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Review

A Critical Review on the 3D Cephalometric Analysis Using Machine Learning

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Abstract: Machine learning applications have momentously enhanced the quality of human life. The past few decades have seen the progression and application of machine learning in diverse medical fields. With the rapid advancement in technology, machine learning has secured prominence in the prediction and classification of diseases through medical images. This technological expansion in medical imaging has enabled the automated recognition of anatomical landmarks in radiographs. In this context, it is decisive that machine learning is capable of supporting clinical decision support systems with image processing and whose scope is found in the cephalometric analysis. Though the application of machine learning has been seen in dentistry and medicine, its progression in orthodontics has grown slowly despite promising outcomes. Therefore, the present study has performed a critical review of recent studies that have focused on the application of machine learning in 3D cephalometric analysis consisting of landmark identification, decision making, and diagnosis. The study also focused on the reliability and accuracy of existing methods that have employed machine learning in 3D cephalometry. In addition, the study also contributed by outlining the integration of deep learning approaches in cephalometric analysis. Finally, the applications and challenges faced are briefly explained in the review. The final section of the study comprises a critical analysis from which the most recent scope will be comprehended.

Keywords: machine learning; 3D cephalometric analysis; landmark identification; orthodontics

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1. Introduction

The scientific study that propounds on skull measurement is cephalometry. Several dimensions comprised of a series of linear and angular measurements are constructed using precise points of reference called landmarks [1]. These measurements aid orthodontists in analyzing the profile of soft tissue, teeth, and facial skeleton to check for any anomalies and enhance surgical planning [2,3]. The fecund proliferation of artificial intelligence (AI) in orthodontics and dentistry resolves the existing issues with surgical planning [4]. The incorporation of AI into orthodontics and dentistry has mainly been brought to aid medical professionals in lining up with exact diagnosis and efficacious treatment plans [5]. The progression of pre-programmed electronic computers initially marked the emergence of the contemporary AI system, whose rapid mark-up in the later years paved the way for numerous discoveries, programs, and applications in the field of orthodontics [6,7]. Following the emergence of AI, machine learning (ML) and deep learning (DL) methods evolved. These methods are used in analyzing and identifying cephalometric landmarks, mandible segmentation, face analysis, decision making related to tooth extraction, determination of bone age, temporomandibular-bone segmentation, and orthognathic surgery prediction. Orthodontic diagnosis is a process that consumes much time, as it includes the analysis and review of radiographic recordings and photographs, model analyses, and patient examination [8,9]. Various treatment plans have emerged due to this complexity in assessment among orthodontists.

Hence, these diagnostic methods have to be automated in order to enhance consistency, accuracy, and speed. Despite these technical advancements in clinical settings, the application is still quite underexplored [10]. Since then, in 1931, when Hofrath and Broadbent invented the cephalometer, it has greatly supported medical assessment and has proven to be a reliable tool for diagnostics in orthodontic research and practice [11–14]. In recent epochs, ML algorithms have been extensively used in diagnosis, while landmark detection, automated diagnostics, and data mining are frequently used applications grounded in ML approaches [15,16]. This lies in the fact that the working procedure and decision-making abilities are capable of solving real-world issues on a single platform.

New-fangled algorithms have emerged rapidly, and the computational resources associated with the algorithms are also increasing swiftly, resulting in increased reliability, accuracy, and efficiency in the prognosis and diagnosis of medical conditions [15]. Furthermore, the contemporary methods of automated cephalometric landmarks have been established considerably with improved prospects and efficiency for the continued purpose of serving the cause. DL, which is an advanced ML approach, has also received great attention; nevertheless, the prime cause in implementing these methods in the cephalometric automated approaches has been taken lately [17]. While random forest, which is an ML-based algorithm, has ascertained 19 landmarks promptly, the performance of computation has been so efficacious in the identification [18,19]. The chief considerations for efficacious treatment in orthodontics involve treatment planning, exact prognosis estimation, and diagnosis. Moreover, machine learning approaches have been used, as they possess the ability to clarify the need for extractions prior to the treatment and surgeries. As a criterion in orthodontic diagnosis, cephalometric analyses are examined with a motive to attain an enhanced accuracy rate [20]. The classic cephalogram that is used provides plane details from a 3D (three-dimensional) craniofacial structure, while the progression of CBCT (Cone Beam Computed Tomography) offers a precision and detailed comprehension of the diagnostic images, so that appropriate treatment plans can be developed with successful results. These software programs aid clinicians in synthesizing 2D images from diverse angles with several assisted algorithms [21,22].

Hence, numerous images were synthesized from a single CBCT scan and utilized for either 3D or 2D cephalometric analysis. The cephalometric analysis using 2D images, either coronal planes or sagittal, is often inaccurate, and hence the extensive convenience of 3D techniques of imaging, such as MRI (Magnetic Resonance Imaging) and CT (Computed Tomography), make the facial morphology analysis more feasible [23,24]. Due to the characteristic drawback of 2D-based cephalometric analysis, a trend shift has occurred from the 2D approach to the 3D cephalometric approaches [25]. Thus, an orthographic projection of a 3D craniofacial image is done to synthesize the 2D cephalogram, and this yields a clearer profile of the facial tissue. Certain researchers have proposed methods of completely automatic cephalometric landmark identification grounded in ML and DL approaches. Accordingly, the suggested study [26] has utilized ML and DL methods that provide excellent abilities in feature recognition, even from a complicated image. There are numerous factors that impact the accuracy of the landmark-identification, such as the count of dataset, architecture, identification pattern, count of landmark, and image quality. Another study utilized DL architecture and conventional-lateral-cephalogram built on a completely automated cephalometric analysis, and a precision of 2 mm was seen in the model [2].

The shift from conventional or manual cephalometric methods to ML-based analysis is chiefly aimed at reducing errors, saving time, and enhancing accuracy as the database saves the scanned or digital cephalometric images. Thus, landmark identification through software aids automatic cephalometric dimensions [27]. Therefore, the present study is aimed at proffering a review of 3D cephalometric analysis using ML approaches. The major contributions of the study are:

- To elucidate the existing automated approaches in which machine learning has facilitated appropriate treatment and surgical planning in cephalometric analysis.

- To study the accuracy and reliability of ML algorithms in 3D cephalometric analysis to identify landmarks.

Paper Organization

This paper is organized in the following manner. Section 1 is the introductory part of the study, which outlines the major contributions of the study as well. Section 2 elucidates the various automatic approaches to cephalometrics using machine learning. Section 3 comprises the reliability and accuracy of the cephalometric analysis. Section 4 outlines the integration of the deep learning method with machine learning approaches in the identification of landmarks. Section 5 comprises the application of ML in the field of orthodontics; Section 6 describes the challenges faced by researchers in implementing ML in the relevant field; Section 7 describes the future scope; and Section 8 is the conclusion of the work.

2. Cephalometric Automation Using ML Approaches

Computer-aided detection followed by diagnosis has become the foremost domain in medical applications that employ ML. The solicitation of algorithms in processing the picture is pervasive in medical applications, especially for the thorough analysis of images [13,28]. The ML methods in medical image processing do not feed on the original image directly; rather, initially they perform feature extraction of particular images to get features and forward those features to the models such KNN (k-Nearest Neighbor), SVM (Support Vector Machine) in order to successively perform target detection or classify the images to recognized classes in order to attain image detection and classification. While convolutional neural networks (CNN) are extensively used, they perform exceptionally in organising the features of the image, even in areas such as pathological detection and radiographic recognition. [29]. A comparative analysis of the ML approaches used in cephalometric automation is presented in Table 1.

Automated Identification of Landmarks

Arthur Samuel in 1952 stamped out the term "Machine Learning". The main variation between artificial intelligence and machine learning is that ML obtains information from details instead of following the rules framed by human beings. The main aim of ML is to construct a machine to fetch knowledge by itself from old data and discover solutions without the help of humans [30]. The commonly used ML methods include convolution neural network, Bayesian network classifier, extreme learning machine, verdict tree, random forest, reinforce path machine, fuzzified nearest neighbor, and logistic regression. ML has been classified into three classes: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning works on the estimation and sorting of recognized data, while unsupervised learning finds formats with unknown constitutes with unrecognized data. Reinforcement learning develops modified methods that improve consideration [31].

There has been extreme demand for automatic cephalometric land-marking, as manual land-marking requires a large period of time and practice, as well as equity and accuracy error evasion. There have been some characteristic restrictions in the 2D cephalometric analysis. To overcome this exciting issue, an existing study [32] proposed an approach of a shadowed 2D image-dependent machine learning method that used numerous shadowed 2D images with several lighting that view instruction to capture 3D geometric signals. The method used a VGG-net that was qualified and tested with 2700 shadowed 2D images with equal manual land-marking. This alternative method of automatic 3D cephalometric analysis was used in the treatment assessment, diagnosis, and draft plan for surgeries. This tested technology achieved an error of 1.5 mm for 7 major landmarks, namely bregma, nasion, right/left porio, right/left orbitale, and CFM (Centre of Foramen Magnum) of average point-to-point reference. The existing study opened new opportunities for research related to automatic 3D cephalometric analysis by addressing the challenge of dimensionality in training high-dimensional data. Another study aided in the vanquish issue of manual landmarking. Automatic 3D cephalometric annotation that is dependent on multi-stage deep reinforcement learning and volume-rendered imaging has been deployed in the research.

The method used in the suggested study [33] was based on the geometric characteristics of landmarks and simulates the chorologic decision process essential for human professionals' marking outlines. This mainly involved building a two-dimensional or 3D model view before executing a single-stage DRL with a boundary based on gradient estimation. This system resulted in correctness in detection with steadiness in clinical instrumentation, with minimal error and reduced separate differences (1.96 $\pm$ 0.78 mm). The advantage of this system was that no additional steps of dissection were needed. For landmark detection, a 3D mesh object was constructed. The suggested study facilitated speedy cephalometric analysis and scheduling and aided in achieving better accuracy because bigger CT datasets were used for examination and evaluation.

A machine-learning scale-up pipeline has been proposed in a study to gather multi-dimensional morphometric data in the form of two-dimensional images in a flexible biotic structure. Existing research has explained morphometrics, which have become an essential component for demographic analysis of shape and size differences in biotic structures. This information was gathered through manual landmark analysis. This manual landmark analysis became a bottleneck for morphometric-based studies. Hence, the study developed a file-transforming algorithm that aided in supporting datasets of morphometric for computerization. This method permits a complete process, starting from model training to estimation, within a short period of time. These models were trained to estimate the position of a biotic structure that aimed to landmark images and to estimate the shape of every marked structured that is annotated landmark. The study developed an ML pipeline—ML morph—for computerized detection and landmarking of biotic construction in images that aid in collecting morphometric information extensively. This existing study [34] also showed a problem in the automatic detection of landmarks through the supervised learning method. It was found that automatic discovery of landmarking is executed through detection of objects followed by prediction through ML morphometric analysis using machine learning, which increased the number of opportunities for automation inside the community of morphometrics.

Table 1. Comparative Analysis of ML Algorithms Used in 3D-Cephalometrics.

S. No	Machine Learning Algorithm	Applications	Merits	Demerits	References
1.	Support Vector Machine, Naïve Bayes, K-NN, Logistic Regression, ANN, Random forest	Determining the development of the cervical vertebrae in orthodontics	• Models were not prone to overfitting as augmented data were used • Capable of modeling non-linear functions among input data and predicted variables	• Slow training • Complex to comprehend the algorithm structure • Logistic regression and KNN showed the lowest accuracy • Naïve Bayes and SVM showed altering accuracies	[35]
2.	Random Forest	Diagnosing orthodontic extractions	Random forest used as an ensemble classifier minimize overfitting	Several trees could slow the algorithm and degrade its overall performance	[36]
3.	Decision Tree	Inverse bio-medical modelling of tongue through synthetic training data and Machine Learning	• Easy and simple to comprehend • They could deal with numeric and nominal attributes • Could be utilized when particular data are skewed, missing, or possess errors • Pruning minimizes overfitting and enhances the prediction rate • Training order has no impact on training	• Show poor performance when several complex interactions prevail • Sensitive to training set, noise, and irrelevant attributes	[37]
4.	Genetic Algorithm	Orthodontics	• Simple and easy algorithm for use • Attempts to determine the best solution	Complex in representing training data and resultant data	[38,39]
5.	Fuzzy Logic	Diagnosing orthodontics	• Imitates human way of thinking in reasoning • Utilize linguistic and numeric variables	• Requires numerous data and knowledge • Analysis seems to be complex, as fuzzy results could be interpreted in diverse manners.	[40,41]

Several works have established the illustrative adequacy of anatomical references of photo anthropometric description that enhanced accuracy and improved consistency. One such study [42] purposed to construct and estimate computerized technology to identify cephalometric landmarks in digital pictures of frontal faces in the forensic field. The technology implemented here used a mixture of computerized vision and image processing techniques, along with a supervised learning process. The implied technology obtained accuracy that met with the manual cephalometric reference marker. This result was more accurate compared to other facial landmark detection frameworks. This method achieved an error of 0.014 in a normalized mean distance comparable to an inter-expert dispersion of 0.009 and implied better accuracy of 00.26 and 0.101. The methods were also based on three components: detection of the face region, training, and image processing. For every image of the face, a pre-processing step was applied to boost the facial features. The detected face is categorized into eyes, nose, and mouth. Two further processes, namely computerized landmark detection and comparison of their performance with landmark location, were done manually. These outcomes showed that explained technique disabled the two counterparts in arithmetical significant variation and outcome of that result near to manual location dispersion with mean distance error of 0.014 vs. 0.009.

3. Reliability and Accuracy of 3D Cephalometrics Using ML

The algorithms and computational resources are increasing day by day, which results in enhanced accuracy, reliability, and efficiency [43,44]. With such a notion, a study has aimed to develop 5 distinct supervised models of classifiers and compared the performance for CVM (Cervical Vertebral Maturation) analysis. Additionally, CDSS (Clinical Decision Support System) was developed in this study. The method of the study involved a count of 647 lateral digital radiographs where vertebrae from C2 to C5 were selected. The samples were manually labeled with the CDSS by evaluating 100 radiographs. For every sample, 54 features were stored in the format of text, and LR (logistic regression), ANN (Artificial Neural Network), random forest, decision tree, and SVM models were used for classification. Visual evaluation and classification concordance were evaluated using a weighted k-coefficient. Among the CVM classifier models, ANN showed a better weighted coefficient of k = 0.926. Among vertebrae morphology models of classification, LR showed better results with k = 0.968 for concavity, and the decision tree model showed k = 0.949 [45]. Facial landmarks have been majorly used in several studies that involve craniofacial identification, facial recognition, sex, and age determination. In forensic detection, facial analysis focuses on specific facial parameters, which are known as cephalometric landmarks [46,47]. In another study, facial growth (FG) direction was predicted using machine learning, where 2D images were used. Algorithms such as neural networks, ensemble networks, and logistic regression have been employed to counter the effects of time lapse. The analysis revealed the complexity and enumerated the causes of trouble in predicting the FG direction using 2D images, and the results of the particular method showed an accuracy of 71% to 75% [48].

Existing studies have elucidated the vivid suitability of the anatomical references for photo anthropometric explanation, which is an indirect application. This maximized the precision of the marking points, leading to enhanced reliability. Nevertheless, a majority of the work has concentrated on manual operations compromising the accuracy and reliability of the evaluation that are inherent to the investigators. With this notion, the progression and development of automated methods were studied in [42] to identify the landmarks of cephalometrics from images. For this purpose, the method used a combination of image processing methods and computer vision with a supervised ML approach, where image processing was done with detection of the face region and the training process followed after the detection. The result showed an increased accuracy compared to the manual methods with a dispersion value of 0.009 and a mean distance error value of 0.014. The below Table 2 gives the comparative analysis in terms of reliability and accuracy in landmark identification.

Table 2. Comparative Analysis of Landmark Identification in terms of Reliability and Accuracy.

S. No	References	Objective/Method	Accuracy/Outcome	Advantages/Disadvantages
1.	[49]	The study has endeavored to use a hybrid method to accomplish automatic CLA (Cephalometric Landmark Annotation) on CBCT (Cone Beam Computed Tomography) volumes.	Outcomes showed a mean-localization error of 2.51 mm.	• The hybrid system has explored that a quick initial two dimensional landmark-search could be valuable for optimal 3D-annotation. • This could also save computational time in comparison with the full-volume evaluation. • It has also been exposed that the full-bone structures from CBCT seem to be manageable in a PC (Personal Computer) for a three-dimensional modern cephalometry.
2.	[50]	Template-Matching algorithm has been used to perform automatic landmark identification on a three dimensional CBCT image.	Overall detection has been identified as 64.16% within 2 mm range, 85.89% within 3 mm range and 93.60% within 4 mm range.	Robustness of endorsed system has to be further tested for confirming its effectiveness.
3.	[43]	The research has assessed automatic three dimensional dense CMF (Craniomaxillofacial) phenotyping of human mandible through identification of outliers commonly known as meshmonk toolbox.	• ICC (Intraclass Correlation Coefficients) for multi-variational collection of 325-inter-landmark distances have all greater than 0.90, representing maximum similarity among the shapes quantified through automatic phenotyping or classic phenotyping. • Findings have explored optimal prediction.	• Optimal repetitive measurement • Reliability • Better accuracy
4.	[51]	The work has intended for testing the reliability and accuracy of ALI (Automated Landmark Identification) developed through Stratovan Corporation when compared with ground-truth undertaken by the human-judges.	Results showed that, 98% of the landmarks possessed MAE (Mean Absolute Error) lesser than 3 mm in comparison to human judges.	ALI has shown precise results in comparison to humans while determining the landmarks on similar image at distinct time interval.
5.	[52]	Template and Knowledge oriented method has been exploited for locating the landmarks in the three dimensional surface-model of a skull.	Localization error has been found to be at an average rate of 2.19 mm $\pm$ 1.5 mm in comparison with automatic landmarks for the reference location. Visual analysis proved the reliability of the suggested method.	Suggested system has confirmed to be an optimal alternative strategy for manual annotation of landmark and robust to deteriorating situation of skull.
6.	[53]	The research has intended for examining the prediction rates of NNM (Neural Network Models) and NBM (Naïve Bayes Model) trained with varied ratios of the cervical vertebra in cephalometric radiographs to find the growth as well as the development.	Better performance has been revealed by NNM with 0.95 success rate.	The study has disregarded landmark automation.

4. The Nexus of DL Approaches in 3D Cephalometric Analysis

In the recent epoch, researchers and scientists have seen rapid growth in studies that focus on deep learning methods used for oral, craniofacial, and oral imaging. In orthodontic diagnosis, precise cephalometric analysis is mandatory. Numerous steps have been taken to minimize the consumption of time by programming the process with machine learning since they can only extract data from one report. This research paper [54] aimed to implement a completely automated cephalometric analysis process through deep learning with related web-based applications without high-rise hardware. The method used here was a dataset composed of 2075 cephalograms and 23 landmarks from two reports and qualified two-staged programmed techniques with a fixed hourglass deep learning model for finding landmarks in pictures. In addition, the suggested algorithm was combined with a web-based application to attain a completely automated cephalometric analysis so that accessibility would be increased. The methods were evaluated with datasets from different devices and reports that included a broadly used dataset and attained a point-to-point error of 1.37 ± 1.79 mm with 23 cephalometric landmark ground truth positions. The analysis achieved 88.43% successful categorization. An existing study [2] aided in different clinical analyses and diagnoses. An investigation [55] outlined a quick and accurate method of confining anatomical landmarks in medical pictures. The method used a global to local detection method by fully convolutional neural networks—FCNNS. The FCNNS considers input images in a patch-based manner and estimates the position of numerous landmarks in global landmark localization. This method is followed by local analysis, which is a landmark distinguished by an FCNN. Calculating the median Euclidean distance and interquartile range among manually defined reference and computed estimated values. The results revealed a better processing time per scan on three datasets, namely, 2D cephalometric X-rays, 3D olfactory MR scans, and 3D CCTA scans. Such an investigation aided in locating the positions of numerous as well as single landmarks with numerous images.

This research proposed the cephalometric landmark identification model. This system has used two-neural networks that were pointed to analyze with patch classification and that are qualified with numerous scale patches, which was reduced from 935 cephalograms. Their shape and size were dependent on landmark-dependent conditions that were analyzed by orthodontists. This method found 22 hard tissues and 11 soft tissues. To evaluate the model, Euclidean distance errors among true and estimated values were analyzed. By using this analysis, this model identified the hard tissue landmark with an error of 1.32~3.5 mm and soft tissue landmark with an error of 1.16~4.37 mm. It has a success rate of about 75.2% [56].

One of the previous studies [57] addressed the obstacles through approaching classified deep learning technology. The technology is composed of four stages, where a basic landmark annotator is facilitated for skull-pose normalization of the 3D image; next, for the mid-sagittal plane, a deep learning landmark annotator is used. Following this, a variational auto encoder (VAE) is used for the representation of the landmarks, and finally, a local–global landmark annotator is used. The study implemented VAE that permits 2D image-based 3D phonological analysis with examination of differences and similarities of combined vectors of cephalometric landmarks. This method accomplished an average error of 3.63 mm for 93 landmarks of cephalometrics using qualified datasets. The VAE captured the difference in craniofacial structural appearance. The construction of learning datasets considered by specialists has permitted deep learning methods to identify landmarks in 2D cephalograms. However, there are complications in the applied method for 3D cephalometrics, as there is a requirement in a number of datasets. Another study developed an alternative approach with DL for automated analysis using 3D cephalometrics. For this purpose, the study used resampled image data and 3D-CNN in order to overcome the technical drawbacks of diagnosis. The study showed no landmark variance in the horizontal, midsagittal, and mandible plane [58].

Another study conducted a comparative analysis of the computational efficiency and accuracy of contemporary DL methods, namely SSD (Single-shot multi-box Detector) and YOLOv3 (You Only Look Once—version 3), in identifying cephalometric landmarks. For this purpose, the study selected a total of 1028 radiographic images as data for learning. A total of 80 target-labeling landmarks were selected. Testing of the algorithm was done with 283 images, and accuracy was calculated using the rate of success detection and point-to-point error. Scattergrams were used for visualization. The results of the study showed that YOLOv3 outperformed SSD with an accuracy rate of 38 landmark identifications out of 80, while the remaining 42 landmarks did not have a significant relationship. The YOLOv3 error plot showed a smaller range with a higher isotropic tendency. The mean computation times per image for SSD and YOLOv3 were 2.89 and 0.05 s, respectively. YOLOv3 showed an overall increase in accuracy of 5% compared to other existing works and proved that it can be suitably used for clinical practices [59].

5. Applications of Machine Learning in Orthodontics

The combined method of ML and medical imaging became significant, as it is a current trend in the medicinal field. Numerous articles have been published about the application of machine learning and the sub-category deep learning in several places in dentistry [60]. Many researchers have estimated the application of ML in clinical imaging [61]. However, no reviewer has been able to encapsulate the application of ML in oral, dental, and cranio-facial imaging. This is particularly true in dentistry and maxillofacial surgery. This review has attempted to summarize the application of ML in orthodontics, as well as a few in orthognathic surgery, by identifying the problem that persistently unsolved and predicting the enhancement of this technique in the research field. This review will be beneficial for specialists who are fascinated by AI, as well as dentists and maxillofacial and oral surgeons. The modified design of orthodontic treatment is fundamental and essential for cephalometric analysis. The foremost concerns for various malocclusion types are the ideal period of time for the treatment process, enduring therapeutic procedure, and optimum time. Therapeutic interventions aid in eradicating the seriousness of several conditions and detecting complications that affect the growth and development of the individual [62].

From cephalometric radiographs, orthodontists can improve the format of initial time through resolution of cervical vertebrae stage (CVS). Seven different AI techniques were used to implement a sequence of examination on CVS categorizations, namely artificial neural network (ANN) and estimating other condition [35]. These techniques estimate 2nd to 4th cervical vertebrae and category radiographs to stages of 6. These various stages were constantly employed to analyze the conclusions built on the time of the treatment. In evaluating real C-V-S with estimated C-V-S, ANN acquires maximum constancy through the result of AL techniques. In various phases of the area under the ROC (receiver operating characteristic curve—AUC) evaluation, the ANN and SVM attain maximum value. More importantly, SVM attains high-rise precision in founding CVS3 with CVS5, although ANN shows its specialty in further stages.

The purpose of SVM was to exploit the variations among dissimilar classes. ANN is suggested for CVS determination, as it can show both steadiness and high relative accuracy. A study conducted to compare the efficiency of ANN with manual inspection stated that compared to manual inspection, ANN was a little inferior [63]. Other studies have suggested that ANN with maximum accuracy enables the acquisition of CVS estimation of 86.9% for every radiograph with 13 linear marks [64]. These modifications may happen by implementing various calculation techniques. In orthodontics, AI-assisted methods have been deployed in many ways. To resolve the requirements of teeth extraction and orthognathic–orthodontic surgery, there is a chance of using ML, which has been discussed by various studies. Issues such as systematic errors, dull images, sounds, and artifacts can be vanquished through deep learning techniques [65–68]. By enhancing structural imagining and accurate evaluation, orthodontists, oncologists, and clinicians in different areas will benefit from minimizing computer-controlled denoising and metal artifacts. The two-dimensional landmark built using CNN established more accurate results. There is a lack of three-dimensional fields, as there is an absence of training in datasets that restricts the growth of ML in that field, as ML is structured to learn straight-form data [69]. Problems such as taking over a large period of time for computer programming and manual reporting are still prevalent, as several studies used manually processed images for data training; hence, these remain obstacles to the growth of AI-supported presentation in the clinical field.

In neural networks, presentations such as C-V-S and orthodontic–orthoganic operations established their dominance. The practice of picture processing aided in the application of techniques for the enhancement of programmed treatment of orthodontics. The completely programmed ML methods aid in image super imposition, induction of orthodontic treatments, and complete surgical process format [70]. 361 samples were studied for developing an ML model for orthognathic surgery with other denofacial deformities [71] to calculate the success rate of decision making in surgeries. For this purpose, 12 adjacent cephalometric estimations and six indexes were used as models. This existing study [72] has shown that ML can be implemented to examine the attractiveness of the face and the age appearance of orthognathic patience. A previous study [54] evaluated the facial appeal of fore-head and ten side images of left clip lip with ten convolution neural networks and determined that M-L is a dominating tool for facial appeal.

One of the previous studies approached machine learning, a subdivision of artificial intelligence. ML is the method of making models that have accomplished certain tasks accompanied by absolutely programming as a human for detection of complicated interlinks inside huge records. The study stated that ML was an enhancing methodology in orthodontics. Ordinary medical diagnostic methods are based on clinical analysis, lab analysis, clinical phenomena, and symptoms that take more time and are also slow processes. To overcome the above-mentioned issue, ML was implemented as they study and store data at great speed and resolve critical complications with constant analysis of stored information. The study explained the advantage of transferring the usual orthodontics to ML models, as they might have found concealed craniofacial trends in huge data of large patients with faster outcomes. It clarified that the ML showed the effects of skeletal defects and the phenomenon of renormalization on treatment and development. The results showed that ML will be used in collaboration with orthodontists to develop their clinical knowledge and performance. The Ml technique has been predominantly applied in various research and orthodontic practices [73].

This research stated that machine learning and artificial intelligence were anticipated for the revolution in digital analysis in medicinal methods through techniques to implement research on collected information. ML aided in the enhancement of performance by increasing the point of monotonous patterns and the large amount of available information. One of the existing studies has analyzed the superimposition of 3D clinical image of the skull and tissue of soft face with the intention of developing a virtual patient. This helps in absolute clinical analysis and induces treatment and documentation follow-up. It has improved interdisciplinary communications and tools in education in the dental sector. The results showed that the ML method intended to use arithmetic tools to increase results and enhance estimations from old records. ML minimizes human bias in the diagnosis and planning of treatment with fast report extraction [74]. Utilization of ML methods in analyzing X-ray images became a fundamental part of diagnosis. The current reviewed report states that ML showed 5–15% better accuracy in landmark identification. ML applied in programmed diagnosis from cephalograms counting with sagittal connections among maxilla and mandible also includes overbite and overjet ratios of posterior and anterior facial heights. With the help of an artificial neural network, analytical models were built to forecast the post-treatment peer assessment rating. This method correctly predicted a PAR score of 94.0%. Supervised ML techniques have shown better results when programmed in the clinical process in order to accomplish or assist diagnosis for the planning of treatment. Such techniques require qualified data that produce the desired outcome [75].

6. Challenges of ML in Cephalometric Analysis

Besides the enhancement of ML experimental performance, the aspect of revolutionizing the application of ML in orthodontics and other such fields requires substantial consideration, as there are certain challenges associated with machine learning algorithms [76]. One such challenge would be the presence of black-box features in machine learning, which requires an enhancement of the visuals and forming doctors' and patients' trust before clinical solicitation using ML [77]. Since the interpretability of the machine learning method remains a challenge, the adoption of clinical trials is necessary, as it can aid as robust medical evidence in supervision [73]. Such trial methods are required to control biased risk. For example, conducting reliability validation is essential through consistency validation [78]. Additionally, schemes of allocation have to be free from subjective biases. Further to this, the few other challenges, such as reproducibility crisis, overfitting, and data insufficiency, are found to delimit the application of ML cephalometrics. Such challenges are elucidated below.

6.1. Reproducibility Crisis

A huge number of studies have identified the issue of reproducibility crises in ML. This implies that the repetition of research results cannot be done if the same experimentation is performed by another set of researchers. This lies in the fact that such phenomena include deficiencies in metric knowledge and algorithms. In addition to this, a number of researchers disregard the result sensitivity to corresponding hyper-parameters, including initialization strategy, iteration times, and study rate [79,80].

6.2. Insufficiency of Data

The inconsistencies in the training data make the evaluation of various ML algorithmic models questionable. Even though the supervised model of ML is the apt choice for malocclusion diagnosis, the increased cost and requirement for labeling the target makes it difficult to make high-quality and standardized datasets for orthodontics [81].

6.3. Overfitting

A majority of ML models and other AI models are associated with the overfitting issue, which implies the prediction of unknown samples. Overfitting arises for numerous reasons, such as training and test data, which are derived from the same internal set of data. Hence, these models are countered with overfitting issues [82].

7. Critical Analysis

An analysis that has been performed by considering different focuses of the conventional works in cephalometric analysis is projected in Figure 1. The diverse concepts are summarized and considered for analysis based on the reviewed studies, which include cephalometric analysis using DL, AI in cephalometrics, ML, and orthodontics, AI-based cephalometric landmark-annotation, 3D cephalometry, and reliability and accuracy of automatic 3D cephalometric landmarking. This analysis assists in determining the particular cephalometric area that has gained maximum attention and has been researched in traditional works.

From the analytical conclusions, it is clear that 3D cephalometry, ML, and orthodontics have been researched by traditional articles at the same rate of 18%, while AI-based cephalometric landmark-annotation, reliability, and accuracy of automatic 3D cephalometric landmarking have been considered by existing works at an equal rate of 6%. On the other hand, cephalometric analysis using DL has been focused on at a rate of 22%, while AI in cephalometrics has been regarded by conventional works at a rate of 30%. Thus, from the analysis, it has been revealed that AI in cephalometrics has gained more attention in research than other considered concepts.

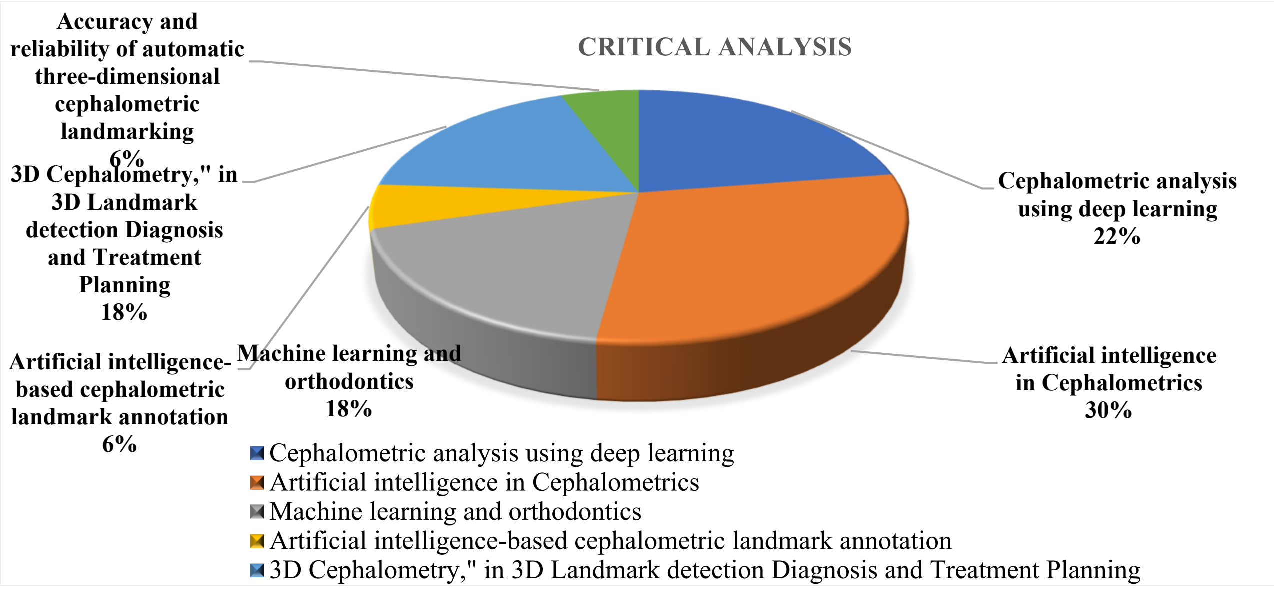

Figure 1. Critical evaluation of 3D cephalometry using different conventional methodologies.

8. Future Scope

With the technical advancements in medical diagnosis, decision-making, and surgical planning have been so fruition. However, there are certain CDSS that have gained a little attention. In addition, clinicians have to be more cautious regarding the predictions provided by ML and DL approaches. Owing to the growing prominence of ethical principles and medical responsibility, the legalization of efficient AI models is necessary to get into the scope. Furthermore, few-shot and transfer learning can serve as a better alternative to data insufficiency issues. Moreover, the external generalization capability of machine learning methods can be improved with versatile clinical scenarios that validate the model's performance. Overfitting can be avoided with dropout, regularization penalty, and early stopping. This will perhaps make ML- and DL-based analysis methods an ancillary tool and make the acquisition of the practice and theory of medical professionals faster and easier [83].

This review would have missed studying some of the ML methods used in cephalometric analysis, owing to language and year constraint criteria. However, the overall aim is to extensively review the recent trends and techniques of machine learning methods in this specific area.

9. Conclusions

Machine learning is being exploited in orthodontic diagnosis due to its distinct advantages. Thus, this review endeavored to evaluate the contribution of ML to 3D cephalometric analysis. As different ML algorithms have been considered in traditional studies, a tabular analysis has been performed to explore those algorithms with their applications, merits, and demerits. In addition, the accuracy of the conventional approaches along with its advantages/disadvantages have also been tabulated. With the recent growth of DL approaches in 3D cephalometric analysis, the present review emphasizes the significance of DL in this area. Following this, ML applications in orthodontics and ML challenges in cephalometric analysis were discussed. It was found from the review that the ML model's external generalization ability could be improved with adaptable clinical scenarios. In addition to this, overfitting could also be averted with regularization penalty, initial stopping, and dropout. These suggestions will transform ML-based analytical techniques into supplementary tools for assisting medical practitioners in reliable and fast prediction.

Such discussions will also help researchers resolve the pitfalls of ML and employ it to accomplish maximum reliability in cephalometric studies. Additionally, a critical analysis was performed to reveal the particular cephalometric area that had obtained maximum attention. From the analysis, it was found that AI in cephalometrics gained more attention than other considered concepts. Moreover, in comparison to ML, DL algorithms have gained more attention at a rate of 22%. This critical research will assist researchers and clinicians in comprehending several aspects of this area.

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