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Automated Cephalometric Landmarking Using Artificial Intelligence - A Systematic Review

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ABSTRACT

Background: Cephalometry is the field of studying the measurement of the dimensions of the head, contemporarily on X-ray images, is regularly used in fields such as orthodontics, dentofacial orthopedics and maxillofacial surgery to assess, predict and modulate growth, formulate a treatment plan, evaluate the effects of the treatment, and compare cases. Research in the area of automated cephalometric landmark detection and analysis with artificial intelligence has seen significant advances over the last 20 years

Methods: Research articles from the Pubmed, MEDLINE, and Google scholar databases within the last 20 years with keywords Artificial Intelligence, Neural networks, orthodontics, and Cephalometry were selected for this review. 11 articles were considered for the final qualitative analysis.

Results: There have been significant improvements in the field of automating the identification of cephalometric landmarks. There seems to be a developing interest in this field with a gradual increase in research of automated cephalometry. The advantages and limitations of A.I.-based solutions for the field of Orthodontics are unique thus demanding careful application of this technology.

Conclusion: The current state and potential of A.I.-driven systems in Orthodontic cephalometric landmarking and analysis requires careful understanding and deliberation to ensure meaningful progress in this field..

Keywords:
Artificial Intelligence, Neural network, Orthodontics, Cephalometric landmarks, Automated diagnostics

1. Introduction

The twenty-first century has seen incredible development in the field of Artificial Intelligence (A.I.) with the increase in computational power and capabilities.[1] It has been applied successfully in fields ranging from e-commerce and human resource management to self-driving automobiles and targeted advertising. This new technology exhibits a high-level understanding of the problem and improves with increasing data and time. Artificial neural networks mimic empirical knowledge as they are capable of estimating complex nonlinear relationships between input and output values. While this takes years of experience for an individual human the difference is that an artificial neural network can learn this process at a much faster rate. [2]

With recent advancements in computer vision, artificial intelligence has had a significant role in the detection and classification of diseases from medical images.[3] Orthodontics and dentofacial orthopedics is a specialty that deals with several variables in each step; objective answers to complex problems seem to be extremely rare in the field of Orthodontics. The advent and development of A.I. and Machine learning-based systems are beginning to shift the paradigm; ranging from diagnostic procedures, treatment modality success prediction, and objective treatment plan suggestion A.I. show significant promise in helping the Orthodontist [4–6]. Cephalometry is the field of studying the measurement of the dimensions of the head, contemporarily on X-ray images, is regularly used in fields such as orthodontics, dentofacial orthopedics and maxillofacial surgery to assess, predict and modulate growth, formulate a treatment plan, evaluate the effects of the treatment, and compare cases. It involves tracing the

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hard tissue and soft tissue outlines as well as detecting relevant landmarks with accuracy and precision. In a clinical setup, an orthodontist may make errors due to increased workload or inexperience; automated cephalometry promises to save the orthodontists time and labor. It has been accomplished with traditional software with moderate success but A.I.-enabled automated cephalometry has been shown to outperform it. [7,8]

There have been efforts to use machine learning techniques in multiple ways in the field of orthodontics. The Institute of Electrical and Electronics Engineers focused on the field of automated landmark identification. They held a challenge for automated detection of landmarks on cephalometric X-Ray images at the IEEE International Symposium on Biomedical Imaging in 2014[9] which gave a fixed dataset of lateral cephalogram images. Several researchers attempted this challenge thus leading to several approaches being explored with varying levels of success.

2.Materials and methods

Data sources

This review was carried out by carefully reading the "Preferred reporting items for Systematic reviews and Meta-analyses extension for Diagnostic Test Accuracy" (PRISMA-DTA) guidelines.[9] Identification and selection of the literature was done by searching thoroughly in electronic databases like Pubmed and Google scholar which were published within the last two decades (January 2001 - January, 2021) by using keywords such as orthodontics, cephalometry, artificial Intelligence, neural networks. PICO (problem/patient/population, intervention/indicator, comparison, and outcome) elements were used to search for the literature (Table 1).

Table 1: Description of the Population, Intervention, Comparison, Outcome elements.

Research question	What are the advances and developments in the field of A.I-enabled automated cephalometric analysis?
Population	Patients lateral cephalometric radiographs as indicated by the orthodontic standard.
Intervention	AI based models for identifying cephalometric landmarks
Comparison	Opinions of experts and reference standards
Outcome	Average accuracy of detecting landmarks within 2mm

Resource's selection

Retrieval of full-length articles was performed. Electronic searching was done to browse through the literature. A two-stage process was done to select the required data. The preliminary search based on the titles and abstracts resulted in 76 articles that closely addressed the review's aim. A graph of papers published and projected to be published related to use of A.I. in the field of orthodontic cephalometric shows a developing interest in the field. (Figure 1) The next stage was to apply the following criteria:

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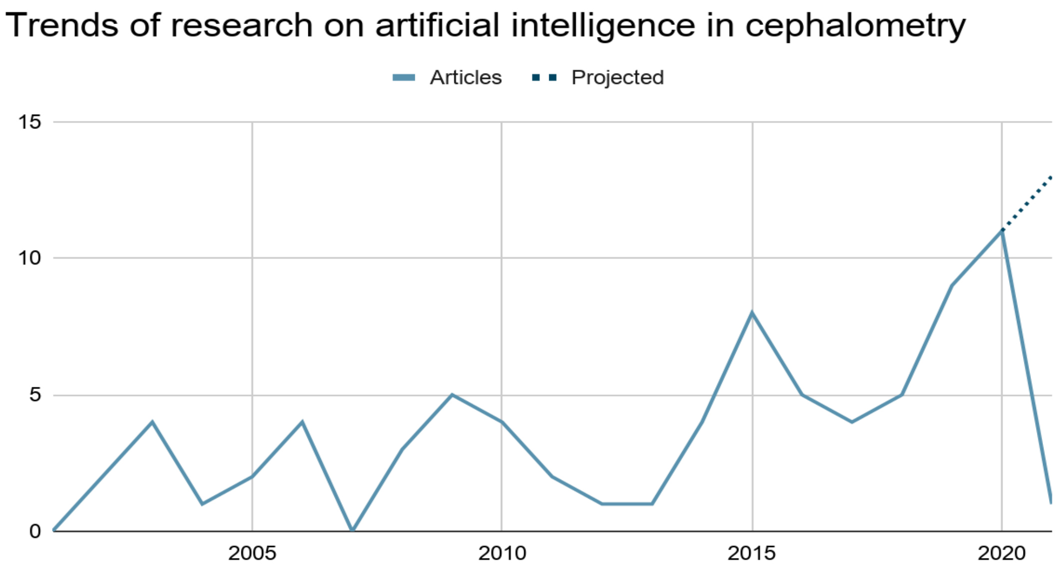

Figure 1 : Trends of research on artificial intelligence in cephalometry

Selection criteria of studies in this review

Criteria for inclusion

1. Articles focused on A.I with application related to landmark detection on a two-dimensional lateral cephalogram
2. There must be success detection rate with respect to the 2.0mm precision range
3. Proper mention of datasets used to assess the model must be mentioned.

Exclusion criteria

1. Articles that are not related AI based automation
2. Unpublished articles.
3. Articles consisting of abstracts only.
4. Articles written in languages other than English.

These criteria filtered the number of articles to 24. Finally critical assessment was carried out for all the articles that were qualitatively synthesized in this systematic review. 13 more articles were excluded on the basis of flaws in the research methodology of the excluded articles. The final number of included articles is 11. The process of identification, screening and including of articles for the systematic review is described in the flowchart. (Figure 2)

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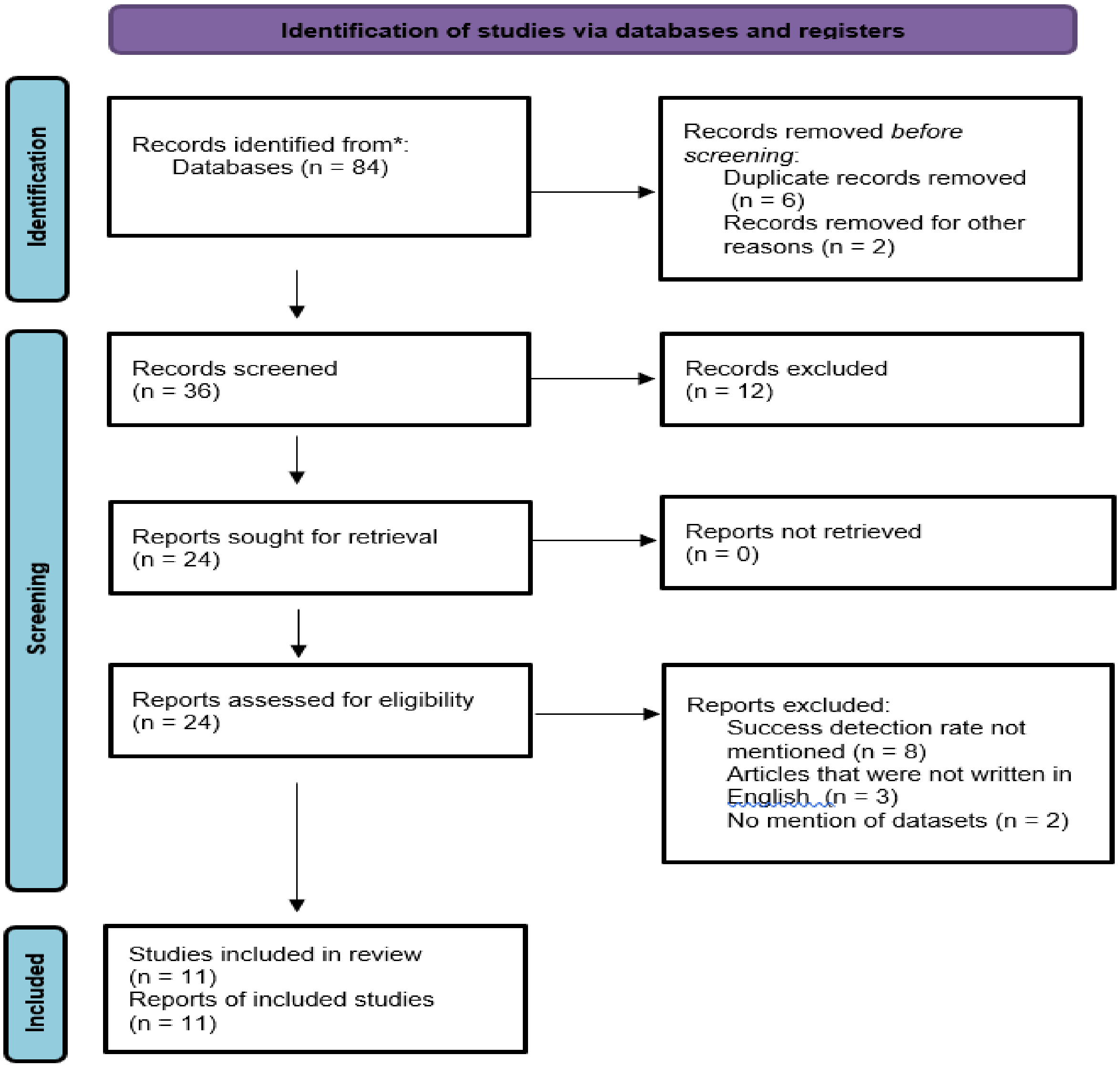

Figure 2: Identification of studies via databases and registers

3.Discussion

A.I has been making waves in several branches of medical and dental diagnosis, treatment planning and treatment. In the case of cephalometric analysis which is a routine and time-consuming part of diagnosis and treatment planning the incentive to automate the process was significant. While prior automated cephalometric analysis was dependent on the user to mark the landmarks or was unable to be clinically viable the challenge was to train the AI program to identify these landmarks. Traditionally humans are trained to identify these landmarks by correlating to adjacent structures and guidelines provided by existing literature. It has been noted that even among experienced orthodontists' differences of opinions regularly arise when marking landmarks.[10] Thus the challenge was to train the Algorithm to accurately locate the landmarks and to match or outperform the inter-observer variability. Several researchers tried architecturally different algorithms to complete the task in a precise and fast manner.

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The criteria for evaluation is the ability of the A.I to detect the landmark within a certain range of the human identified landmarks. A single pixel was marked by experts as a reference landmark location. It is classified as a successful detection if the absolute difference between the reference and A.I detected landmark is less than z millimeters. The success detection rate (SDR) p_z with precision less than z is formulated as follows:

$$p_z = \frac{\#\{j : \| L_d(j) - L_r(j) \| < z\}}{\#N} \times 100\%$$

where "L_r" and "L_d" represent the locations of the referenced landmark and the detected landmark, respectively; z stnads for the range of precision , "#N" represents the number of detections that were made. We focused on the 2.0 mm precision range as a method for comparison for the articles as it was most relevant for accuracy.

An overview of the details of articles that have been used in the synthesis are mentioned in Table 2

Authors	**Year of publi-cation**	**Algorithm Architecture**	**Study objective**	**No. of land-marks located**	**Average accuracy at 2mm (%)**	**Algorithm tested against**	**Outcomes**	**Authors suggestions/ recommendations**
Yue et al [10]	2006	Image processing technology combined with statistical model	Craniofacial landmark localization with tracing of structure	12	71	Four experts	First ever craniofacial feature point localization and anatomical structure tracing	Advanced analysis, such as automated superimposition can be done
Ningrum et al [11]	2014	Projected Principal-Edge Distribution algorithm	Identify a 10-point landmarks used in cephalometric Downs's analysis	10	59.7	Existing medical records	Accuracy of projections mainly on bilateral landmarks greatly affect the outcome of the identification.	Cephalometric analysis can also be done by the NN*

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Arık et al [12]	2017	Convoluted neural network	Fully automated quantitative cephalometry	19	71.52	Two experienced orthodontists	CNNs,which merely input raw image patches, are promising for accurate quantitative cephalometry	A promising future direction for deep-learning based automated cephalometric analysis is landmark-free pathology assessment that can potentially improve cephalometric analysis.
Qian et al [13]	2019	Faster R-CNN based method, CephaNet	Improve detection accuracy of small landmarks	19	77.45	Two experienced orthodontists	CephaNet is a successful exploration for applying the advanced deep CNN structure	Further improvements are possible by specific adjustments of networks and a larger dataset
Park et al [14]	2019	YOLOV3 and SSD	Comparison of latest deep learning algorithms for automatic landmarking	80	80.4	Single orthodontist with 28 years of clinical experience	YOLOv3 outperformed SSD in accuracy, computational time and isotropic error detection.	Increased size of training dataset, Intra/ inter examiner reliability statistics and reproducibility are needed
Song et al [15]	2020	Two-step convolutional neural network	Automated detection of cephalometric landmarks	19	80.2	Two experienced orthodontists	The proposed method is accurate enough for supervised clinical application	Access possibility for better performance by utilizing a global-context information.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 901 - 913
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Nishimoto et al [16]	2020	multi-phased deep learning	Enhance accuracy of landmark predicting utilizing multi-phase deep learning and voting	19	77.345	Two experienced orthodontists	Multi-phase deep learning may be a solution to deal with large images	If the training data plot is not clinically "correct", the predicted value will not be "correct". High quality coordinate values in training datasets are essential.
Noothout et al [17]	2020	Global-to-local localization approach using full CNN	Automated detection of cephalometric landmarks	19	78	Two experienced orthodontists	Suitable for application in studies which have a large dataset or real-time localization.	Training the network with more images that depict these types of anatomical deviation or modeling of these anatomical deviations by exploiting data augmentation could be beneficial to increase the variation in the dataset and ultimately improve localization.
Lee et al [18]	2020	Bayesian Convolutional Neural Networks	To develop a novel methodology for automated cephalometric landmarks location with confidence	19	82.11	Two experienced orthodontists	The framework may serve as a computer-aided diagnosis tool that improves the accuracy and	Confidence regions are an efficient and powerful tool for helping and training inexperienced dentists with cephalometric tracing.

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			regions				reliability of decisions by specialists.	
Zeng et al [19]	2020	Cascaded convoluted neural network	Detect cephalometric landmarks automatically	19	81.01	Two experienced orthodontists	Cascaded framework could predict cephalometric landmarks better than traditional methods with a small dataset	An end-to-end convoluted neural network would be more efficient
Hwang et al [20]	2021	modification of YOLO version 3 algorithm	Comparison of cephalometric analysis based on the latest deep learning methods	19	75.45	A board - certified orthodontist	Comparable accuracy of cephalometric analysis to experts was demonstrated	AI will maintain, and may improve, its accuracy effectiveness under supervision by orthodontists.

Yue et al. (2006)[11] combined image processing technology and statistical mode to automatically locate the landmarks as well as trace the outline of anatomical structures. The model was trained by selecting 12 landmarks as reference and according to anatomical knowledge division of every training shape was done in to 10 regions; principal component analysis was done for processing the region shape variations and statistical profile of feature points. Once trained, the program locates landmarks on input images in two steps. Firstly identification of the reference landmarks is done by image processing and pattern matching resulting in a shape partition. Modified active shape model are used to locate feature points for each region. These points are then connected outlining the anatomical structure with subdivision curves and prior knowledge gained from training. Users were permitted to modify the results interactively in multiple ways.

Ningrum et al. (2014)[12] used the Projected Principal-Edge Distribution algorithm to locate cephalometric landmarks used in Down's analysis. They conducted the research in 3 phases: preprocessing, feature extraction and identification. The preprocessing phase included image size normalization, contrast enhancement and identification of region of interest for each landmark. The Projected Principal-Edge Distribution algorithm was used for image feature extraction and

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measuring the similarity between the template and test result. They also found that Euclidean distance gives good results and a counterintuitively large number of image samples do not always give the best results. To improve systems performance, they used a multithreading technique, they also found that the accuracy of projections mainly on bilateral landmarks greatly affects the outcome of the identification.

The “Automatic Cephalometric X-Ray Landmark Detection Challenge (ACXRLDC)” which was held at the “IEEE International Symposium on Biomedical Imaging 2014 (ISBI 2014)” [9] was aimed to access and identify technologies for automatic landmark detection on cephalometric radiographs and provided a standardized framework consisting of a clinical data set, containing 300 unique cephalograms for evaluation. 19 commonly used and clinically significant landmarks were selected to be used as targeting landmarks (Figure 3). This challenge was the pioneer in the field of dental radiography, giving a reference publication and boosting interest in this emerging area of research. An added benefit to the challenge is that as the dataset was fixed the variable factor was the algorithmic structure leading to clearer comparison metrics.[13]

No.	Anatomical landmarks
1	Sella turcica
2	Nasiaon
3	Orbitale
4	Porion
5	Subspinale
6	Supramentale
7	Pogonion
8	Menton
9	Gnathion
10	Gonion
11	Lower incisal incision
12	Upper incisor incision
13	Upper lip
14	Lower lip
15	Subnasale
16	Soft tissue pogonion
17	Posterior nasal spine
18	Anterior nasal spine
19	Articulate

Figure 3: Lateral cephalogram with identified landmarks

Arik et al (2017)[14] used Convolutional neural networks (CNNs) which is one of the rapidly improving deep learning techniques to fully automate cephalogram analysis. CNNs were used to model the consistent patterns of intensity appearance of landmarks and then using the trained networks to recognize the same patterns in unseen cephalograms. The training and test dataset used was the dataset from the ACXRLDC. They concluded that CNNs outperform random Forest’s technique as used by Ibragimov et al. in cephalometric analysis yielding higher success detection. The accuracy of the proposed framework was also reported to be very close to the interobserver accuracy.

Qian et al. (2019) [15]demonstrated the first successful use of faster R-CNN called CephaNet to locate cephalometric landmarks. While CNNs had seen significant use and success till then, a variant called Faster R-CNN was not applied to the task as the landmarks were too small, the

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dataset from the ACXRLDC was insufficient to train the NN and superfluous detected or undetected landmarks in the results caused a low detection accuracy. They overcame these limitations in CephaNet by reducing intra-class variations by designing a multitask loss containing center as well as adopting the multi-scale training strategy to increase the training dataset thereby improving the performance in detecting minute landmarks. Upon encountering abnormal detection of landmarks, a two-step repair strategy was adopted to complete or delete them by construction of a undirected graph of the landmarks or a 'max-confidence' is used to choose the best landmark.

Park et al. (2019)[16] compared the "You-Only-Look-Once version 3 (YOLOv3)" and "Single Shot Multibox Detector (SSD)" methods training the NNs with their own clinical dataset. They trained the algorithms to detect 80 landmarks citing that more landmarks lead to more accurate prediction of treatment outcomes. SSD was outperformed by YOLOv3 in accuracy for 38 of 80 landmarks and the rest of the landmarks didn't show statistically significant differences between the two methods. Their superior results were enhanced due to the ample size of the dataset.

Song et al. (2020)[17] proposed a two-stage method for automated detection of cephalometric landmarks. First, a rough landmark location is obtained by matching the test image to the most identical image in the training dataset. Extraction of a region of interest patch centered at the rough landmark location based on the matching result is done. Refinement is done with their state-of-the-art pre-trained network with the backbone of ResNet50 used to detect the landmarks in the extracted Regions of interest. Training and evaluation of the algorithm was done using the dataset from the ACXRLDC.

Nishimoto et al. (2020)[18] used multi-phase deep learning to increase prediction accuracy of landmark detection High prediction means that ground truth values were consistently scored in training and evaluating datasets in supervised learning and prediction. The expected value will not be "right" if the training data plot is not clinically "correct." In training datasets, high-quality coordinate values are important. When compared to a single-phased model, the device dramatically improved accuracy. When compared to a single-phased model, the device dramatically improved accuracy. Multi-phase deep learning could be a solution for dealing with large images, since there is always a physical limit to computation.

Noothout et al. (2020)[19] employed a fully convolutional neural network(FCNN) based on the global-to-local localization method. A global FCNN first locates several landmarks by analyzing image patches and performing regression and classification at the same time. Following that, local analysis is conducted for and landmark that has been located using global localization. Specialized FCNNs refine global iconic sites in a similar way by analyzing local sub-images. The average processing time for all landmark localization was 0.05 0.009 seconds per scan.

Lee et al. (2020)[20] proposed Bayesian Convolutional Neural Networks (BCNN) as a novel framework for locating cephalometric landmarks with confidence regions dependent on uncertainties. They calculated the confidence area (95 percent) of an established landmark when considering model uncertainty using Bayesian inference over iterative CNN model calculations significantly improving the in-region accuracy. Low-Resolution Screening (LRS) and High-Resolution Screening (HRS) were used to split the framework into two procedures. By dividing complex tasks into smaller subtasks, higher performance was achieved. The LRS' goal was to establish the region of interest for the corresponding landmark, while the HRS' goal was to approximate the exact landmarks while accounting for uncertainty. After determining the expected region's center using the LRS, each pixel inside the region of interest must be judged to see whether it corresponds to the target landmark point.

Zeng et al. (2021)[21] treated landmark detection as a problem of multi-level regression solved by sub-tasks performing a rough-to-fine procedure for prediction. The first stage involves aligning and locating the area of interest on the lateral cephalogram. This was treated as a bounding regression problem which was solved by a CNN called Align-Net. The next stage involves the proposal of landmark locations done by a CNN called Proposal-Net. Third, the image patch surrounding its proposal location in the original image is extracted and CNN called Refine-Net to learn the optimal position. Their experimental results showed that a cascaded NN was better at predicting landmarks than traditional methods when dealing with small training datasets.
Hwang et al. (2021) [22] applied a modified YOLO version 3 algorithm. They used their own 1983 cephalogram training dataset and the ACXRLDC dataset for study. According to the SDR data, the new AI successfully detected most landmarks within 2 mm in nearly 90% of cases. In terms of SDR, some landmarks produced less accurate results than others. Because of overlapping cranial base structures, certain landmarks, such as the Porion, Orbitale, and PNS, can be difficult to detect. These error patterns were also seen among human examiners.

4.Conclusion

Artificial intelligence in the form of neural networks have the following limitations when locating landmarks on a lateral cephalogram:

- The quality of input data is directly proportional to the performance of the algorithm
- Their internal structure cannot be well explained
- Addition of minimal noise, while invisible to humans could cause misidentification

These limitations are balanced by the advantages of using AI for locating landmarks:

- With minor manual modifications, the results improve drastically.
- Improvement of SDR is significant with each successive paper being published.
- Significant less time and adequate accuracy can be expected when compared to human landmark location

The following optimizations can be kept in mind while programming an NN to locate cephalometric landmarks:

- CNN perform better when the cephalograms are processed in multiple steps or phases
- Faster R-CNN saves significant time compared to R-CNN.
- YOLO is orders of magnitude faster than other methods but has issues locating bilateral landmarks

It is envisioned that AI will improve its effectiveness under supervision by orthodontists.

Future trends

There seems to be an increasing interest in the field of automated cephalometry and each new iteration usually sees improving results.

Conflict of interest

The authors have no conflict of interest relevant to this article

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Figure legends:

Figure 1 : Trends of research on artificial intelligence in cephalometry

Figure 2 : Identification of studies via databases and registers

Figure 3 : Lateral cephalogram with identified landmarks

Table legend:

Table 1 : Description of the PICO

Table 2 : Details of the studies using A.I- based algorithms to automatically identify cephalometric landmarks