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Review Article

Artificial intelligence and its application in orthodontics: A scoping review

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Abstract

The aim of this article is to give an overview of the current scenario related to artificial intelligence and its application in orthodontics and dentofacial orthopaedics. Artificial intelligence is the branch of computer science which is used to design machines and algorithms which mimic human intelligence. AI is a set of technologies for solving problems and its works on pre-defined rules. AI in orthodontics have multiple applications like (a) Diagnosis based on cephalometric analysis, facial analysis by clinical imagery based on intraoral scan, growth prediction, skeletal age determination, (b) Treatment planning based on decision like extraction or orthognathic surgery, (c) Treatment outcome prediction, (d) Cleft related studies, (e) TMD Classification. In addition this article also touches on the existing limitations if AI. Although AI is in its most advanced phase of evolution but still it will not be able to replace the knowledge and experience of humans.AI aims to support practitioners in borderline cases in orthodontics or general dentist in choosing the ideal way of treatment thus maximizing benefit to the patients.

Keywords: Artificial intelligence, machine learning, deep learning, artificial neural network, application in orthodontics.

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1. Introduction

In general AI system functions by consuming large amount of labelled training data. This data is analysed for correlation and pattern and finally the prediction is made using those patterns. Artificial intelligence system focuses on intellectual abilities like a) learning b) reasoning c) self-correction d) creativity. Artificial intelligence learns by formulating rules known as algorithms from data which are step by step instructions to complete a task. Reasoning involves choosing the right algorithm to reach the desired outcome. Self-correction means usage of algorithms to continuously learn and re-address the error to get the most accurate result possible. For creativity Artificial Intelligence uses neural network, statistical methods to generate new images, text, music and ideas.[1]

2. History of AI

One of the 1st publication related to Artificial Intelligence was published by McCulloch and Pitts in 1943 which described a computer model based on learning like neuron.[2] Alan Turing in October 1950 published a work entitled “Computing Machinery and Intelligence” which involves a blinded human interrogator questioning a human respondent and a machine respondent and if interrogator is not capable of discerning the two, the machine was considered to have passed the Turing Test.[3] In 1958 John McCarthy developed lisp programming language which became popular within AI community.[4] In 1959 Arthur Samuel introduced the term ‘machine learning’ in which he proposed that the computer could be programmed which could surpass their creators in performance. In 1997 IBM’s Deep Blue defeated world chess champion Gary Kasparov.[5] Sepp Hochreiter and Jugren Schmidhuber introduced long short term memory recurrent neural network which could process the entire data like speech and vedio.[6] In 2011 Jurgen Schmidhuber, Dan Claudiu Veli Meier and Jonathan Masci created initial CNN.[7] In 2012, Geoffrey Hinton, Ilya Sutskever and Alex Krizhevsky presented deep CNN structure.[8] In 2014, Ian Goodfellow and his team pioneered generative adversarial networks (GANs), a type of machine learning framework employed for producing images, altering pictures crafting deepfakes.[9] In 2022, Open

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AI launched Chat GPT offering a chat oriented interface to its GPT 3.5LLM.[10]

2.1. Types of AI [11]

Capability based AI

1. Narrow or weak AI.
2. General or Strong AI
3. Super intelligent AI

Functionally based AI

1. Reactive machines
2. Limited memory
3. Theory of Mind AI
4. Self-aware AI

2.2. Main branches of artificial intelligence across different sorts

1. Machine learning: Main branch of AI that enables machines to analyse, interpret and process data from all angles to generate correct output.
2. Deep learning: It is a convolutional neural network consisting of different layers to extract and classify different components of data.
3. Natural language processing: It is self-evolved technology for basic human-computer communication. It is mainly used to design conversational chat bots.
4. Robotic process automation deals with designing, constructing and operating robots that impersonate human's actions and converse with other humans.
5. Expert System learn and imitate a human being's decision using logical notations and conditional operators.
6. Fuzzy logic or hypothesis exhibits the degree of truth of an output. Say if TRUE equals 0 and output says 1. It is inferred that the null hypothesis is untrue.
7. Random forest algorithm is often known as an "ensemble" or "decision tree" as it combines different decision trees to measure output accuracy.

3. Discussion

3.1. How AI works

Deep learning is a part of machine learning which imitates human brain while utilizing the computing power of graphic processing unit.[12] It employs artificial neurons that work on weighted inputs which result in a single amalgamated output value by a simple gradation model that is identical to human style remembrance.[13, 14]

ANN: An ANN typically has a minimum of three layers namely an input layer, an output layer and a hidden layer. Multiple hidden layers displayed remarkable execution in tasks like classification and segmentation.[15] **(Figure 1)**

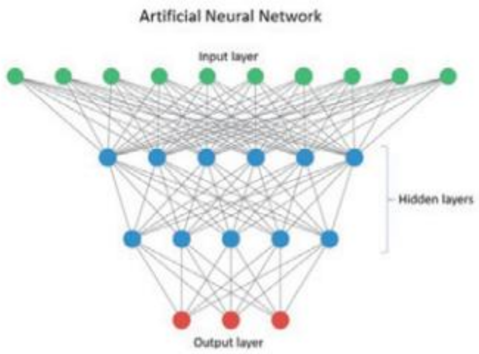


Figure 1: ANN has three layers namely an input layer, an output layer and a hidden layer.

CNN: In CNN, the hidden layers are replaced with three well defined functional layers the convolutional layers, pooling layers and fully connected layers. Convolutional layers decrease the image complexity thus tasks like recognizing objects, shapes and patterns become easy. The pooling layers lessen the dimension of feature maps while keeping hold of the essential information. Following several repetition of convolutional and pooling layers the outputs are combined in fully connected layers for further decision making.[16] (**Figure 2**)

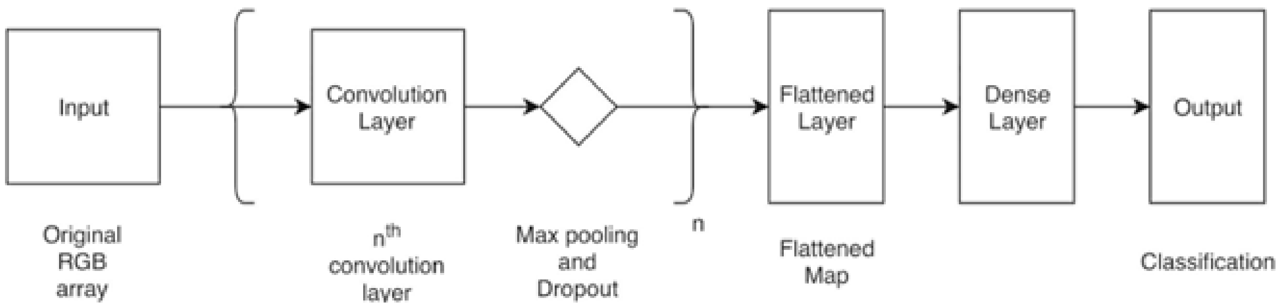


Figure 2: Facial Photo: Four convolution, max pooling, dropout, flatten, dense, dropout, and another dense layer.[16]

4. Applications

4.1. Automated landmark detection on lateral cephalogram

One of the drawback of manual Lateral Ceph. Landmark detection is variability across orthodontist.[18] But recent advancement made in the field of AI has allowed improvement in the efficiency, precision and replicability of cephalometric analysis.[19,20]

Two CNN algorithms YOLOv3 and single shot Multibox Detector (SSD) were compared by Park et al.21 to identify 80 landmarks in lateral cephalometric radiographs images in which YOLOv3 exhibited greater accuracy. Automated detection error of 1.36± 0.98 mm and 1.038 ±0.893 mm was reported by Yao et al.22 and Kim et al.23 using CNN algorithm.

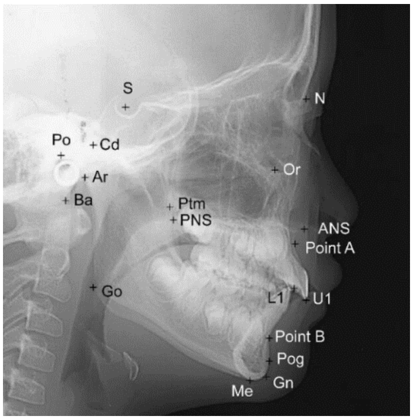


Figure 3: Automated landmark detection[24]

*4.2. Automated landmark detection on postero-anterior cephalogram (**Figure 3**)*

Use of CNN model has been reported for landmark detection in posterior anterior cephalograms for identification of any mandibular deviation.[23] According to Blum *et al.*a CNN based model exhibited 95 % reduction in processing time with mean error of 2.73 mm. Deep reinforcement learning has been utilised for 3D landmark detection.[25]

4.3. Limitations of automated 3D cephalometrics

Though automated 3D cephalometrics is widely used for landmark detection but it still lacks in accuracy regarding linear and angular measurement. According to Schwendicke *et al.* a number of studies regarding AI in cephalometric showed bias. Some studies concluded that use of AI for cephalometric analysis should be accompanied with human supervision by experienced clinicians.[27,28]

4.4. Skeletal age determination

Estimation of pubertal growth spurt and assessment of remaining growth potential is of great use in correcting any skeletal malformation especially in adolescents. Skeletal age helps in determining the growth, as chronological age in itself is not sufficient for estimating the amount of growth remaining.[29]

Cervical vertebral maturation method which employs the use of the vertebral bodies and hand wrist radiographs are method of skeletal age estimation.[30,31] Out of the two methods cervical vertebral maturation method is more beneficial as it can be determined in lateral cephalo graph and thus reducing extra radiation exposure.[32] In CVM Method the vertebral bodies C2-C4 are analysed according to the six stages of skeletal maturation.[34] but for inexperienced practitioners interpretation may be difficult as well as there may be individual differences.[33] To overcome this problem artificial intelligence is being used to accurately determine skeletal age.[35]

According to some authors[36] there was 58-71% agreement between the results of CVM interpretation by human and artificial intelligence. Maximum disagreement was found related to peak growth according to some studies.[37-39] But according to Seo *et al.*[41] agreement between AI and human interpretation was 90%. Kok *et al.*[40] analysed several machine learning algorithms in predicting the stages of cervical vertebral maturation and concluded that ANN was most stable algorithm. According to Makaremi *et al.*[42] CNN is more popular than ANN especially in cases of image related tasks.

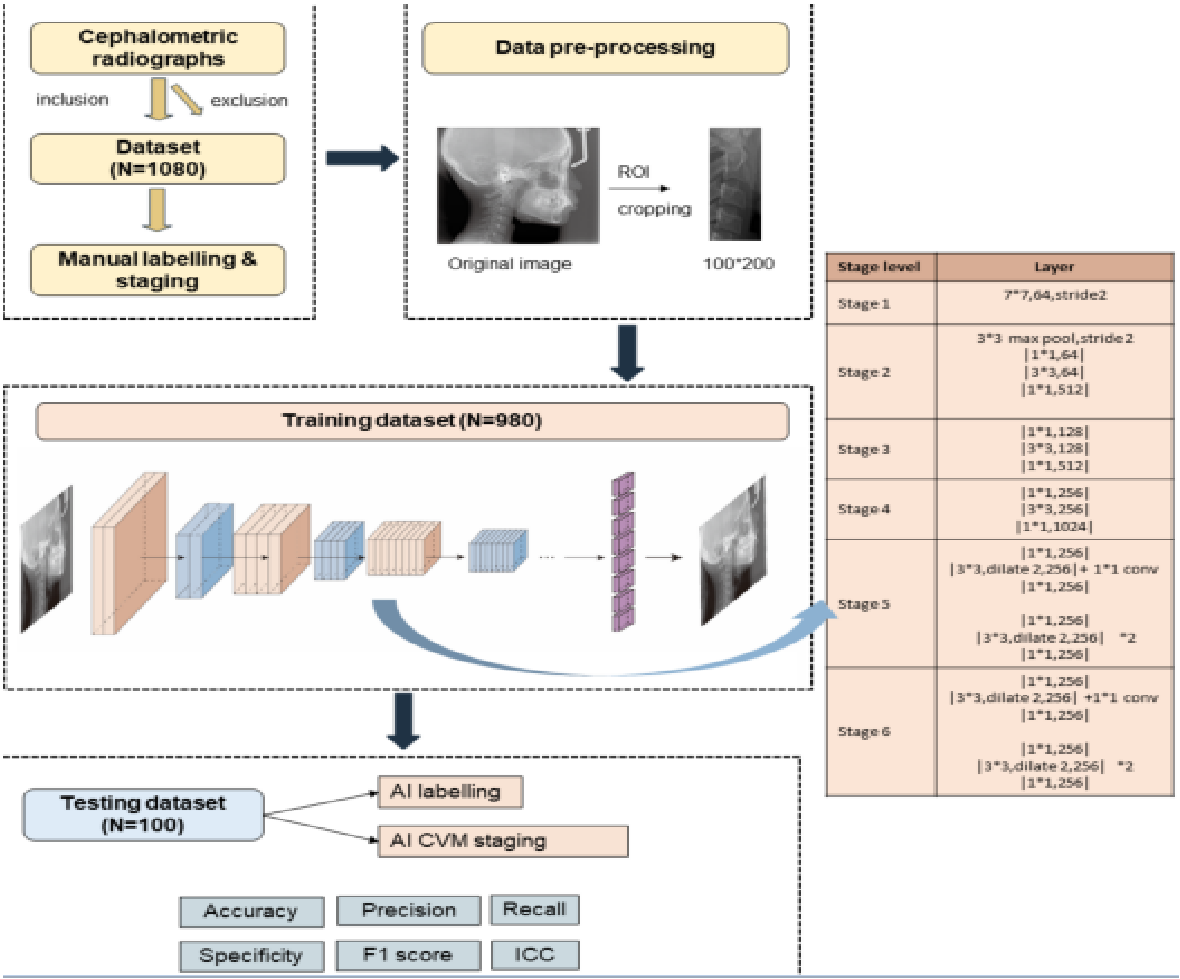
*4.5. Facial analysis (**Figure 4**)*

Facial analysis was done on facial images by Rao *et al.*[43] using an active shape model algorithm and 50% of the landmarks had an error within 3 mm. Yurdakurbau *et al.*[44] used a machine learning software to detect facial midline and asymmetry and there were statistically non-significant difference between the two methods.

CNN was employed by Rousseau *et al.*[45] to analyse the vertical dimension of patients which showed high precision and efficiency than manual method. Many AI approaches Grad-CAM and De ConvNet can generate heat maps to highlight the contributing regions of the input images.[46]

4.6. Dental analysis (**Figure 5)**

Intraoral photographs were used by Talaat *et al.*[47] to detect malocclusion (specifically tooth crowding) using VoLo algorithm. The results showed an accuracy of 99.99%. Ryu *et al.*[48] used four algorithms to assess the dental status of dental crowding by using intraoral images. According to him VGG19 showed minimum error in maxilla (0.84 mm) and mandible (1.06 mm). Im *et al.*[49] used Dynamic graph convolutional neural network which automatically segments the tooth in a digital model thereby reducing computational time and achieve high accuracy when compared to software's like Ortho Analyser and Auto lign. Besides some studies,[50] have reported accurate landmark detection on teeth which helps in accurate dental analysis after proper segmentation of teeth.



<table>
<tr><th>Stage level</th><th>Layer</th></tr>
<tr><td>Stage 1</td><td>7*7,64,stride2</td></tr>
<tr><td>Stage 2</td><td>3*3 max pool,stride 2
|1*1,64|
|3*3,64|
|1*1,512|</td></tr>
<tr><td>Stage 3</td><td>|1*1,128|
|3*3,128|
|1*1,512|</td></tr>
<tr><td>Stage 4</td><td>|1*1,256|
|3*3,256|
|1*1,1024|</td></tr>
<tr><td>Stage 5</td><td>|1*1,256|
|3*3,dilate 2,256|+ 1*1 conv
|1*1,256|

|1*1,256|
|3*3,dilate 2,256| *2
|1*1,256|</td></tr>
<tr><td>Stage 6</td><td>|1*1,256|
|3*3,dilate 2,256| +1*1 conv
|1*1,256|

|1*1,256|
|3*3,dilate 2,256| *2
|1*1,256|</td></tr>
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Figure 4: The experimental design of the study. Step 1: Inclusion and exclusion. Step 2: Data pre-processing. Step 3: Model training and testing. Step 4: Performance evaluation[38]

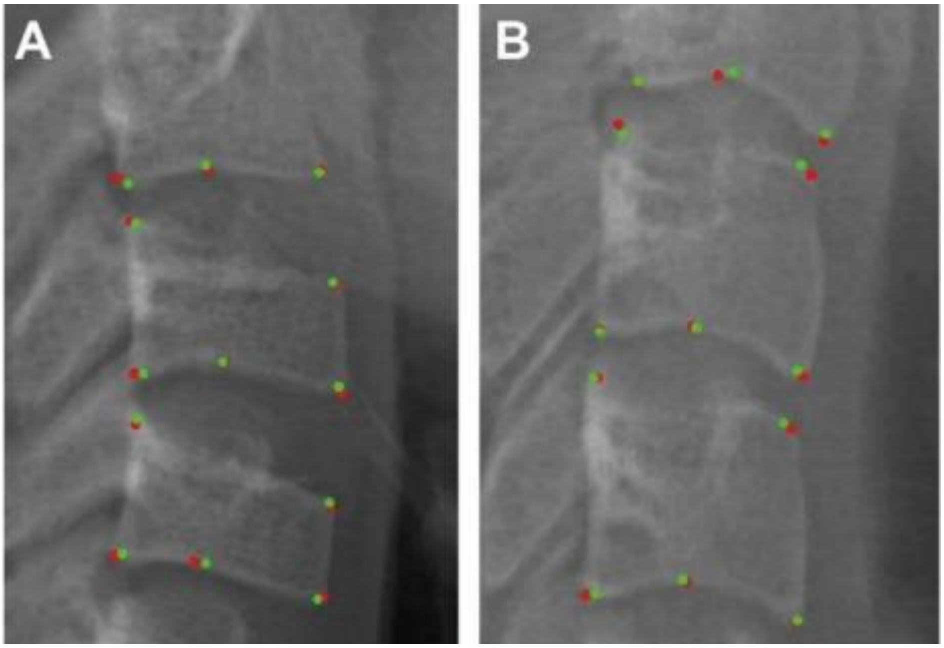

Figure 5: Anatomic landmarks that AI (points in red) and human (points in green) labelled in testing dataset. (A). AI and human labelled landmarks for CS 3 (B). AI and human labelled landmarks for CS6.38

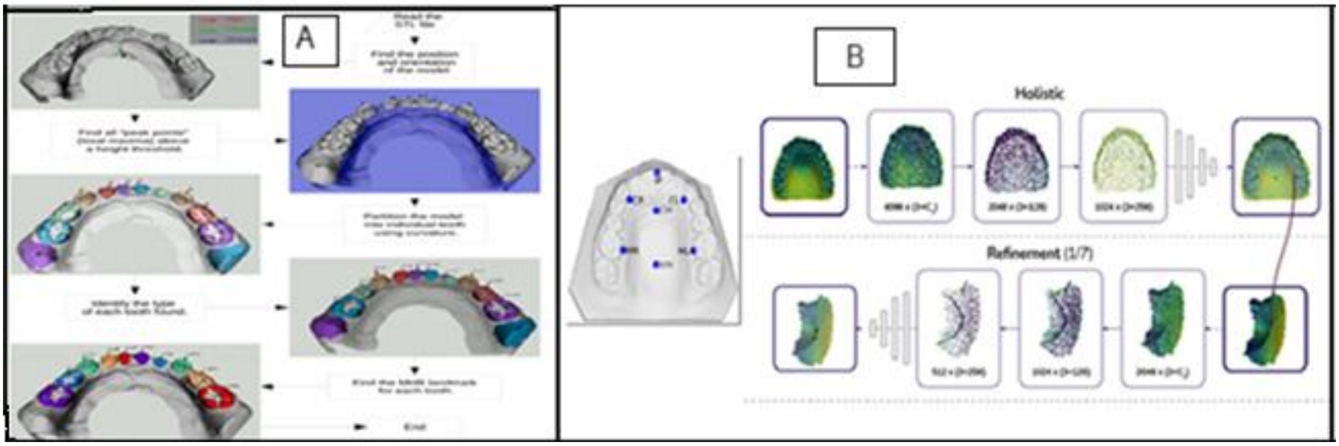

Figure 6: A) Flowchart summary of the automatic landmark finding process[50], B) Landmark prediction with learned hierarchical features[55]

4.7. Palatal shape analysis ***(Figure 6)***

Palate is an important anatomical structure located at the junction of oral and nasomaxillary cavities. Its shape affects a lot of function like mastication and speech.[51,52] Shape of palate is affected by a lot of factors like developmental stage, mode of breathing, tongue size and its posture and malocclusion.[53,54] According to a study by Croquet *et al.*[55] maxillary cast was laser scanned which created a digital 3D mesh surface which was used for automated landmark identification. Several software have been used for automated landmark identification.[56] AI can help in calculating the depth, width, surface area.[96, 97]

4.8. Photographic analysis

Artificial intelligence can be used for photographic image analysis by using convolutional neural network system in medical and dental fields. It uses artificial neurons that calculate weighted inputs to generate a single integrated output value by a simple classifier model similar to human pattern. CNN utilizes a hierarchical structure for passing information about prominent features to following layers and explores the local correlation between these structures.[12,57] According to J Ryu[16] the method for photographic analysis consisted of taking digital photos by several doctors which included extra oral frontal, frontal smile, right profile and three quarter profile. Intraoral photograph like front, left and right buccal, maxillary and mandibular occlusal view were taken. All samples were first divided into training set and testing set. Training set was further divided into learning set and validation set for preventing over fitting. Finally testing set were used for model evaluation.

The 2-D 128 by 128 pixel input data is reduced to 64 by 64 pixel and then transformed through a flattened layer and categorized into 4-5 classification with a soft max activation.[58] The pixels of 2-D photographs are collected to make 1 photo on which deep learning technology works and recognises morphological differences, lip contour or white teeth exposure during smiling.[59](**Figure 7**)

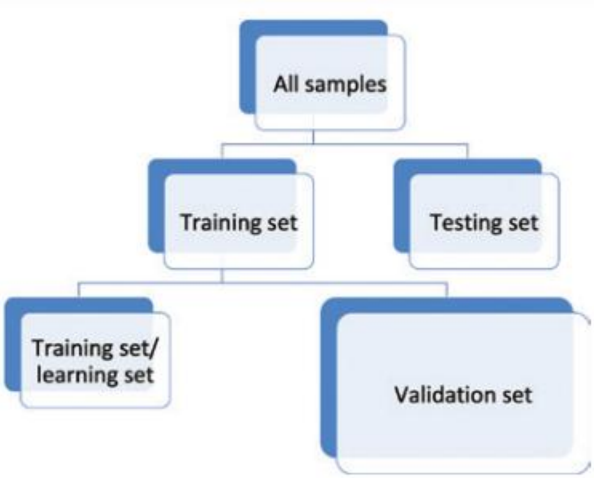

Figure 7: Method of sample division into training, testing and validation set

*4.9. Upper airway obstruction assessment using AI (*Figure 8**)**

Adenoid hypertrophy which often is a cause of upper airway obstruction is critical for orthodontic diagnosis and treatment planning. For screening this Fujioka gave AN ratio (Adenoid-Nasopharyngeal).[60] Shen *et al*.[61] employed a CNN model to locate 4 key points in Fujioka's method on lateral cephalogram and obtained a mean AN ratio error of 0.026 while Zhao *et al*.[62] employed a similar method and obtained high accuracy (0.919), sensitivity (0.906) and specificity (0.938). The volume of upper airway is also important for assessing upper airway obstruction. Sin et.al [64] used CBCT images to calculate volume of pharyngeal airway and achieved a dice ratio of 0.919.

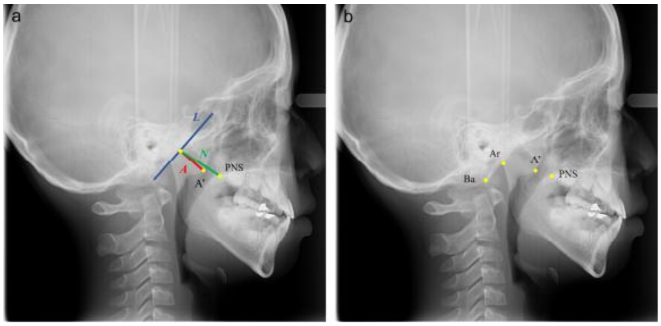

Figure 8: Line segment L is drawn along the straight part of the anterior margin of the basiocciput, line segment A indicates the size of the adenoid; line segment N indicates the size of the nasopharyngeal space).[62]

5. TMD Classification

According to a study Bu Shoukri *et al.*[64] AI successfully classified condylar morphology into groups by using data of 259 condyles (CBCT images) the temporo mandibular joint osteoarthritis stage classified by AI was t-gen compared to clinical expert finding and accuracy of 91.2% was achieved.

6. Cleft Related Studies

Zhang *et al.*[65] used AI by employing machine learning algorithms to limited predictive models with 43 single nucleotide polymorphism which were detected using genome wide association for determining the defective gene variants like MTHFR and RBR4 responsible for folic acid and vitamin A biosynthesis which lead to Non Syndromic Cleft lip/palate. Pateas *et al.* used a CNN model using >13000 face images and >17000 ratings for attractiveness to compare facial attractiveness between treated cleft patients and control. The results showed that AI still need improvement in its interpretation of cleft features which affect facial attractiveness.[66]

7. Decision Making in Extraction and Non-extraction

Decision regarding extraction or non-extraction is crucial factor for treatment. It depends upon orthodontists experience as a wrong decision regarding orthodontic extraction can lead to a number of post treatment complications like undesirable change in profile, deranged occlusion and difficulty in space closure.

Jung *et al.*[67] built an AI system using neural network machine to decide for extraction, non-extraction case and detailed extraction pattern by using 12 cephalometric variables and 6 other indices. The accuracy rate for extraction/non extraction decision was 93% where as detailed extraction pattern was 84%.A multilayer perceptron ANN was used by Li *et al.*[68] to predict the extraction and pattern in several cases. It achieved an accuracy of 94% and 84.2% respectively. It also predicted the anchorage pattern with 92% accuracy

The three machine learning algorithm. Random forest, logistic regression and support vector machine were compared by Leavitt *et al.*[69] for predicting extraction pattern. According to him their accuracies were not very satisfactory with SVM achieving the highest accuracy of 54.55%. According to some studies, random forest performed well as ensemble method to prevent over fitting but still more studies are needed to prove its effectiveness.[70,71]

8. Use in Orthognathic Surgery

Support vector machine was utilized by Knoops *et al.*[72] to predict a surgery/ non surgery decision using 3D facial images which showed an accuracy of 95.4% while Jeong *et al.*[73] used CNN model to predict surgery or non-surgery based on frontal and right facial photographs which showed an accuracy of 89.3%. Lee *et al*.[74] used random forest, logistic regression to predict the surgery decision in Class III patients but only 90% and 78% accuracy was obtained respectively.

AI helps in setting up automated orthodontic virtual setup for predicting the outcome of orthognathic surgeries thereby saving time and labour as the methods proposed by Kesling involves tooth segmentation and repositioning which is tiring.[75] Park *et al.* predicted lateral cephalogram changes of Class II patients after using modified C-palatal plates by usig CNN model which showed an accuracy of 1.79± 1.77 mm.[76] Tanikawa *et al.*predicted changes in facial morphology after orthognathic surgical treatment by using geometric morphometric methods and an average error of 0.94± 0.43mm and 0.69± 0.28 mm were recorded.[77]

8.1. To predict the treatment outcome post orthodontic treatment

Park *et al.* used a conditional generative adversarial network (c GAN) to predict 3D facial changes based on patient's age, gender and incisor movement.[78] cGAN generates high quality 3D facial images and colour distance maps which were used to predict 6 perioral landmark between real model and predicted model with mean error of 1.2±0.01 mm accuracy of 80.8%.[79]

Xu *et al.*[80] used ANN mode to predict the patients experience after invisalign treatment using 17 clinical features which showed high prediction accuracies of 87.7% for pain, 934% for anxiety and 92.4% for quality of life. According to a study by Nanda SB *et al.* ANN models can be effective when one has to predict the soft tissue changes post extraction /non extraction orthodontic treatment especially with respect to nose, lips chin.[81]

8.2. Clinical practice guidance

El Dawlaty *et al.*[82] suggested a computer based decision support system for deep overbite correction which could provide a detailed treatment protocol including intrusion or proclination of incisors, levelling the curve of speed with 94.4% accuracy. Akcam *et al.* used a computer assisted inference model to select the right type of headgear according to the clinical situation and this is of valuable help to less experienced orthodontist in decision making while choosing the right type of headgear.[83]

Choi *et al*.[84] developed an AI algorithm which could read TMJ osteoarthritis on OPG. This could help in places where there is an absence of an expert or where patient's TMJ arthritis or other bony changes may be misread. Tao *et al*.[85] successfully used 3D- Unit with squeeze and excitation module which can do automated segmentation and thickness measurement of palatal bone and soft tissue with the help of CBCT. It can also help in predicting the ideal site for palatal mini screws based on bone and soft tissue thickness. Hu *et al*. and Lee *et al*. used AI to predict the position of tooth roots based on intraoral scans where deep learning could accurately segment teeth in CBCT scans and merge them with the intra oral scanned dental crowns to construct integrated tooth models.[86,87]

9. Remote Care

Dental monitoring through AI has gained widespread popularity as it allows patients to scan their dentition with the help of smartphone. This not only reduces chair side time but also improves patient's compliance.[88,89] Dental monitoring can be applied to conventional fixed appliances and clear aligners, detecting ill-fitting clear aligners, losses of attachments, arch wire passivity, bracket breakages.[90-92] According to Homsi *et al*.[93] remotely reconstructed digital model generated by DM were highly accurate as intraoral scans.

10. Clinical Documentation

Ryu *et al*.[16] used CNNs to automatically classify facial and intraoral photographs including four facial and five intraoral photos which obtained an overall valid prediction rate of 98%. Li *et al*. used deep hidden identity (deep ID) based deep learning model and expanded categories of orthodontic images into 14 images i.e. 6 facial images, 6 intra oral images, 1 panoramic film and 1 lateral cephalogram.[94] This deep learning model extracted features from images and Bayesian feature was used for verification process. This AI model reached an accuracy of 99.4%.

11. Future Prospects

AI can be used in unexplored area of orthodontics like automated detection of orthodontic treatment need using index of orthodontic treatment need and index of orthognathic functional treatment need.[95,96] AI could also assist in orthodontic treatment procedure like correcting deep bite, avoiding bone dehiscence or fenestration. In near future we would be moving towards precision orthodontics in which treatment would be customised based on patient's characteristics to enhance treatment outcome.[97]

12. Conclusion

AI in orthodontics have multiple applications. Efforts should made to create a cloud based platform where data with high quantity and quality could be gathered for achieving results with high accuracy and better interpretation through machine learning process.

13. Conflict of Interest

None.

14. Source of Funding

None.

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