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Review

Trends and Application of Artificial Intelligence Technology in Orthodontic Diagnosis and Treatment Planning—A Review

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Abstract: Artificial intelligence (AI) is a new breakthrough in technological advancements based on the concept of simulating human intelligence. These emerging technologies highly influence the diagnostic process in the field of medical sciences, with enhanced accuracy in diagnosis. This review article intends to report on the trends and application of AI models designed for diagnosis and treatment planning in orthodontics. A data search for the original research articles that were published over the last 22 years (from 1 January 2000 until 31 August 2022) was carried out in the most renowned electronic databases, which mainly included PubMed, Google Scholar, Web of Science, Scopus, and Saudi Digital Library. A total of 56 articles that met the eligibility criteria were included. The research trend shows a rapid increase in articles over the last two years. In total: 17 articles have reported on AI models designed for the automated identification of cephalometric landmarks; 12 articles on the estimation of bone age and maturity using cervical vertebra and hand-wrist radiographs; two articles on palatal shape analysis; seven articles for determining the need for orthodontic tooth extractions; two articles for automated skeletal classification; and 16 articles for the diagnosis and planning of orthognathic surgeries. AI is a significant development that has been successfully implemented in a wide range of image-based applications. These applications can facilitate clinicians in diagnosing, treatment planning, and decision-making. AI applications are beneficial as they are reliable, with enhanced speed, and have the potential to automatically complete the task with an efficiency equivalent to experienced clinicians. These models can prove as an excellent guide for less experienced orthodontists.

Keywords: artificial intelligence; automated diagnosis; digital diagnosis; supervised learning; orthodontics; dento-facial orthopedics; deep learning; machine learning; artificial neural networks; convolutional neural networks

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1. Introduction

Artificial intelligence (AI) is a new breakthrough in technological advancements based on the concept of simulating human intelligence. AI models are designed to assist humans in completing tasks more efficiently and are developed through training and programming, using a large number of datasets, and then executing these models to turn the data into actionable information in performing a specific task [1]. These emerging technologies highly influence the diagnostic process in medical sciences, with enhanced accuracy in diagnosis [2]. AI models have been applied in healthcare in order to assist healthcare professionals and enhance the accuracy in diagnosis, decision making, and predicting prognosis, with the ultimate goal of enhancing patient care and treatment outcomes. AI models have also demonstrated performances that are on par with trained and experienced healthcare professionals [3].

AI technology has been widely applied in dentistry. These models are based on Machine Learning (ML) systems, which are designed using algorithms that can be trained using a large number of data sets and later applied to new sets of data for testing and evaluation. ML based AI models have displayed excellent accuracies in making predictions based on the datasets without human interventions [4–6]. AI models based on the newly developed and advanced system known as Deep Learning (DL) are designed to mimic the functioning of the neural system of the human brain; hence they are termed artificial neural networks [7].

The AI system has been gaining high popularity in dentistry, as they have been widely applied for diagnosing and predicting oral diseases such as dental caries, periodontal diseases, and oral cancer [8–11]. AI models have demonstrated exceptional performances in diagnosis, determining the treatment needs, and predicting the prognosis of diseases [1,5,8–13]. Along with this, AI models have also been designed and applied in the field of forensic odontology, where the models have demonstrated excellent precision in performing tasks [14]. Considering these developments in AI, this review article intends to report on the trends and application of AI models designed for diagnosis and treatment planning in orthodontics.

2. Materials and Methods

2.1. Search Strategy

Data search for the articles that have reported on the application of AI models in orthodontics was carried out in the most renowned electronic databases. These databases mainly included PubMed, Google Scholar, Web of Science, Scopus, and Saudi Digital Library. This search was mainly carried out for original research articles published over the last 22 years, from 1 January 2000 until 31 August 2022. Several Medical Subheadings (MeSH terms) were used for searching the articles in the electronic databases. MeSH terms included: artificial intelligence, automated diagnosis, computer-assisted diagnosis, digital diagnosis, supervised learning, orthodontics, dentofacial orthopedics, unsupervised learning, diagnosis, prognosis, prediction, deep learning, machine learning, artificial neural networks, and convolutional neural networks. Boolean operators AND/OR were used to generate a combination of these key words in the advanced search. Language filters for the English language were also used. A manual search for articles was also performed simultaneously in the college central library after screening the references of the articles obtained from the electronic search.

At this stage, article selection was based on the title and abstract; 628 articles related to our research topic were extracted. Later, 436 articles were excluded due to duplication. The remaining 192 articles were applied for the eligibility criteria for being included in this review article.

2.2. Eligibility Criteria and Study Selection

Original research articles that reported on the application of AI models in orthodontics were included in this systematic review. Articles with no full text, narrative reviews, scoping reviews, letters to editors, opinion letters, case reports, short communications, conference proceedings, and articles other than English, were excluded (Figure 1).

A total of 56 articles that fulfilled the eligibility criteria were subjected to qualitative synthesis (Table 1).

Table 1. Details of the studies that reported in application of AI based models in orthodontics.

Serial No	Authors and Reference	Year of Publication	Type of Algorithm Architecture	Objective of the Study	No. of Patients/Images/ Photographs for Training Testing	Study Factor	Modality	Comparison If Any	Evaluation Accuracy/ Average Accuracy/ Statistical Significance	Results (+)Effective, (−)Non Effective (N) Neutral	Limitations of the Study	Authors Suggestions/ Conclusions
1	Nishimoto s et al. [15]	2019	CNNs	Automatic cephalometric landmark detection	153 samples for training, 66 for validating	Landmarks	Lateral cephalogram	Specialist	Not clear	(N) neutral	CNNs based model predicted cephalometric analysis were not significantly different from those plotted manually	This model still in the state of development
2	Park JH et al. [16]	2019	ANNs	Automatic identification of cephalometric landmarks	1028 samples for training, 283 for validating	Landmarks	Lateral cephalogram	Benchmarks in the literature	YOLOv3 algorithm outperformed SSD in accuracy	(+)Effective	The accuracy was inferior to other methods when the size of objects is small	This model can be of great use for use in clinical practice.
3	Chen S et al. [17]	2020	ML	Automatic landmarks identification	60 samples	Landmarks	Cone-Beam Computed Tomography (CBCT) images	Not mentioned	Not clear	(+)Effective	Not mentioned	Fast and efficient CBCT image segmentation will be analyzed more efficiently
4	Kunz F et al. [18]	2020	CNNs	Automated cephalometric X-ray analysis	50 samples	Landmarks	Cephalometric X-rays	12 experienced examiners	No statistically significant differences	(+)Effective	Not mentioned	Results were of the same quality level as experienced examiners
5	Hwang HW et al. [19]	2020	CNNs	Automated identification of cephalometric landmarks	1028 samples for training and 283 samples for testing	Landmarks	Cephalograms	Human examiners	Accuracy similar to human examiners	(+)Effective	When the data set was less than 500 the AI model did not identify the landmarks correctly	Larger quantity of datasets will be required in the future.
6	Zeng M et al. [20]	2020	CNNs	Automatic cephalometric landmark detection	150 for training dataset and 250 test images	Landmarks	Cephalograms	Not mentioned	Significant performance	(+)Effective	The model needs improvement in the future work.	This is a good model for detecting landmarks
7	Lee JH et al. [21]	2020	BCNNs	Locating cephalometric landmarks	150 images for training, 250 test images	Landmarks	Cephalograms	Two expert Examiners	Significantly higher performance	(+)Effective	The model was trained on regional geometrical features only	Improves the accuracy and reliability of decisions of the specialists
8	Bulatova G et al. [22]	2021	CNNs	Automatic cephalometric landmark identification	110 samples	Landmarks	Cephalograms	Senior orthodontic resident	No statistical difference between the two	(+)Effective	The operator is supposed to put a digital ruler which can be subjected to human errors.	Can increase efficiency in routine clinical practice

Table 1. *Cont.*

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9	Hwang HW et al. [23]	2021	CNNs	Automated cephalometric analysis	1983 for training, 200 for testing	Landmarks	Cephalograms	Expert Examiner	Superior than Human examiner	(+)Effective	The performance of the model can be affected with the noise issues inherent in medical imaging.	Superior performance than those reported in literature
10	Kim J et al. [24]	2021	CNNs	Automated identification of cephalometric landmarks	3150 for training, 100 for testing	Landmarks	Cephalograms	Two orthodontists	Significant performance	(+)Effective	Only hard tissue landmarks for training	This model can replace human task
11	Kim YH et al. [25]	2021	CNNs	Automatic cephalometric landmark identification	800 for training, 100 for testing	Landmarks	Cephalograms	Two Calibrated examiners	Significant performance	(+)Effective	Not mentioned	This model achieved better results than examiners
12	Kim MJ et al. [26]	2021	CNNs	Automatic cephalometric landmark identification	860 samples	Landmarks	CBCT images	One experienced orthodontist	Significant performance	(+)Effective	Did not compare the prediction accuracy of a model trained by a more experienced clinician	This model showed better consistency than manual identification
13	Kim MJ et al. [27]	2021	CNNs	Automatic cephalometric landmark identification	860 samples 80% training, 20% validating	Landmarks	CBCT images	One experienced orthodontist	Significant performance	(+)Effective	Amount of data required to achieve the expected accuracy could not be explained	This model showed superior results compared to previous studies
14	Yao J et al. [28]	2022	CNNs	Automatic cephalometric landmark location	512 samples training, 200 for testing and validating	Landmarks	Cephalograms	Two experienced orthodontists	Higher accuracy	(+)Effective	Amount of data volume was less and need to increased	This model meets the requirements of different cephalometric analysis methods.
15	Le VNT et al. [29]	2022	CNNs	Human–AI collaboration for the identifying cephalometric landmarks	1193 samples training, 100 for testing	Landmarks	Cephalograms	Twenty dental students	Accuracy was higher than dental students	(+)Effective	Amount of dataset was small and obtained for very young patients	This beginner–AI collaboration model was effective in detecting the landmarks
16	Gil SM et al. [30]	2022	CNNs	Automated identification of cephalometric landmarks	2075 samples for training, 343 for validating	Landmarks	Cephalograms	One experienced examiner	Demonstrated an high successful detection rate	(+)Effective	The comparison was made with one single examiner	This model is an effective alternative to manual identification

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17	Dot G et al. [31]	2022	CNNs	Automatic localization ocephalometric landmarks	160 samples for training, 38 for validating	Landmarks	Computed tomography (CT) scans	One experienced operator	Excellent agreement with the human examiner	(+)Effective	This model still requires improvement as the data sets were limited	This reliability of the model is par with that of the clinician
18	Kök H et al. [32]	2019	ANNs	Determining growth and development by cervical vertebrae stages	300 samples	Reference points	Cephalometric radiographs	One trained orthodontist and Seven different AI algorithms	This model displayed second-highest accuracy	(+)Effective	More datasets needed for training and evaluation	This model can be used as decision support to clinicians
19	Kök H et al. [33]	2020	ANNs	Growth and development periods and gender from the cervical vertebrae	419 samples 70% for training, 15% testing and, 15% for validating	Reference points	Cephalometric and hand-wrist radiographs	Researcher	Displayed high accuracy	(+)Effective	More datasets needed for training and evaluation	The success of this model was satisfactory
20	Kök H et al. [34]	2020	ANNs	Determining growth and development based on cervical vertebra ratios	360 samples	Reference points	Cephalometric radiographs	Naïve Bayes models (NBMs)	More successful than the reference model	(+)Effective	Datasets belonged to one population, need to study different and multi-racial	This model was more successful than the previous models
21	Amasya H et al. [35]	2020	ANNs	Determining cervical vertebral maturation (CVM) analysis	647 samples	Reference points	Cephalometric radiographs	One examiner Five different ML models	Best results was achieved by ANN model	(+)Effective	Absence of hand-wrist radiographs	This model can be used for prediction of cervical vertebrae morphology
22	Amasya H et al. [36]	2020	ANNs	Cervical vertebral maturation analysis	647 samples	Reference points	Cephalometric radiographs	Three experienced dentomaxillofacial radiologists and one experienced orthodontist	Displayed better performance	(+)Effective	The data obtained was from the wide age range (10–30 years)	This model performed close to or even better than human observers
23	Seo H et al. [37]	2021	CNNs	Cervical vertebral maturation analysis	600 samples	Reference points	Lateral cephalometric radiographs	Experienced radiologist, Six deep learning models	All models demonstrated excellent accuracy Inception-ResNet-v2 performing the best	(+)Effective	Small number of data set used	This model will help practitioners in making accurate diagnoses and treatment plans

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24	Zhou J et al. [38]	2021	CNNs	Cervical vertebral maturation status	1080 samples (980 for training and 100 for testing)	Reference points	Cephalometric radiographs	Two experienced examiners	There was a good agreement between AI the Human examiners	(+)Effective	Smaller size of data set for testing	This model is a useful and reliable tool for assessing CVM.
25	Kim DW et al. [39]	2021	ML	Predicting the hand-wrist maturation stages based on the cervical vertebrae (CV) images,	499 samples	Reference points	Hand-wrist radiographs and lateral cephalograms	Three specialists	Better prediction accuracy	(+)Effective	Smaller size of data set along with more pediatric patients	This model can aid as a decision supporting tool
26	Kim EG et al. [40]	2022	CNNs	Estimating cervical vertebral maturation	600 samples	Reference points	Lateral cephalograms	Four experienced specialists	Demonstrated best accuracy	(+)Effective	Datasets were developed using radiographs from single institution	This model displayed best accuracy and is of practical applicability
27	Mohammad-Rahimi H et al. [41]	2022	CNNs	Cervical vertebral maturation (CVM) degree and growth spurts	890 samples	Reference points	Lateral cephalometric radiographs	Two orthodontists	Substantial agreement between the experienced examiners and the AI model	(+)Effective	Improvements need to be done in data quality	This model can provide practical assistance to practicing dentists
28	Li H et al. [42]	2022	CNNs	Estimating cervical vertebral maturation	6079 samples (70% for training, 15% testing and, 15% for validating)	Reference points	Cephalometric radiographs	Two experienced orthodontists ResNet152, DenseNet161, GoogLeNet, VGG16	ResNet152 demonstrated best accuracy	(+)Effective	Quality and quantity of the datasets was severely affected	This model can be used as an automatic auxiliary diagnostic tool
29	Atici SF et al. [43]	2022	CNNs	Classification of the Cervical Vertebrae Maturation	1018 samples	Reference points	Cephalometric radiographs	Expert Orthodontist, CNN, MobileNetV2, ResNet101, and Xception	This CNN model provide higher accuracy than the models	(+)Effective	Not mentioned	This model can be used as effective tool for analyzing the skeletal maturity stage and timing of the treatment.
30	Croquet B et al. [44]	2021	CNNs	Automated land –marking for palatal shape analysis	1045 samples (732 for training, 209 for testing and 104 for validating)	Landmarks	Dental casts	Single operator	There was no difference between automatic and manual analysis with promising accuracy and reliability,	(+)Effective	The data was of individuals with dentition till second molars may not reflect the true diversity of individuals of interest to orthodontists	This model can be used for land-marking of digitized dental casts for clinical and research purpose.

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31	Nauwelaers N et al. [45]	2021	CNNs	Palatal and dental shape estimation	1324 samples	Landmarks	3D Dental casts	Different models	Singular auto-encoder achieved competitive performance in terms of accuracy, generalization, specificity, and variance	(+)Effective	The model was limited to shapes that underwent an elaborate pre-processing	This model can a useful tool for shape analysis in the future
32	Xie X et al. [46]	2010	ANNs	Determining the need for orthodontic tooth extraction	200 samples (180 for training, 20 for testing)	Indices	Casts and cephalometrics	Humans	80% accuracy in determining the need for extraction	(+)Effective	Limited amount of samples	This model can be considered a decision-making tool
33	Jung SK et al. [47]	2016	ANNs	Diagnosis of orthodontic tooth extractions	156 samples (96 for training, 60 for testing)	Indices	Casts and cephalometrics	Experienced orthodontist	High performance Excellent success rates	(+)Effective	Diagnosis of extractions was confined to nonsurgical procedures	Can be used as an new approach in orthodontics
34	Li P et al. [48]	2019	ANNs	Determining the need of orthodontic tooth extraction	302 samples	Feature variables	Casts and cephalometrics	Two experienced orthodontists	Excellent performance with 94.0% accuracy	(+)Effective	Limited amount of samples	This model can provide a good guidance for less experienced orthodontists.
35	Choi HI et al. [49]	2019	ML	Determining the need of orthodontic tooth extraction	316 samples	Datasets	Casts and cephalometrics	One experienced orthodontist	High performance with 91% accuracy	(+)Effective	Exclusion of skeletal asymmetry cases	Can be applied for the diagnosis of cases
36	Suhail Y et al. [50]	2020	ML	Diagnosis of orthodontic tooth extraction	287 samples	Datasets	Casts and cephalometrics	Five experienced orthodontist	In agreement with the experienced orthodontists	(+)Effective	Limited feature set where the treatment outcomes were confined to only non-surgical orthodontic procedures	Can be considered a decision-making tool in clinical practice
37	Etemad L et al. [51]	2021	ML	Decision on orthodontic tooth extraction	838 samples	Datasets	Casts and cephalometrics	Previous models	Performance was lesser than the previous models	(+)Effective	Not mentioned	This model lacks generalizability and in order to improve it needs advanced artificial intelligence algorithms

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38	Real AD et al. [52]	2022	ML	Determining the need of orthodontic tooth extraction	214 samples	Datasets	Casts and cephalometrics	Two experienced orthodontists	Demonstrated an accuracy of 93.9%	(+)Effective	Degree of over fitting that may have occurred in the models	This model achieved best performance when model and cephalometric data are combined
39	Yu HJ et al. [53]	2020	CNNs	Automated Skeletal Classification	5890 samples (70% for training, 15% testing and, 15% for validating)	Datasets	Clinical data and cephalometrics	Five experienced orthodontists	Demonstrated an highest accuracy at 96.40%	(+)Effective	The data were collected from a single organization	This model has a potential for skeletal orthodontic diagnosis
40	Wang H et al. [54]	2021	CNNs	Automated multiclass segmentation of the jaw and teeth	30 samples	Landmarks	CBCT scans	4 experienced dentists	Accurate in its performance	(+)Effective	Data of complicated dental status need to be considered	This model can reduce the amount of time and effort spent in clinical settings and increase the efficiency and performance of dentists
41	C.H Lu et al. [55]	2009	ANNs	Image prediction post orthognathic surgery (OGS)	30 samples	Landmarks	Lateral Cephalogram Facial images	Profile post-surgery profile	Very less prediction errors	(+)Effective	Not mentioned	Can be applied for predicting post-surgical facial profile
42	H. H Lin et al. [56]	2018	CNNs	Assessing facial asymmetry in patients undergone OGS	100 samples	Landmarks	3D facial images	Specialist	Predications were statistically significant $p < 0.05$	(+)Effective	Small sample size was used for developing the model	Human like efficient tool for decision making
43	R. Patcas et al. [57]	2019	CNNs	Assessing post OGS facial attractiveness	146 samples	Landmarks	Facial photographs	Profile post-surgery profile	Was in comparison with the actual improvement	(+)Effective	Dissimilarities between the subjective patient's view and the computed score could exist	Is an efficient tool for assessing facial attractiveness
44	P. G. M. Knoops et al. [58]	2019	CNNs	Diagnosing of OGS	4261 samples	Landmarks	Data sets 3D face scans	Not mentioned	95.5% sensitivity, 95.2% specificity,	(+)Effective	Larger data sets needed for training the models	An efficient tool for diagnosing OGS
45	R.Stehrer et al. [59]	2019	CNNs	Predicting perioperative blood loss	950 subjects	Comparing with actual blood loss	Data sets	Data on actual blood loss	Statistical significance ($p < 0.001$).	(+)Effective	Data for the model was developed from records from one single clinic	An efficient tool for estimating perioperative blood loss

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46	S.H.Jeong et al. [60]	2020	CNNs	Predicting soft tissue profiles that require OGS	822 samples	Landmarks	Facial photographs	2 orthodontist, 3 maxillofacial surgeons, 1 maxillofacial radiologist.	An Accuracy of 0.893	(+)Effective	Certain level of false positives and false negatives cases were revealed by the model	An efficient tool predicting soft tissue profiles
47	K.S. Lee et al. [61]	2020	DCNNs	Differential diagnosis of OGS	220 samples	Landmarks	Lateral Cephalogram	Four different models	Modified-Alexnet displayed an Accuracy of 0.919	(+)Effective	Comparison was done with a limited data	Modified-Alexnet displayed the highest level performance
48	C.Tanikawa et al. [62]	2020	ANNs	Predicting facial morphology post OGS	137 samples	Landmarks	Lateral cephalogram and 3-D facial images	2 AI models	Excellent success rates	(+)Effective	The model was developed and tested with data from only two clinics.	An efficient tool predicting post OGS facial morphology
49	D. Xiao et al. [63]	2021	CNNs	For planning of OGS	47 samples	Landmarks	CT Scans Clinical data sets	Sparse representation method	Significant (p <0.05).	(+)Effective	The model trained on simulated pairs of deformed-normal bones and the number was limited	This model outperformed an existing sparse representation method
50	G. Lin et al. [64]	2021	CNNs	Assessing the need for OGS in Unilateral Cleft Lip and Palate patients	56 samples	Landmarks	Lateral Cephalogram	Boruta method	An excellent accuracy of 87.4%.	(+)Effective	The data used was limited and was from a single center	This model is capable of predicting the need for surgery
51	H.H.Lin et al. [65]	2021	CNNs	Assessing pre and post OGS facial symmetry	71 samples	Landmarks	CBCT images	4 orthodontists and 4 plastic surgeons and also with previously reported models	Accuracy of 90%.	(+)Effective	This model was trained with a limited data sets	This model exhibited high performance.
52	L.J. Lo et al. [66]	2021	CNNs	Assessing facial soft tissue symmetry before and after OGS	158 samples	Landmarks	3-D facial photographs	Pre and post-operative	Statistically Significant	(+)Effective	Dissimilarities might exist between the patient's subjective view and the machine scoring	The model can aid clinicians in assessing facial symmetry

Table 1. *Cont.*

Serial No	Authors and Reference	Year of Publication	Type of Algorithm Architecture	Objective of the Study	No. of Patients/Images/ Photographs for Training Testing	Study Factor	Modality	Comparison If Any	Evaluation Accuracy/ Average Accuracy/ Statistical Significance	Results (+)Effective, (−)Non Effective (N) Neutral	Limitations of the Study	Authors Suggestions/ Conclusions
53	R.Horst et al. [67]	2021	CNNs	Predicting the virtual soft tissue profile post-surgery	133 samples (119 for training, 14 for testing)	Landmarks	3D photographs and CBCT images	Mass Tensor Model (MTM)	Statistically significant (p = 0.02)	(+)Effective	In asymmetric cases and extreme cranial or caudal displacements, the model under predicted these displacements	This model can accurately predict the soft tissue profile post-surgery
54	W.S.Shin et al. [68]	2021	CNNs	Predicting the need for OGS	413 samples	Landmarks	Cephalogram	2 orthodontists, 3 maxillofacial surgeons, 1 maxillofacial Radiologist.	An excellent accuracy of 0.954	(+)Effective	This model involved only Korean patients from only one hospital	Displayed higher accuracy in predicting the need for OGS
55	Y.H Kim et al. [69]	2021	CNNs	Diagnosing orthodontic surgery	960 samples (810 for training, 150 for testing)	Landmarks	Cephalogram	ResNet-18, 34, 50, and 101	Success rate was displayed by ResNet-18 = 93.80%, ResNet-34 = 93.60%	(+)Effective	The data used was from a single center	This model can diagnose whether to conduct orthognathic surgery
56	G. Dot et. al. [70]	2022	CNNs	Multi-task segmentation of cranio-maxillofacial structures for OGS	453 samples (300 for training, 153 for testing)	Landmarks	CT Scans	2 Operators	Excellent performance	(+)Effective	Cannot assess the reliability of the results as the data was from one single center	This model need to be trained from other databases for better reliability

Footnotes: ML = Machine Learning, ANNs = Artificial Neural Networks, CNNs = Convolutional Neural Networks, DCNNs = Deep Neural Networks, Bayesian Convolutional Neural Networks (BCNN), CT- scans-Computed Tomography, CBCT- Cone-Beam Computed Tomography, OCT-Optical Coherence Tomography.

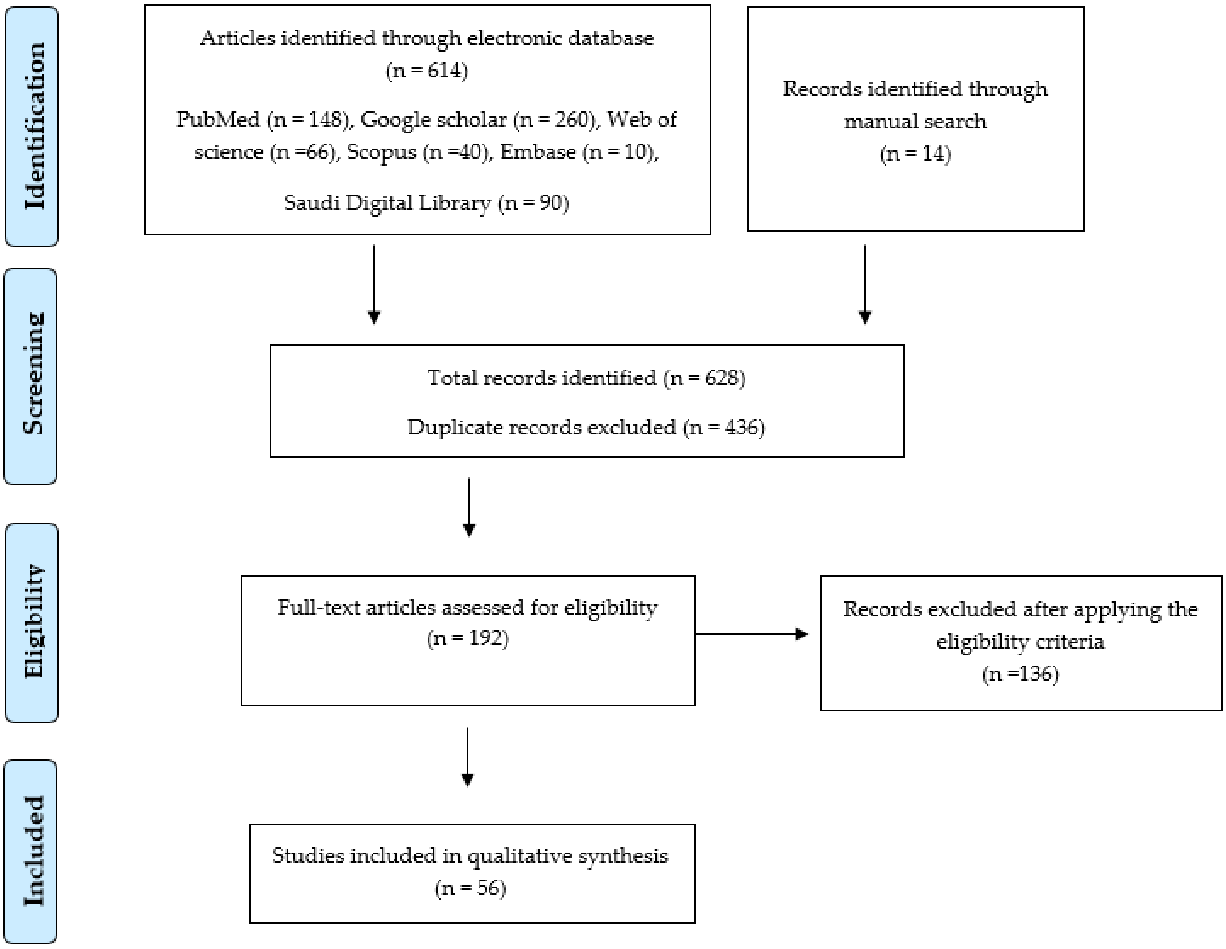

Figure 1. Flow chart for screening and selection of articles.

Summary of AI models designed for different diagnostic tasks is presented in Table 2.

Table 2. Summary of AI models designed for different diagnostic tasks.

AI Technique/Algorithm Architecture	Diagnostic Tasks	Functionality of the AI Model	Input Features
Machine Learning (ML)	Automated identification of landmarks	Landmarks	Cone-Beam Computed Tomography (CBCT) images [17]
	Predicting the hand-wrist maturation stages based on the cervical vertebrae (CV) images	Reference points	Hand-wrist radiographs and lateral cephalograms [39]
	Determining the need of orthodontic tooth extraction	Datasets	Casts and cephalometrics [49–52]
Artificial Neural Network (ANNs)	Automated identification of landmarks	Landmarks, Reference points	Lateral cephalogram [16], Cephalograms [18,35]
	Cervical vertebral maturation analysis	Reference points	Cephalometric radiographs [36]
	Determining growth and development by cervical vertebrae stages	Indices	Cephalometric radiographs [32], Cephalometric and hand-wrist radiographs [33,34]
	Determining the need for orthodontic tooth extraction	Indices	Casts and cephalometrics [46–48]
	Predicting facial morphology post OGS	Landmarks	Lateral cephalogram and 3-D facial images [62]

Table 2. *Cont.*

AI Technique/Algorithm Architecture	Diagnostic Tasks	Functionality of the AI Model	Input Features
Deep Learning/ Convolutional Neural Networks (CNNs)	Automated identification of landmarks	Landmarks	Cone-Beam Computed Tomography (CBCT) images [15,18,26,27,31], Cephalograms [19–25,28–30]
	Cervical vertebral maturation analysis	Reference points	Lateral cephalometric radiographs [37,38,40], Cephalometric radiographs [42]
	Cervical vertebral maturation (CVM) degree and growth spurts	Reference points	Lateral cephalometric radiographs [41]
	Classification of the Cervical Vertebrae Maturation	Reference points	Cephalometric radiographs [43]
	Automated land –marking for palatal shape analysis	Landmarks	Dental casts [44,45]
	Automated Skeletal Classification	Datasets	Clinical data and cephalometrics [53]
	Automated multiclass segmentation of the jaw and teeth	Landmarks	CBCT scans [54,70]
	Image prediction post orthognathic surgery (OGS)	Landmarks	Lateral Cephalogram Facial images [55]
	Assessing facial asymmetry in patients undergone OGS	Landmarks	3D facial images [56]
	Assessing post OGS facial attractiveness	Landmarks	Facial photographs [57]
	Diagnosing of OGS	Landmarks	Data sets 3D face scans [58], Lateral Cephalogram [61,68,69], CT Scans and Clinical data sets [63]
	Predicting perioperative blood loss	Data sets	Data on actual blood loss [59]

3. Results

3.1. Qualitative Synthesis of the Included Studies

The research trend shows a gradual increase in the number of research publications over the last two decades. However, in the last two years, the number of articles reported on the application of AI models in orthodontics has rapidly increased (Figure 2).

Figure 2. Trends in research publications.

3.2. Study Characteristics

AI models developed for application in orthodontics have mainly focused on: the automated identification of cephalometric landmarks [15–31]; the estimation of bone age and maturity using cervical vertebra and hand-wrist radiographs [32–43]; palatal shape analysis [44,45]; determining the need for orthodontic tooth extractions [46–52]; automated skeletal classification [53,54]; and the diagnosis and planning of orthognathic surgeries [55–70] (Figure 3).

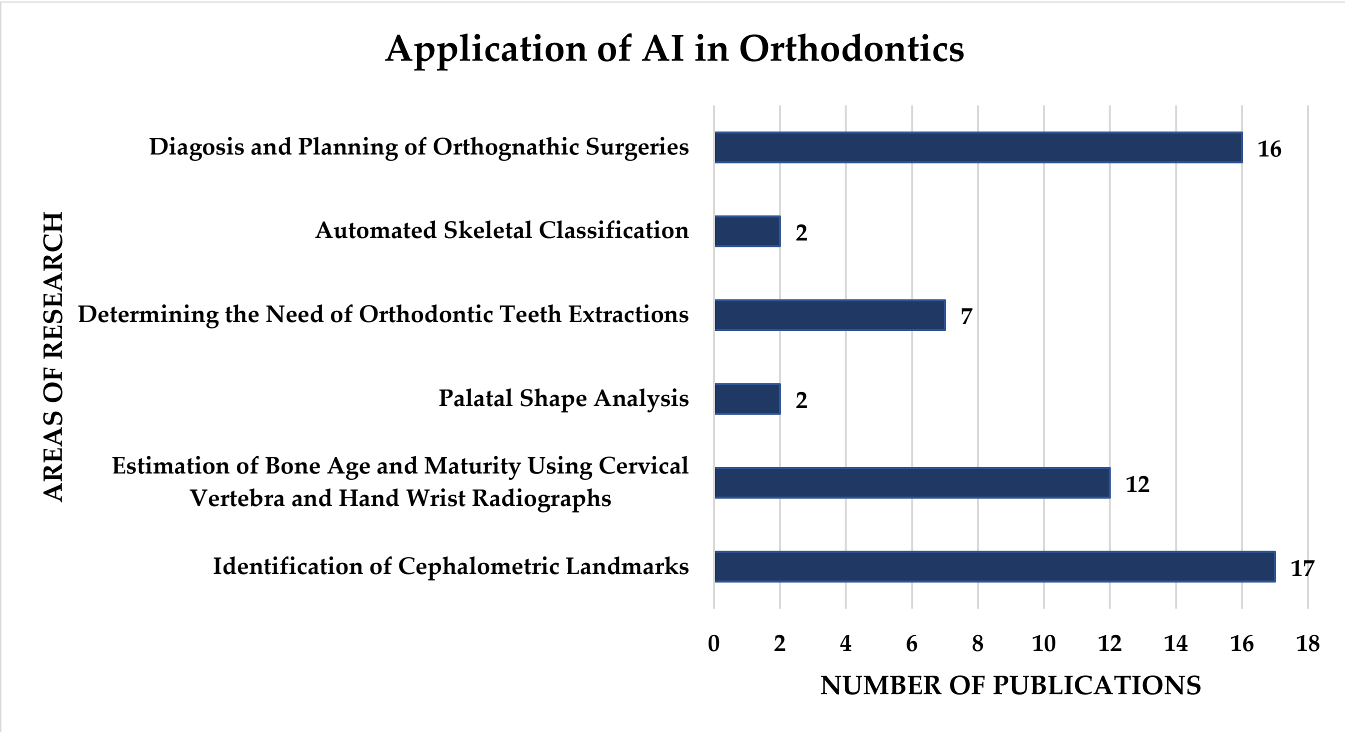

Figure 3. Application of AI in orthodontics.

4. Discussion

Digitalization in medical diagnosis is a new breakthrough in the field of health sciences. In dentistry, digital technology has been widely applied in clinical practice, especially with the use of 3D intra oral scanners designed for scanning dental arches. These technical advancements have simplified the process of impression making and fabrication of prostheses [71,72]. The recent advancements in the field of medical sciences and computer technology have resulted in significant developments in AI based models that have been designed for diagnosing oral diseases, treatment planning, clinical decision making, and predicting treatment outcomes; these models have demonstrated excellent performances [1,9–11].

4.1. AI Models Designed for Automatically Identifying Cephalometric Landmarks

In orthodontics, cephalometric analysis is considered one of the most significant tools for evaluating the skeletal profile of the craniofacial region. The manual tracing of X-ray films and plotting the landmarks requires skill and expertise. Advancements in AI technology have resulted in the development of automated models that can predict landmarks without human assistance. Nishimoto S et al. [15] reported on an automated landmark predicting system based on a deep learning neural network, where the model demonstrated a performance equivalent to manual plotting. Park JH et al. [16] reported on the performance of two automatic deep learning models You-Only-Look-Once version 3 (YOLOv3) and Single Shot Multibox Detector (SSD) designed for identifying cephalometric landmarks. The YOLOv3 algorithm outperformed SSD in accuracy and displayed 5% higher accuracy than the benchmark methods reported in the literature. Kunz F et al. [18] reported on an automatic cephalometric identification model using an (AI) algorithm; this model demonstrated quality levels equivalent to experienced professional examiners. Hwang HW et al. [19] reported on the performance of an automated identification system, You-Only-Look-Once version 3 (YOLOv3), for the automatic identification of cephalometric landmarks. This model displaced excellent accuracies, which were similar to experienced human examiners. Zeng M et al. [20] reported on an AI based model designed for automatically predicting cephalometric landmarks; this model demonstrated competitive performance compared with other models. Bulatova G et al. [22] reported on an AI based model for automated cephalometric landmark identification; this model demonstrated a performance similar to a calibrated senior orthodontist. Hwang HW et al. [23] compared the performance of a deep learning based AI model with previously reported AI models in the literature designed to identify cephalometric landmarks automatically. This model demonstrated superior results in comparison with the previously reported AI models. Kim J et al. [24] reported that a CNN model designed to identify cephalometric landmarks displayed excellent accuracies. Kim YH et al. [25] reported on a deep learning based fully automatic AI model for identifying cephalometric landmarks; this model demonstrated better performance than two calibrated and experienced examiners. Kim MJ et al. [26] reported on a CNN model designed for the automated identification of cephalometric landmarks using cone-beam computed tomography (CBCT) scans; this model displayed better consistency in identifying the landmarks in comparison with the experienced human examiners. Another study conducted by Kim MJ et al. [27] reported on an automatic cephalometric landmark identification system using CBCT images; this model displayed a performance equivalent to the experienced examiners. Yao J et al. [28] reported on a CNN based AI based model for automatically identifying the cephalometric landmarks; this model demonstrated a higher accuracy. Le VNT et al. [29] reported on a human-AI collaboration for identifying cephalometric landmarks. The collaborative system was effective in identifying landmarks. Gil SM et al. [30] reported on a convolution neural network (CNN) based AI model for identifying cephalometric landmarks; this model demonstrated excellent performance, similar to a human examiner's performance.

4.2. AI Models Designed for Bone Age and Maturity Estimation

The timing of orthodontic treatment is crucial in achieving the desired clinical outcomes. In treatment planning, quantifying the skeletal growth, mainly the mandible, impacts the diagnosis, treatment planning, and treatment outcomes [73]. Therefore, if orthodontic treatment is initiated during the optimum development phase, it will produce more favorable results. Otherwise, a much longer treatment time and surgical intervention may be needed to correct the deformities of the jaw [74,75]. The standard method for estimating bone maturity uses a hand-wrist radiograph and a lateral cephalogram to estimate cervical vertebral maturity (CVM). However, studies have reported that the reproducibility of the CVM varies among examiners [76,77]. In recent developments, AI has been widely used to estimate bone maturation using hand-wrist radiographs or CVM. Kok H et al. [32] reported on the efficiency of seven AI classifiers designed to determine growth; based on cervical vertebrae stages. These models demonstrated acceptable performance in determining the stages. Another study conducted by Kok H et al. [33] also reported the application of an artificial neural network (ANN) model for determining growth based on cervical vertebrae. This model demonstrated satisfactory results in determining the growth-development periods. Kok H et al. [34] also reported on the success rates of two AI models, artificial neural network models (NNMs) and naïve Bayes models (NBMs), designed for determining the growth and development based on the cervical vertebrae. NNMs displayed a higher success rate than the NBMs. Amasya H et al. [35] reported on the performance of five AI based Machine Learning (ML) models designed for CVM analysis. These AI models displayed more accuracy in comparison with the human observer. Amasya H et al. [36] also reported on the validation of the ANN model designed for CVM analysis; this model displayed better performance in comparison with four trained human observers. Seo H et al. [37] reported on the performance of six CNN based deep learning models designed for CVM analysis on cephalometric radiographs. These six models demonstrated more than 90% accuracy in performing the task. Zhou J et al. [38] reported on the performance of an AI model designed for automatically determining the CVM status using cephalometric radiographs. This model demonstrated good agreement with the human examiners. Kim DW et al. [39] reported on the AI model designed for predicting the hand-wrist skeletal maturation stages. The model demonstrated excellent accuracy in predicting the skeletal maturation stages. Kim EG et al. [40] reported on an AI based CNN model designed for estimating the CVM using lateral cephalograms. The model displayed 93% accuracy in performing the task. Mohammad-Rahimi H et al. [41] reported on an AI model for determining CVM and growth spurts using lateral cephalograms. The model demonstrated reasonable accuracy in determining the CVM stage and displayed high reliability in estimating the pubertal stage. Li H et al. [42] reported on AI based CNN model for CVM classification. This model demonstrated good accuracy in classifying the CVM. Atici SF et al. [43] reported on an AI based deep learning model designed for estimating the CVM stages; this model displayed higher accuracy in determining the CVM stages.

4.3. AI Models Designed for Palatal Shape Analysis

The palate has a complex structure, and its shape varies among individuals. The palate's shape is related to the facial pattern and a wide range of factors such as breathing pattern and occlusion [78–80]. The shape of the palate is of great interest to orthodontists as it is a potential area for evaluation and assessing the outcome of orthodontic procedures like maxillary expansion [81,82].

Palatal measurements usually include palatal surface area, volume, and depth [78]. These measurements often require greater experience and are often subjected to observer errors. The recent technological advancements have resulted in the development of AI based models designed for palatal shape analysis. Croquet B et al. [44] reported on a deep learning model designed for analyzing the palatal shape. This automatic model demonstrated excellent repeatability with promising accuracy. Nauwelaers N et al. [45] reported on the application of an AI based deep learning model for palatal shape analysis, and this model achieved results similar to conventional approaches.

4.4. AI Models Designed for Determining the Need for Extractions

Determining the need for tooth extraction and deciding which teeth need to be extracted is a critical decision in orthodontic treatment planning as it is irreversible [83]. The orthodontists' decision regarding extraction is based on their training, clinical experience, and treatment philosophies [84]. AI technology has been applied to designing models which can be used as an axillary tool for deciding on the need for orthodontic extractions. Xie X et al. [46] reported on the AI based ANN model for determining the need for extraction; this model was very efficient and displayed an accuracy of 80% in determining the need for extraction. Jung SK et al. [47] reported on the performance of an AI model designed to diagnose the need for orthodontic extraction. The model was very efficient in diagnosing extraction and non-extraction cases. Li P et al. [48] reported on the multilayer perceptron ANN model for predicting extraction and non-extraction cases. The model demonstrated an excellent accuracy of 94% for predicting the extraction and non-extraction cases. Choi HI et al. [49] reported on an AI based model designed to determine the need for extraction. This model displayed a success rate of 91% for determining extraction decisions. Suhail Y et al. [50] reported on a machine learning model to diagnose the need for extraction. The model demonstrated a performance that was in agreement with the trained examiners. Etemad L et al. [51] reported on a machine learning model for predicting the need for extraction and non-extraction. The model displayed acceptable results; however, the authors suggested a need for improvisation in the algorithms to improve generalizability.

4.5. AI Models Designed for Planning Orthognathic Surgeries

Individuals presenting dentofacial deformities, either due to congenital or acquired conditions, may require orthognathic surgeries in order to reposition the jaws into a functional relationship. In recent years, several articles have reported on the application of automated computerized methods designed for analyzing dentofacial deformities and elaborating treatment plans [85]. Patcas R et al. [57] reported on an AI model designed for predicting facial appearance post orthognathic surgery; this model displayed an acceptable performance in predicting facial attractiveness and appearance. Knoops PGM et al. [58] reported on a machine learning model designed for automated diagnosis and treatment planning. This model demonstrated an excellent sensitivity of 95.5% and specificity of 95.2% in diagnosing the patients. Stehrer R et al. [59] reported on an AI model for predicting perioperative blood loss following orthognathic surgery. The model demonstrated an excellent result and efficiently predicted the perioperative blood loss prior to surgery. Jeong SH et al. [60] reported on an AI model designed for judging the soft tissue profiles requiring orthognathic surgery. The model displayed an accuracy of 89.3% in judging the soft tissue profiles requiring surgery. Lee K-S et al. [61] reported on an AI based deep CNN model for differential diagnosis of orthognathic surgery. The model was successful and can be applied for differential diagnosis of orthognathic surgery. Tanikawa C et al. [62] reported on an AI model designed for predicting facial morphology post orthognathic surgery. The model demonstrated an excellent success rate in predicting facial morphology and can be applied for clinical purposes. Xiao D et al. [63] reported on an AI model designed for virtually simulating the surgical plan. The model showed higher accuracy in generating the shape models. Shin W et al. [68] reported on an AI model that automatically predicts the need for orthognathic surgery. The model was efficient with relative accuracy in predicting the need for surgery. Kim YH et al. [69] reported on an AI based deep learning model designed to diagnose orthognathic surgery. The model demonstrated excellent performance in predicting the diagnosis of orthognathic surgery.

A few of the limitations of this paper might be with the search strategy. Even though we have performed a comprehensive search for articles, some might have been missed. In general, these AI models' limitations are mainly due to the limited amount of data sets that have been applied for training these models, and validating and testing. Another limitation of the data sets is the standardization since the data sets applied for assessing the performance of these AI models are obtained from one diagnostic center in most cases. Hence, the performance of these models may vary when exposed to different data sets from multiple centers. However, considering the performance of these AI models, there is an urgent need to develop and implement policies to accelerate the process of approval of these models for marketing and usage in clinical scenarios, which can help clinicians in the diagnosis and decision making process.

5. Conclusions

The past decade has witnessed tremendous advancements in digital diagnostic techniques. AI is a major development that has been successfully implemented in a wide range of image-based applications. These applications can facilitate clinicians in diagnosing, treatment planning, and decision making. These applications are extremely useful as they are reliable and fast methods that have the potential of automatically completing the task with an efficiency equivalent to experienced clinicians. These models can prove to be an excellent guide for less experienced orthodontists. However, there are a few limitations with most of these models, with respect to the limited number of datasets used for training and validating these models, and the reliability of the data, as they are obtained from a single hospital/institution or a single machine. Hence, greater improvisation needs to be conducted in this area for better reliability and generalizability.

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