-CNN further improve accuracy by identifying specific anatomical regions before predicting landmark location, which is clinically useful when structures overlap (e.g. gonial region, orbitale)⁹. Generative Adversarial Networks (GANs) have been explored mainly to improve dataset diversity and synthetic training augmentation when available sample sizes are small¹⁰. Recently, Transformer-based architectures have also been applied since they use global self-attention, helping to capture long-range feature relationships which may be useful especially for soft tissue related points¹¹. Hybrid models integrating CNN backbone with attention or transformer layers have shown promising improved performance, especially for landmarks which have poor visual definition or higher soft tissue variability¹².

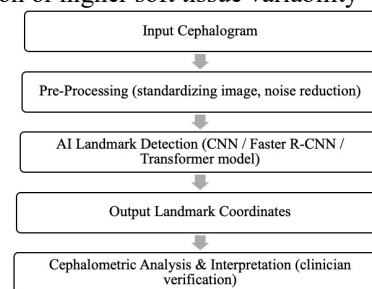


Figure 1. General workflow of AI-based cephalometric landmark detection

TABLE 1. Comparison of AI model types used for cephalometric landmark detection

Model Type	Key Advantage	Limitation	Clinical Relevance	Example Study
Convolutional Neural Network (CNN)	Strong spatial feature learning ability	May have reduced accuracy in overlapping anatomical areas	Best for distinct skeletal points (S, N, ANS,	Lee et al 2020 ³

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			PNS etc.)	
Faster R-CNN (Region based CNN)	Improves localization accuracy using region proposals	Requires more computational resources	Good for overlapping areas (Go, Or)	Wang et al 2021 ⁹
Generative Adversarial Network (GAN)	Useful for data augmentation and improving training robustness	Training is less stable and needs more tuning	Useful when dataset is small or imbalanced	Chen et al 2022 ¹⁰
Vision Transformer	Captures long-range structural and contextual spatial relationships	Limited research still available in cephalometrics	Useful for soft tissue landmark complexity	Kim et al 2024 ¹¹
Hybrid Models (CNN + Attention/Transformer)	Combines strengths of CNN + attention → improving performance	More complex architecture and training requirement	Shows highest emerging accuracy in recent literature	Li et al 2023 ¹²

Understanding datasets, landmark and annotation and evaluation measures

AI-based cephalometric landmark detection models depend heavily on the quality of datasets used for training and validation. Most studies have used lateral cephalograms collected from orthodontic records, but the dataset size, population diversity, and image quality vary widely between studies⁸. This variation influences how well a model can generalize to real clinical cases outside the dataset it was trained on. CBCT-derived cephalometric images are also being explored in newer research, but widespread use is still limited compared to 2D

cephs. Landmark annotation is another important factor. Most studies consider expert orthodontists' manual landmark identification as the "ground truth" reference. However, even experienced clinicians can differ in how they mark certain points, especially when soft tissue borders are not clearly visible (for example: pogonion, pronasale). This inter-examiner variation directly affects the model evaluation results⁷.

To measure accuracy, different studies use different outcome measures. The most widely used metric is Mean Radial Error (MRE), and clinically, an error of less than 2 mm is generally considered acceptable³. Many newer studies also report Success Detection Rate (SDR), which measures the percentage of landmarks detected within a certain distance threshold (commonly 2 mm or 2.5 mm). Because studies use different dataset sizes and evaluation criteria, comparing results between different AI models must be done cautiously.

Clinical Evidence and Current Accuracy Trends

Several studies have evaluated the performance of AI in cephalometric landmark identification, usually by comparing the AI-predicted coordinates with expert orthodontists' manual tracings, which are considered the reference standard³. Overall, deep learning models have shown clinically acceptable accuracy for most skeletal hard tissue landmarks such as Sella, Nasion and ANS³. The main challenge still remains soft tissue landmark identification because soft tissue contours are visually less sharp and less consistent on radiographs, which leads to slightly higher prediction error values⁸. A mean radial error (MRE) of less than 2 mm is generally accepted as clinically acceptable for cephalometric use in orthodontics³. Many recent AI-based models are now achieving values close to or within this benchmark for the majority of landmarks, which indicates a strong potential for clinical translation. However, reported values still vary depending on dataset characteristics, ethnicity distribution, image acquisition quality, and the neural network architecture used. Larger, multicentric, and diverse datasets will further improve the consistency and generalizability of these systems⁸.

Study / Year	Model Type	Key Findings	Notes
Lee et al 2020 ³	CNN	Hard tissue landmark accuracy within clinically acceptable range (< 2 mm)	Reliable for skeletal landmarks
Abdalla et al 2023 ⁸	Various Deep Learning models	Soft tissue accuracy still comparatively lower	Dependent on dataset & landmark visibility

Wang et al 2021 ⁹	Faster R-CNN	Better localization in overlapping anatomical zones	Helpful in complex landmarks like Go/Or
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Practically, this means AI can reduce tracing time, improve measurement consistency, and serve as a supportive diagnostic aid in orthodontics. However, AI outputs should still be interpreted along with clinical judgement, especially for soft-tissue sensitive areas, mixed dentition, and complex craniofacial cases. At present, AI acts best as an assistive tool rather than a direct replacement for expert landmark tracing.

Comercially Available Ai-Based Cephalometric Platforms

- WebCeph (South Korea)

Widely used among postgraduate orthodontic students because of accessible interface and cloud-based workflow. Supports automatic cephalometric landmark detection and basic cephalometric tracing. Good for day-to-day academic use and case record discussions.

- CephX (ORCA Dental AI, USA)

FDA cleared platform. Frequently referenced in AI literature because it is clinically validated and supports cephalometric analysis, treatment simulations and progress comparison. Used in international clinical practice settings more than India.

- Dolphin Imaging AI Module

Integrated within the larger Dolphin software ecosystem. Has AI landmark assistance inside a broad practice management + imaging suite. Preferred mostly in private clinic setups with full digital workflow.

Limitations and barrier to everyday clinical use

- Soft-tissue points are harder. Borders are less distinct, so errors are typically higher than for clear bony points (e.g., Sella, Nasion).^{3,8}
- Dataset bias. Many models are trained on limited ethnic or age groups; performance can drop on different populations or image qualities.^{1,8}
- Annotation variability. Even experts don't always place the exact same point—ground truth has noise, which caps model accuracy.⁷
- Heterogeneous methods. Studies use different datasets, filters, and metrics (MRE vs SDR), so head-to-head comparison is tricky.^{3,8}
- Generalisation vs clinic reality. Mixed dentition, craniofacial anomalies, appliances, and poor-quality films still challenge models.⁸
- Workflow and medico-legal questions. Responsibility remains with the clinician;

AI outputs need verification and documentation.¹

Future direction

- Larger and more diverse datasets are needed so that AI performs consistently across different populations.
- Standard evaluation guidelines (same MRE / SDR benchmarks) will help compare studies more fairly.
- Hybrid models that combine CNNs with attention-based / transformer methods may further improve soft tissue point accuracy.
- Combining 2D cephalograms with CBCT slices or photographs can strengthen model confidence for difficult landmarks.
- Privacy-safe approaches like federated learning can allow multi-centre collaboration without sharing patient records.
- Eventually, AI landmark detection may integrate smoothly into routine analysis software and assist chairside planning.

CONCLUSION

The effectiveness and reliability of cephalometric landmark detection have been greatly enhanced by artificial intelligence, especially for well-defined skeletal reference points. The accuracy levels reported in recent studies are improving and getting closer to clinically acceptable thresholds, despite the fact that soft-tissue landmarks still exhibit relatively higher variability. Instead of taking the place of expert interpretation, AI currently works best as a supplementary tool that enhances clinician judgment. Larger and more varied datasets, consistent assessment criteria, and model optimization will be necessary as research progresses in order to improve reliability in various clinical scenarios. AI-assisted cephalometric tracing is anticipated to progressively become more integrated into standard orthodontic practice with these advancements, especially in today's widely used digital treatment planning environments.

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