



Development of cephalometric radiography in orthodontic imaging: a literature review

Shinta Amini Prativi^{1,2} , Andriyan Bayu Suksmono² ,
Tati Latifah Mengko² , Donny Danudirdjo²

ABSTRACT

Objectives: This review article aims to discuss the development of lateral cephalometric radiography use in science until now.

Review: The search for studies on the identification of lateral cephalometric anatomical landmarks based on artificial intelligence was conducted by involving four databases: PubMed, IEEE Xplore, Google Scholar, and Scopus. The article selection was conducted using the keywords "Cephalometric Radiograph," "Automatic Cephalometric," "Cephalometric Landmarking," and "Cephalometric Digital" from January 2000 to March 2022. A total of 11 articles were obtained for this study. Cephalometric radiography is a radiographic technique that shows a picture of the skull and is widely used in dentistry to analyze and assess the relationship between teeth, jaws, and facial bones. Cephalometric analysis can be done by identifying

anatomical landmark points and measuring angles on lateral cephalometric radiographs. The development of cephalometric radiography in biomedical imaging, especially in terms of the processing of cephalometric radiograph images from the process of forming X-rays to their potential use in the process of determining automatic anatomical landmark points

Conclusion: The results of the literature review of the development of dental radiology, especially digital cephalometric radiography, continue to increase, and its development is supported by computing technology, especially Artificial Intelligence.

Keywords: Lateral cephalometric; biomedical imaging; artificial intelligence

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INTRODUCTION

One of the extraoral radiographic images in dentistry that is commonly used is cephalometric radiography, second only to panoramic radiography. Cephalometric radiography is a radiographic technique that shows a picture of the skull that is widely used in the fields of dental radiology, orthodontics, oral surgery, and maxillofacial to assess the relationship between the teeth, jaw, and the facial bones.^{1,2} This assessment is important to know the development of the skull, jaw, and teeth. Cephalometric radiographs are essential for performing cephalometric analysis and for aiding in the initial diagnosis, treatment planning, progress evaluation, and assessment of orthodontic treatment outcomes.³ Cephalometric analysis can be done by identifying anatomical landmark points and measuring angles on lateral cephalometric radiographs. Tracing accuracy relies heavily on the precise identification of landmark points.^{4,5}

Since the 1970s, digital imaging has been extensively utilized in medical research and clinical diagnosis, with multimedia software and hardware becoming the standard for displaying both 2D and 3D images.⁶ The development of radiograph digitization and the conversion of conventional radiographs to digital formats not only reduces radiation exposure to patients but also provides several advantages, including enhanced performance through simultaneous analyses and comparative studies, easier treatment predictions, improved data storage efficiency, and advanced radiographic image processing.^{7,8}

There are several obstacles in the assessment of a radiograph that shows a two-dimensional image of a 3-dimensional object, especially in determining anatomical landmark points in the cephalometric analysis process. The obstacles include the superimposition of anatomical structures in 2D skull images, variations in X-ray machine settings, and



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¹Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Universitas Sriwijaya, Palembang, Indonesia 40132

²Department of Electro and Informatics Engineering, Institut Teknologi Bandung, Indonesia 60293

*Correspondence to:
Shinta Amini Prativi
✉ shintaaaminiprativi@fk.unsri.ac.id

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poor radiograph quality, all of which reduce the visibility of hard and soft tissue structures and make it more difficult to identify landmark points.^{1,4,9} In order to minimize all these shortcomings, AI-assisted cephalometric analysis has been introduced and is gradually replacing traditional manual tracing.¹⁰ Numerous studies in the literature have evaluated the validity and accuracy of digital cephalometry versus manual measurements, demonstrating that digital techniques are superior in minimizing subjective errors and reducing procedure time.¹¹

This literature review focuses on reviewing the development of cephalometric radiography in its use in biomedical imaging, especially from the process of forming X-rays to its current application in dental radiology.

REVIEW

LITERATURE SEARCH

The literature review was performed using databases including PubMed, IEEE Xplore, Google Scholar, and Scopus. Articles were selected based on keywords such as "Cephalometric Radiograph," "Automatic Cephalometric," "Cephalometric Landmarking," and "Cephalometric Digital" from January 2000 to March 2022.

CEPHALOMETRIC RADIOGRAPHY

Cephalometric radiography was first introduced by J. Pacini in 1922, followed by Hofrath in 1934, and has been used to assess malocclusion and skeletal disproportions.¹² A cephalometric radiograph shows a lateral view of the skull, taken using a cephalostat, which ensures proper alignment between the skull, film, and X-ray beam. Extraoral lateral cephalometric radiography is the most frequently used technique in dentistry, particularly in orthodontics.¹ The purpose of cephalometric projection is to evaluate facial growth and development, identify trauma, disease, or developmental disorders, and examine the relationships between the teeth, jawbones, and facial bones.¹³

Cephalometric radiographs display the bones of the face and skull, as well as the soft tissues.^{5,9} In general, the clinical indications for the use of cephalometric radiography are for orthodontics and orthognathic surgery. Cephalometric radiographs are used for initial diagnosis, treatment planning, treatment evaluation, and assessment of orthodontic treatment results. In the UK, the guidelines for the indications and selection criteria of cephalometric radiographs are provided in the British Orthodontic Society's 2008 booklet *Orthodontic Radiographs – Guidelines for the Use of Radiographs in Clinical Orthodontics* (3rd Edition) and the Faculty of General Dental Practice (UK)'s 2004 *Dental Radiograph Selection Criteria* booklet. These resources are intended to support the justification process, ensuring that radiographs are used effectively to establish a diagnosis and plan treatment.³

IMAGING MODALITY

Cephalometric radiography can be performed using several modalities. Traditionally, X-ray radiography has been widely used due to its non-invasive nature. Along with conventional and digital radiography, Cone Beam Computed Tomography (CBCT) has emerged as a new option, offering detailed three-dimensional images. CBCT is proving to be a promising imaging modality in dentistry, and its popularity within orthodontics continues to grow.

CONVENTIONAL RADIOGRAPHY

The basic requirements for conventional two-dimensional dental imaging include an X-ray machine, a patient, and an image receptor, which can be placed either intraorally or extraorally. Initially, the image receptor used was a film coated with a photographic emulsion that would darken upon exposure to X-rays.³ X-rays, discovered by Röntgen in 1895, have the ability to penetrate human tissue. They are a form of high-energy electromagnetic radiation, part of the electromagnetic spectrum, and are described as energy wave packets. Each packet, known as a photon, is equivalent to one quantum of energy. To fully understand the production and interaction of X-rays, a basic knowledge of atomic physics is essential.^{1,2,14}

The X-ray machine generates X-rays that travel through the patient's tissue and strike a digital receptor or film, creating a radiograph. The main components of an X-ray machine are the X-ray tube and its power supply. The X-ray tube is housed in the tube head, along with various power supply components. Electrical insulating material, typically oil, surrounds both the tube and the transformer. The tube itself consists of a cathode and an anode, located within a vacuum-sealed glass tube.^{2,14} Electrons flow from the filament at the cathode to the target at the anode, producing X-rays. To function properly, the X-ray tube requires a power supply to (1) heat the cathode filament to generate electrons and (2) build up a high voltage potential between the anode and cathode to accelerate the electrons toward the anode. The conversion of the kinetic energy of electrons into X-ray photons is inefficient, as more than 99% of the kinetic energy is converted into heat. Targets made of high atomic number materials are most efficient for producing X-rays. Since heat is generated at the anode, a target with a high melting point is necessary. The focal point is the area on the target where the focusing cup directs the electrons, and from which the X-rays are produced. The sharpness of the radiographic image improves as the size of the focal point decreases.^{2,3}

In dental imaging, an X-ray beam enters the patient's face, interacts with both hard and soft tissues, and then strikes a digital sensor or film. This beam contains photons with high energy but is partially heterogeneous. As the beam passes through the patient, its intensity is attenuated, meaning it is reduced. In absorption interactions,

photons ionize absorber atoms, transferring their energy into the kinetic energy of electrons that are released. In scattering interactions, photons interact with absorber atoms and then move in the opposite direction. The frequency of these interactions varies depending on the type of tissue affected (e.g., bone and soft tissue). Bone absorbs more X-ray photons, while soft tissue is more easily penetrated by them.¹⁵

Conventional film radiography is one of the most commonly used imaging options due to its simplicity and affordability, making it the least expensive of all medical imaging techniques. An additional advantage of this technique is its ability to capture both soft tissue and bone structures in a single image, which is particularly useful for detecting foreign objects around bones. However, it has several limitations, including its inability to provide 3D information and the issue of tissue superimposition. As a result, some conditions may not be visible, or objects may not appear in their actual location or size, leading to suboptimal image quality.^{1,2}

DIGITAL RADIOGRAPHY

Today, film is increasingly being replaced by digital sensors with images created on a computer and displayed on a monitor. The portions of the digital sensor that are exposed to the X-rays appear black on the computer-generated image. The extent to which the emulsion or computer-generated image is blackened depends on the number of X-rays reaching the film or sensor and the density of the object.^{1,2,15}

At present, imaging is transitioning from film to digital systems. Many diagnostic limitations caused by inadequate film processing and the challenges of maintaining quality chemical processing have been well documented. Digital imaging eliminates the need for chemical processing, including the use of hazardous materials. Additionally, digital images can be electronically transferred to other healthcare providers without any loss of image quality. Moreover, intraoral digital receptors require less radiation than traditional film, thus reducing patient exposure.^{1,2}

Digital images are made up of a large number of discrete picture elements (pixels). The small size of these pixels results in a smooth image when viewed at normal magnification. The location of each pixel is typically identified by its specific coordinates within the image matrix, represented by its row and column. The value assigned to each pixel represents the intensity, or grey level, of the image at that specific location. Digital image receptors are available in a variety of technologies, with different sizes and shapes. The most commonly used receptor materials fall into two main categories: (1) Solid-state technology and (2) Photostimulable phosphor technology (PSP). Solid-state technology is further divided into four types: Charge-coupled device (CCD), Complementary Metal Oxide Semiconductor (CMOS), Flat Panel Detector (FPD), and Thin-Film-Transistor-Based Digital Radiography Systems (TFT-DR).^{1,14}

CONE BEAM COMPUTED TOMOGRAPHY (CBCT)

Cone Beam Computed Tomography (CBCT) has been developed in recent years specifically for use in oral and maxillofacial examinations. CBCT is referred to as digital volume tomography or cone beam volumetric imaging because it uses cone-shaped X-rays. The size of the imaged volume or field of view (FOV) varies, namely, small, medium, and large, to obtain an image of the entire skull using a 17 cm FOV, which can be used for cephalometric assessment.²

The advantages of CBCT imaging include multiplanar image slices and data manipulation, which allow anatomical and pathological conditions to be viewed in different planes. It also offers lower radiation doses compared to medical CT, geometrically accurate images, excellent spatial resolution, fast scan times, and compatibility with implant planning and cephalometric software. However, there are several disadvantages, including the presence of artifacts and limited soft tissue visualization. Unlike CT, CBCT utilizes a cone-shaped beam and specialized detectors.^{2,4}

Research on identifying anatomical landmark points on cephalometric radiographs has increasingly utilized CBCT images, yielding promising results. In a study by Kim et al. (2021), CBCT data achieved a Successful Detection Rate (SDR) of 87% within an accuracy range of 2 mm. However, this outcome was similar to the accuracy assessed using 2D radiographs.^{16,17}

APPLICATION OF CEPHALOMETRIC ANALYSIS

Cephalometric tracing provides a representation of anatomical points on cephalometric radiographs, which are connected for line and plane measurements to illustrate the relationship between the mandible and maxilla relative to the cranial base and skeletal patterns. Numerous cephalometric analyses have been developed, each offering insights into skeletal and facial positions to enhance aesthetic appearance. Cephalometric analysis gained popularity after the Second World War, beginning with Down's analysis and evolving into other analyses, such as those by Steiner, Sassouni, Harvold, Wits, McNamara, Tweed, and Jefferson.¹²

Cephalometric analysis involves the study of craniofacial measurements in orthodontics, providing a sagittal view of the skull, soft tissue profile, and tooth structure. Conventional 2D cephalometry has long been regarded as the "gold standard" diagnostic tool for evaluating craniofacial growth and skeletal deformities.¹⁵ The transition from manual to computer-assisted cephalometric analysis was developed to enhance diagnostic accuracy by reducing errors and saving time. A significant source of error in this process is identification error, influenced by factors such as the examiner's experience and subjectivity, the judgment involved in defining and interpreting landmarks, and the quality of the radiographic image.^{6,7}

ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) techniques have been continuously evolving since 1955, when John McCarthy coined the term to describe the ability of machines to perform tasks typically considered intelligent. In fields like radiology and orthodontics, machine learning algorithms are widely used for applications such as automatic diagnostics and landmark detection.¹⁸ The growing use of AI can be attributed to several breakthrough advancements, including the availability of labeled data, progress in machine learning, deep learning, neural network architecture, and the development of parallel hardware.^{19,20}

ARTIFICIAL INTELLIGENCE IN DENTAL RADIOLOGY

In radiology, current AI applications primarily focus on anomaly detection, segmentation, and image classification. Familiarity with common terminology and concepts in this field will allow the radiology community to critically analyze the opportunities, challenges, and potential pitfalls involved. The advent of AI requires radiologists to take an active role in scientific research and development.¹⁹ AI has the potential to automate manual tasks and accelerate processes, providing valuable support to practitioners through digitized medical data. According to Putra et al. (2021), AI publications in dental radiography have grown significantly each year, particularly in 2020, with Deep Learning being the most commonly used method in dentistry (59%), followed by machine learning methods (26%) and other techniques.²¹

The dental field has seen widespread use of AI for tasks such as the detection and diagnosis of dental caries, diagnosis of proximal dental caries, detection, and numbering of teeth, detection of vertical root fractures, detection of apical lesions, location of minor apical foramen, assessment of root morphology, diagnosis of salivary gland disease, diagnosis of maxillary sinusitis, maxillofacial cysts, lymph node metastasis,

detection of osteoporosis, determination of gender using mandibular morphometric parameters, estimating age based on the development of third molar teeth, classifying cancer tissue, detection of periodontal bone loss, detection of the level of alveolar bone loss, prediction of orthodontic diagnosis, assessment of orthodontic treatment space needs, determination of cervical vertebral growth and development stages, cephalometric analysis, identifying cephalometric landmarks, diagnosis of orthognathic surgery.¹⁷

DISCUSSION

Computer-based cephalometric analysis has been widely developed, including Dolphin® Imaging, Dentofacial Planner®, quick Ceph®, and FACAD®. All of the articles considered for the studies are shown in Table 1. Numerous comparative studies have been conducted between manual and computer-based cephalometric analysis.¹⁷⁻²⁰ One such study by Sayinsu et al. (2007) compared computer-based and manual cephalometric methods and found no difference between the two examinations.¹⁹ Similarly, Alqhatani et al. (2019) evaluated cephalometric analysis using the CephX® website-based platform and FACAD® software, concluding that there was no difference between the two examinations. The field of computing continues to evolve rapidly, with Artificial Intelligence currently driving further advancements.²²

Artificial intelligence has been applied to the automatic determination of anatomical landmark points on cephalometric radiographs to assess individual skeletal conditions. Various methods have been developed to save time and reduce errors in this process. Anatomical landmark identification techniques on cephalometric radiographs can be categorized into two main approaches: knowledge-based techniques and artificial intelligence (Figure 2).⁸

Table 1. Included Studies in the article

Author (year)	Title	N Landmarks and reference test	Test Sampling	Method	Result
Sayinsu et al. (2007) ¹⁹	An evaluation of the galats in cephalometric measurements on scanned cephalometric images and conventional tracings	33 landmarks by 2 orthodontists	30 dataset	Dolphin Imaging Software 9.0	No difference between the two examinations
Alqhatani et al. (2019) ²²	Evaluation of. an online website-based platform for cephalometric analysis	16 landmarks	30 dataset	Comparing two web-based platform for cephalometric analysis (CephX® and FACAD®)	No measurement showed a difference of more than 2 units

Gupta et al. (2015) ²³	A knowledge-based algorithm for automatic detection of cephalometric landmarks on CBCT images	20 landmarks by 3 orthodontists	30 dataset	Three dimensional with stacking of slices knowledge based algorithm	MRE 2.01 ± 1.23 mm, SDR 64.67% within the precision ranges of 2 mm
Park et al. (2019) ²⁴	Automated identification of cephalometric landmarks: part 1- comparisons between the latest deep-learning methods YOLOV3 and SSD	80 landmarks by an expert	1311 (1028 training, 283 test)	Comparing YOLOv3 with modification and Single Shot Multibox Detector (SSD)	YOLOv3 showed SDR 80.4% within the precision ranges of 2 mm
Lindner et al. (2016) ²⁸	Fully Automatic System for Accurate Localisation and Analysis of Cephalometric Landmarks in Lateral Cephalograms	19 landmarks by two orthodontists	400 dataset	Fully automated landmark annotation (FALA) system that combined Random Forest regression-voting and Constrained Local Model Framework (RFRV-MLC)	SDR 84.7% within the precision ranges of 2 mm
Wang et al. (2018) ²⁹	Automatic Analysis of Lateral Cephalograms Based on Multiresolution Decision Tree Regression Voting	19 landmarks by two experienced doctors	300 (150 training, 130 test). Own Dataset 165 radiograph	Multiresolution decision tree regression voting (MDRTV) with patch feature	MRE 1.69 ± 1.43 mm, SDR 73.37% within the precision ranges of 2 mm
Arik et al. (2017) ³⁰	Fully automated quantitative cephalometri using convolutional neural networks	19 landmarks by 2 experts	400 (150 training and 250 testing)	Custom CNN combined with a shape model for refinement	SDR 75.58% within the precision ranges of 2 mm
Kim et al. (2020) ³¹	Web-based fully automated cephalometric analysis by deep learning	19 landmarks by two orthodontists	3 group 2075 (1675 training, 200;175 validation, 200; 225 and 400 testing)	Stacked Hourglass-shaped Network	MRE 1.28 ± 1.75 mm, SDR 81.35% within the precision ranges of 2 mm
Lee et al. (2020) ³²	Automated cephalometric landmark detection with confidence regions using Bayesian convolutional neural networks	19 landmarks by 1 junior and 1 senior orthodontist	400 (250 training, 150 test)	Custom CNN for ROI and custom Bayesian CNN for identification landmark	MRE 1.53 mm, SDR 82.11% within the precision ranges of 2 mm
Lee et al. (2022) ³³	Cephalometric landmark detection via global and local encoders and patch-wise attentions	19 landmarks by two medical doctors	400 (150 training, 150 test1, 100 test 2)	Global stage and local stage. CNN single-passing for global and encoder CNN individual patch-wise for feature local	MRE 1.19 ± 0.80 mm, SDR 86.4% within the precision ranges of 2 mm

Yao et al. (2022) ³⁴	Automatic localization of cephalometric landmarks based on convolutional neural network	37 landmarks by two orthodontists	512 (312 training; 100 validation, 100 testing)	The system consisted of a global detection module (ResNet18) and a locally modified module	SDR 94% within the precision ranges of 2 mm
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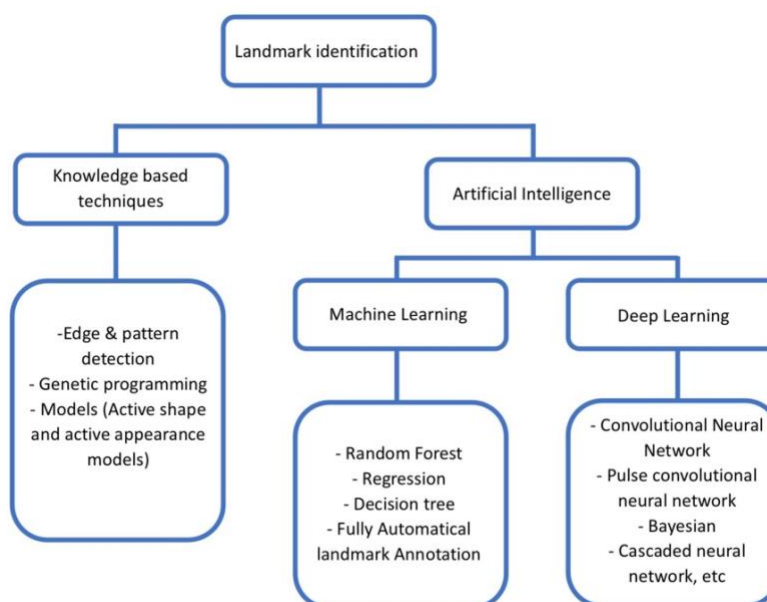


Figure 1. Categories of anatomical landmark identification techniques.⁸

Gupta et al. (2015) developed an AI model that can perform automatic cephalometric measurements using a knowledge-based algorithm and showed no significant difference between automatic and manual measurements.²³ Park et al. (2019) compared the efficiency and accuracy of the latest deep learning algorithm for automatic cephalometric anatomical landmark identification on cephalometric radiographs. The results showed quite accurate results in assessing landmarks.²⁴

MACHINE LEARNING METHOD

The development of an automatic anatomical landmark determination system began with Cohen et al. (1984), who conducted a study on the

identification and recognition of skeletal landmarks using a computer.²⁵ Levy-Mendel et al. (1986) employed the knowledge-based landmarking method,²⁶ while Uchino et al. (1995) were the first to develop the use of machine learning for this purpose.²⁷ Lindner et al. (2016) conducted a study using the Machine learning rainforest system to determine 19 landmarks on lateral cephalometric radiographs with an FALA system accuracy of 83.4% and became the winner of the ISBI Challenges in Beijing, China.²⁸ Later, Wang et al. (2018) applied Multiresolution Decision Trees Regression Voting to determine 45 landmarks, resulting in an algorithm with an average accuracy of 72% within a 2 mm precision range.²⁹

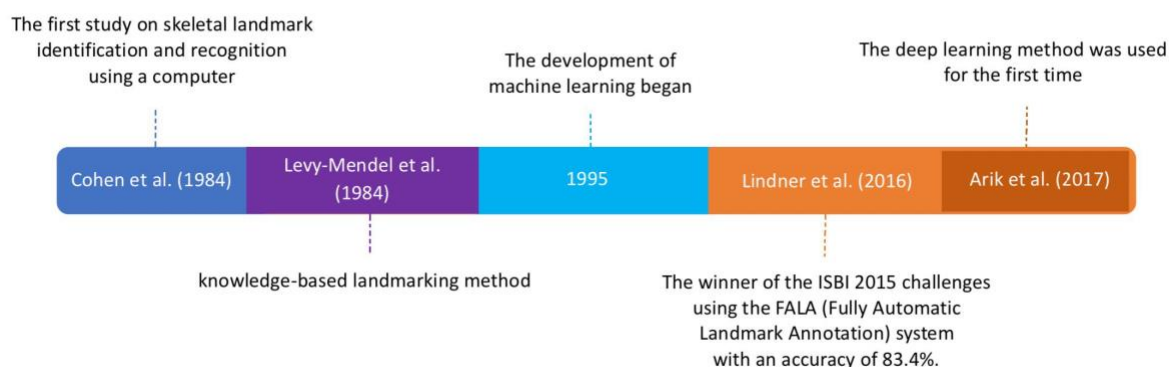


Figure 2. Timeline of the evolution of cephalometric usage.^{25,26,28,30}

DEEP LEARNING METHODS

Based on the results of literature searches, research on automatic cephalometric anatomical landmark point determination predominantly utilizes convolutional neural network (CNN) techniques with various modifications and different architectures. The first use of CNN for landmark detection was by Arik et al. (2017), who employed a shape-based model.³⁰ Subsequent studies, such as Kim et al. (2020), utilized web-based deep learning based on CNN.³¹ Lee et al. (2020) used Bayesian

Convolutional Neural Networks (BCNN) and stated that Laplacian filters for image preprocessing could improve accuracy, similar to the research by Lee et al.^{32,33} with many more studies conducted between 2017 and 2020. Lee et al. (2022) used a single-pass CNN with the visual results depicted in Figure 2.³³ The average SDR value within an accuracy of 2 mm ranged from 75% to 86.4%. Yao et al. (2022) applied a CNN with the ISBI Grand Challenges dataset, achieving an MRE value of 0.979 mm and the best SDR value of 94% within a 2 mm accuracy range.³⁴

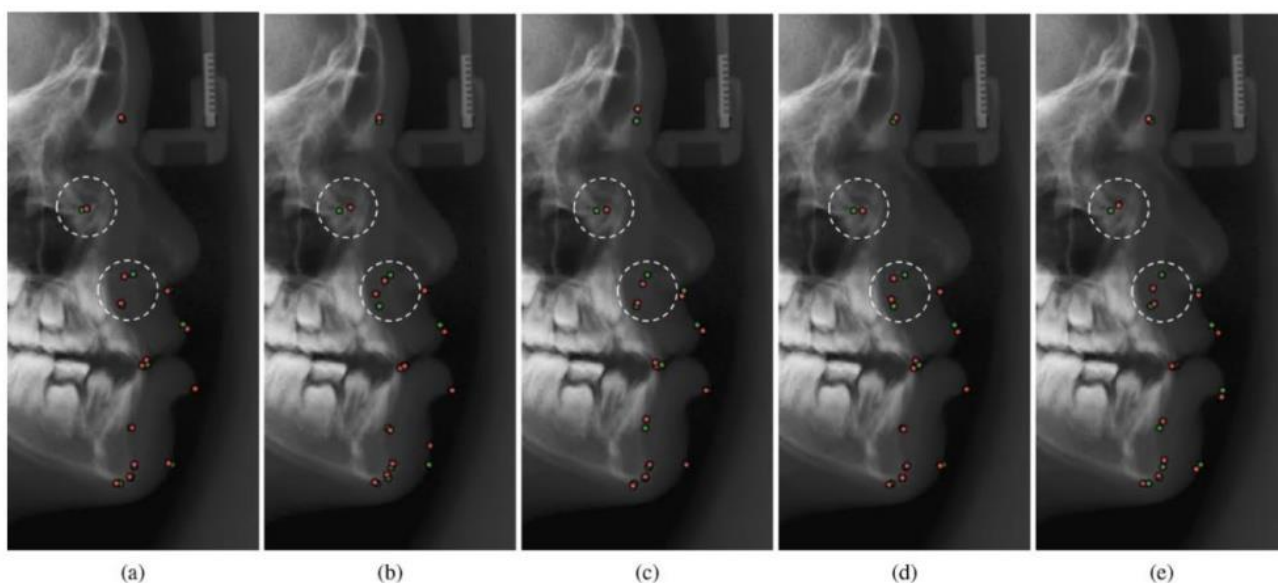


Figure 3. The visualization of the results shows the green color as the ground truth and the red as the predicted points.³³

In recent decades, several digital cephalometric software and applications based on AI technology have been developed for fully automated anatomical landmark identification, including CephX®, CEFBOT, WebCephTM, and Wedoceph. Bonnetti et al. showed good reliability of all selected parameter measurements performed by AI-assisted cephalometric analysis. However, they found errors of 0.807 mm and 1.854 degrees for the Posterior Face Height and Facial Axis Angle measurements.³⁵

CONCLUSION

The development of dental radiology, particularly cephalometric radiography in both conventional and digital forms, continues to advance with growing research opportunities closely linked to developments in computing technology and Artificial Intelligence. Although it has become a reliable and efficient tool, advances in digital technology cannot replace the important role of clinical doctors in interpreting and identifying radiograph results.

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FOOTNOTES

All authors have no potential conflict of interest to declare for this article.

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