Advances in Artificial Intelligence and Machine Learning; Review 4 (3) 2731-2745 Received 17-07-2024; Accepted 23-09-2024; Published 30-09-2024

Predicting Mandibular Bone Growth Using Artificial Intelligence and Machine Learning: A Systematic Review

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Abstract

Introduction. The accurate prediction of mandibular bone growth is crucial in orthodontics and maxillofacial surgery, impacting treatment planning and patient outcomes. Traditional

Citation: Mahmood Dashti, et al. Predicting Mandibular Bone Growth Using Artificial Intelligence and Machine Learning: A Systematic Review. Advances in Artificial Intelligence and Machine Learning. 2024;4(3):159.

methods often fall short due to their reliance on linear models and clinician expertise, which are prone to human error and variability. Artificial intelligence (AI) and machine learning (ML) offer advanced alternatives, capable of processing complex datasets to provide more accurate predictions. This systematic review examines the efficacy of AI and ML models in predicting mandibular growth compared to traditional methods.

Method. A systematic review was conducted following the PRISMA guidelines, focusing on studies published up to July 2024. Databases searched included PubMed, Embase, Scopus, and Web of Science. Studies were selected based on their use of AI and ML algorithms for predicting mandibular growth. A total of 31 studies were identified, with 6 meeting the inclusion criteria. Data were extracted on study characteristics, AI models used, and prediction accuracy. The risk of bias was assessed using the QUADAS-2 tool.

Results. The review found that AI and ML models generally provided high accuracy in predicting mandibular growth. For instance, the LASSO model achieved an average error of 1.41 mm for predicting skeletal landmarks. However, not all AI models outperformed traditional methods; in some cases, deep learning models were less accurate than conventional growth prediction models.

Discussion. The variability in datasets and study designs across the included studies posed challenges for comparing AI models' effectiveness. Additionally, the complexity of AI models may limit their clinical applicability. Despite these challenges, AI and ML show significant promise in enhancing predictive accuracy for mandibular growth.

Conclusion. AI and ML models have the potential to revolutionize mandibular growth prediction, offering greater accuracy and reliability than traditional methods. However, further research is needed to standardize methodologies, expand datasets, and improve model interpretability for clinical integration.

Keywords: Artificial intelligence, Machine learning, Mandibular growth, Orthodontics, Predictive modeling, Systematic review, Maxillofacial surgery.

1. INTRODUCTION

In the realm of modern medicine, Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing diagnostic and predictive capabilities [1]. These advanced technologies have transcended traditional methods, offering unprecedented accuracy and efficiency in analyzing complex datasets [2]. AI and ML algorithms can process vast amounts of medical data, identifying patterns and making predictions that were previously unattainable. Their application ranges from predicting disease outbreaks to personalizing treatment plans, showcasing their potential to transform healthcare [1]. This systematic review delves into one such innovative application: the prediction of mandibular bone growth using AI and ML.

Accurate prediction of mandibular bone growth is crucial in various medical and dental fields, particularly in orthodontics and maxillofacial surgery [3]. Understanding how the mandibular bone will develop can significantly impact treatment planning and outcomes for patients with congenital anomalies, trauma, or those undergoing corrective procedures. Traditional prediction methods often rely on linear growth models and clinician expertise [4], which can be limited by human error and the variability of individual growth patterns. AI and ML offer a more sophisticated approach by analyzing multifaceted data inputs, such as genetic, environmental, and anatomical factors, to provide more precise growth predictions.

The integration of AI and ML into mandibular growth prediction involves using various algorithms and models to analyze large datasets of patient information. Techniques such as neural networks, support vector machines, and decision trees are employed to identify and learn from patterns within the data. These models can continuously improve their accuracy as they are exposed to more data, offering dynamic and adaptive prediction capabilities. Research has demonstrated that AI and ML can outperform traditional prediction methods [5–10], providing more reliable forecasts that can aid clinicians in making better-informed decisions and improving patient outcomes.

In this systematic review, we test the following null hypothesis: AI and ML models do not significantly improve the accuracy of mandibular bone growth predictions compared to traditional prediction methods. By evaluating existing studies and data, this review aims to determine whether the advancements in AI and ML offer a substantial benefit over conventional approaches, thereby establishing their potential role in enhancing predictive precision in clinical settings.

2. MATERIAL AND METHODS

The systematic review conducted in this study extracted, selected, and screened research papers in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [11]. Specific search terms used, databases searched, and the timeframe of our search are detailed in TABLE 1.

Table 1: Keywords specific for each database.

Database	Keyword	Result
Pubmed	("Machine Learning"[Mesh] OR "Deep Learning"[Mesh] OR "Supervised Machine Learning"[Mesh] OR "Unsupervised Machine Learning"[Mesh] OR "Neural Networks, Computer"[Mesh] OR "artificial intelligence") AND ("mandibular growth")	7
Embase	('machine learning'/exp OR 'machine learning' OR 'deep learning'/exp OR 'deep learning' OR 'supervised machine learning'/exp OR 'supervised machine learning' OR 'unsupervised machine learning'/exp OR 'unsupervised machine learning' OR 'artificial neural network'/exp OR 'artificial neural network' OR 'artificial intelligence') AND ('mandibular growth')	6
Scopus	(TITLE-ABS-KEY ("Machine Learning") OR TITLE-ABS-KEY ("Deep Learning") OR TITLE-ABS-KEY ("Supervised Machine Learning") OR TITLE-ABS-KEY ("Unsupervised Machine Learning") OR TITLE-ABS-KEY ("Neural Network") OR TITLE-ABS-KEY ("artificial intelligence")) AND (TITLE-ABS-KEY ("mandibular growth"))	6
Scopus Secondary	(TITLE-ABS-KEY ("Machine Learning") OR TITLE-ABS-KEY ("Deep Learning") OR TITLE-ABS-KEY ("Supervised Machine Learning") OR TITLE-ABS-KEY ("Unsupervised Machine Learning") OR TITLE-ABS-KEY ("Neural Network") OR TITLE-ABS-KEY ("artificial intelligence")) AND (TITLE-ABS-KEY ("mandibular growth"))	2
WOS	(TS=("Machine Learning" OR "Deep Learning" OR "Supervised Machine Learning" OR "Unsupervised Machine Learning" OR "Neural Networks, Computer" OR "artificial intelligence")) AND TS=("mandibular growth")	10

2.1 Screening

Initially, we screened studies based on their titles and abstracts, followed by full-text assessments for eligibility. Our criteria for inclusion and exclusion were strictly defined and adhered to. Eligibility: The selection process details, including the number of studies screened, assessed for eligibility, and included in the review, are documented in a PRISMA flow diagram (FIGURE. 1). Included Studies: We provided detailed summaries for each included study, including study characteristics, methodologies, and outcomes of interest (TABLE 2).

Table 2: Characteristics of the included studies.

Author	Country	Objective	Dataset size	Datasets Inclusion Criteria	Datasets Exclusion Criteria	Dataset Source
Kim et al. (2023) [5]	Japan	Predicting x- and y-coordinates of landmarks and lengths and angles used in orthodontics at age 13 using values from ages 6 to 12	59 individuals (27 males and 32 females)	Class II malocclusion or ANB > 3.5, no orthodontic treatment, analyzable radiographs	Poor quality cephalograms, craniofacial anomalies	Obtained annually from students enrolled at Shioiri Elementary School between 1965 and 1973.
Zakhar (2023) [6]	USA	Predicting Mandibular length and angle in Males with Class II Malocclusion at age 16 with 2 and 4 years prediction	123 males	Class II malocclusion or ANB > 3.5, no orthodontic treatment, analyzable radiographs	Craniofacial anomalies, asymmetries, missing teeth (excluding third molars), incomplete records	American Association of Orthodontists Foundation (AAOF) Craniofacial Legacy Collection(multicenter)
Zhang et al. (2023) [7]	China	predicting normal or overdeveloped mandible at post-18 in children with anterior crossbite based on values at age 8-14	296 individuals (142 males and 154 females)	Anterior crossbite, Class III or Class I molar relationship, ANB < 0°, no functional mandibular setback, aged 8–14 years, good quality cephalograms	Maxillary retrusion, anterior crossbite from misaligned teeth, congenital deformities, infection, trauma history	Zhejiang University School of Medicine Orthodontic Center
Wood et al. (2023) [8]	USA	Predicting Mandibular lengths and angle in Males with Class I Malocclusion at age 16 with 2 and 4 years prediction	163 males	Angle's Class I, no orthodontic treatment, analyzable radiographs	Craniofacial anomalies, skeletal asymmetries, missing timepoints, poor quality cephalograms	American Association of Orthodontists Foundation (AAOF) Craniofacial Legacy Collection(multicenter)
Asiri et al. (2021) [9]	USA	Predicting maxillomandibular relationships of class I/ II individuals at 15 based on radiographs at 10	222 individuals (116 males, 106 females)	Class I or Class II dental occlusion/ malocclusion Availability of two longitudinal cephalograms	Poor quality cephalograms, craniofacial anomalies	Three school districts representing the socioeconomic backgrounds of the Montreal area
Jiwa et al. (2020) [10]	USA	2-year prediction X and Y coordinates of mandibular landmarks	101 individuals (52 males and 49 Females)	Caucasian descent, 10 or more time points, fiducial landmarks for calibration, skeletal Class I, II, III, fraternal twins and siblings	Second monozygotic twin, orthodontic appliances, missing sequential cephalograms, craniofacial anomalies, Poor quality cephalograms	Forsyth Moorrees Twin Study

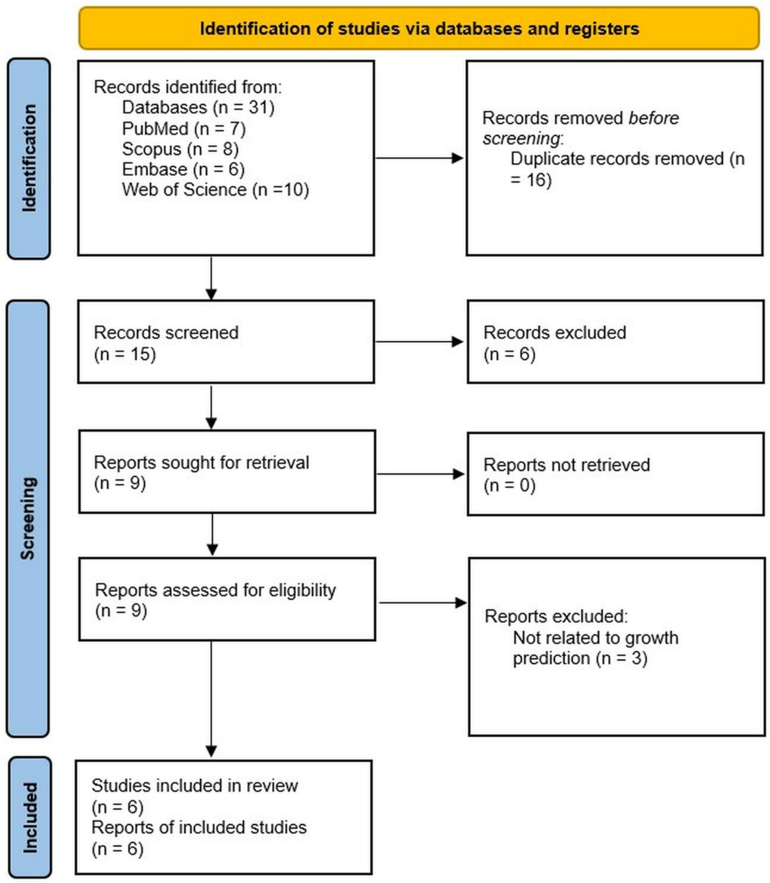

Figure 1: PRISMA flowchart.

2.2 Risk of Bias Assessment

The risk of bias in individual studies was assessed using established tools, influencing our findings' interpretation (TABLE 4). Synthesis of Results: We described methods of data extraction and synthesis, including statistical methods used for meta-analysis (FIGURE. 2).

Figure 2: QUADAS-2 assessment of the individual risk of bias domains and applicability concerns.

The framed research was "Are artificial intelligence and machine learning algorithms capable of predicting the growth of mandibular bone?"

2.3 Eligibility Criteria

For the systematic review, the following inclusion criteria were applied: 1) studies utilizing AI and ML algorithms for prediction the mandibular growth; 2) claims of growth predication for their results; 4) publications up to July 2024, anticipating inclusion of recent deep learning-related data; and 5) English-only publications. Only research meeting these prerequisites was included. Excluded were studies that: 1) conducted a scoping review, systematic review, or meta-analysis; 2) were published in languages other than English; 3) did not focus on mandibular growth prediction.

2.4 Research Strategy and Screening

Our systematic approach to finding and evaluating research articles involved using five different databases: PubMed, Scopus, Scopus Secondary, Embase, and Web of Science, limited to publications up until July 2024. The PRISMA guidelines were followed in the study selection process for inclusion in the meta-analysis. TABLE 1 lists the keywords used for each database, carefully chosen to analyze articles from different fields. Titles and abstracts were independently evaluated by two reviewers (S.S. and N.Z.), with a third reviewer (M.D.) resolving any disputes. All studies meeting the eligibility criteria with full texts available were included.

TABLE 2 presents the data extracted from study articles. Information was gleaned based on study features such as author, publication year, country of study, objective, dataset size, dataset inclusion criteria, dataset exclusion criteria, and dataset source. TABLE 3 presents the data extracted such as Author, year, objective, AI models, Result, and best predicting parameter. Studies employing multiple test datasets or model types were thoroughly extracted.

Table 3: Data extracted from the included studies.

Author	Objective	Ai models	Results	Best Predicting Parameter
Kim et al. (2023) [5]	Predicting x- and y-coordinates of landmarks and lengths and angles used in orthodontics at age 13 using values from ages 6 to 12	Multiple Regression Analysis (MRA) Least Absolute Shrinkage and Selection Operator (LASSO) Radial Basis Function Network (RBFN) Multilayer Perceptron (MLP) Gradient-Boosted Decision Tree (GBDT)	**Prediction of Skeletal Landmark Coordinates** MRA: Average error 2.49 mm LASSO: Average error 1.41 mm RBFN: Average error 8.34 mm MLP: Average error 4.66 mm GBDT: Average error 3.43 mm **Prediction of Skeletal Linear Parameters** MRA: Average error 2.45 mm LASSO: Average error 1.49 mm RBFN: Average error 4.81 mm MLP: Average error 3.29 mm GBDT: Average error 2.24 mm **Prediction of Skeletal Angular Parameters** MRA: Average error 4.31° LASSO: Average error 1.94° RBFN: Average error 6.24° MLP: Average error 4.44° GBDT: Average error 3.02°	Coordinate Values: Porion and Condylion Linear Parameters: N–ANS Angular Parameters: NSGn (Lasso Model)
Zakhar (2023) [6]	Predicting Mandibular length and angle in Males with Class II Malocclusion at age 16 with 2 and 4 years prediction	XGBoost Random Forest Lasso Ridge Linear Regression Support Vector Regression (SVR) Multilayer Perceptron (MLP)	**Mandibular Length Prediction (2-Year)** Lasso: 98.35% Ridge: 98.21% MLP: 97.93% XGBoost: 97.81% Random Forest: 97.79% SVR: 97.23% Linear Regression: 95.26% **Mandibular Length Prediction (4-Year)** Lasso: 98.19% Ridge: 97.95% MLP: 97.59% XGBoost: 97.50% SVR: 97.33% Random Forest: 97.23% Linear Regression: 95.88% **Mandibular y-Axis Prediction (2-Year)** Lasso: 98.76% Random Forest: 98.30% XGBoost: 98.26% SVR: 98.10% MLP: 98.11% Ridge: 97.95% Linear Regression: 96.02% **Mandibular y-Axis Prediction (4-Year)** Lasso: 98.18% XGBoost: 97.79% MLP: 97.83% Ridge: 97.56% Linear Regression: 97.59% Random Forest: 97.50% SVR: 97.50%	**2-Year Mandibular length Prediction:** Mandibular length Facial angle **4-Year Mandibular length Prediction:** Mandibular length Age **2,4-Year mandibular y-Axis Prediction:** y-axis at earlier time points SN-MP (Sella-Nasion to Mandibular Plane) (Lasso Model)

Table 3: Continued..

Author	Objective	Ai models	Results	Best Predicting Parameter
Zhang et al. (2023) [7]	predicting normal or overdeveloped mandible at post-18 in children with anterior crossbite based on values at age 8-14	ResNet50	Sensitivity: 0.95 Specificity: 0.75 AUC: 0.9775	Chin: 100% Lower edge of the mandible: 70% Incisor teeth: 17.5% Airway area: 5%
Wood et al. (2023) [8]	Predicting Mandibular lengths and angle in Males with Class I Malocclusion at age 16 with 2 and 4 years prediction	Least Squares (Linear) Ridge Lasso Elastic Net XGBoost Random Forest Neural Network	**Mandibular Length Prediction (2-Year)** Least Squares: 95.80% Ridge: 97.35% Lasso: 97.46% Elastic Net: 97.43% XGBoost: 97.10% Random Forest: 97.64% Neural Network: 96.85% **Mandibular Length Prediction (4-Year)** Least Squares: 97.00% Ridge: 96.94% Lasso: 97.18% Elastic Net: 96.96% XGBoost: 97.30% Random Forest: 97.30% Neural Network: 97.33% **Mandibular y-Axis Prediction (2-Year)** Least Squares: 96.60% Ridge: 98.09% Lasso: 98.34% Elastic Net: 98.34% XGBoost: 98.00% Random Forest: 97.95% Neural Network: 98.16% **Mandibular y-Axis Prediction (4-Year)** Least Squares: 97.85% Ridge: 97.89% Lasso: 97.88% Elastic Net: 97.88% XGBoost: 97.52% Random Forest: 97.57% Neural Network: 97.79%	**2-Year Mandibular length Prediction:** Mandibular length Maxillary lengthLower face height **4-Year Mandibular length Prediction:** Mandibular length Maxillary lengthLower face height **2-Year mandibular y-Axis Prediction:** Y axis of growthLower face height Mandibular plane angle **4-Year mandibular y-Axis Prediction:** Y axis of growth Occlusal plane angle SNB angle (Lasso Model)
Asiri et al. (2021) [9]	Predicting maxillomandibular relationships of class I/ II individuals at 15 based on radiographs at 10	Decision Trees	Unpruned Decision Trees Accuracy: 85.4% Pruned Decision Trees Accuracy: 83.2%	Y-axis ANS-N-Pg NSB MPA
Jiwa et al. (2020) [10]		Deep Learning Algorithm (DLA) using a multilayer perceptron	DLA MAE for Skeletal Landmarks: 4.22 mm DLA MAE for Dental Landmarks: 4.18 mm DLA MAE for All Landmarks: 4.21 mm	ArticulareCondylionDC Point

2.5 Quality Evaluation

The methodological quality of the included studies was evaluated using the quality assessment of diagnostic accuracy studies-2 (QUADAS-2).15 This tool examines four components: patient inclusion, index tests, reference standards, and patient flowcharts throughout the study, including the exact order of index tests and reference standards. Each item was independently reviewed for potential bias risk by both authors (M.D., N.Z.). Risks of bias were categorized as ”low,” ”high,” or ”unclear,” with a third author involved when necessary. The results were analyzed according to ”patient participation,” ”methodology,” and ”outcome adequacy,” and the heterogeneity of findings across included studies was examined.

3. RESULTS

3.1 Study Selection

The systematic search identified a total of 31 articles. After removing duplicates, 15 unique articles remained. Following title and abstract screening, 9 studies were selected for full-text review. Full-text screening was conducted by two assessors (MSS, MD), with conflicts resolved by a third reviewer (MS). Six studies met the inclusion criteria for the review. The reasons for exclusion included irrelevance to growth prediction (6 studies) and being review articles (3 studies). The included studies were assessed based on study type, design, dataset size, inclusion criteria, dataset origin, AI models used, and predictor factors.

3.2 Study Characteristics

Six articles were chosen to be included in the systematic review [5–10], the studies ranged from 2020 to 2023, with the majority published in 2023. Most were journal articles, with two being theses. The studies were conducted in various countries, including Japan, the USA, and China.

3.3 Dataset and Methods

All studies used cephalometric radiographs, with dataset sizes ranging from 59 to 296 individuals. Most studies included both male and female patients, except for two (Zakhar, Wood), which only included male individuals. Inclusion criteria for dataset samples varied among studies, including Class I, II, III, and anterior crossbite patients without orthodontic treatments. Common exclusion criteria were craniofacial anomalies, infection or trauma history, and low-quality radiographs. The source of datasets for each study is indicated in TABLE 1. Mandibular growth forecast periods ranged from 2 to 10 years, with some studies focusing on specific ranges (2 years, 4 years, and 5 years predictions).

The methodology of growth prediction varied based on each study’s objective. Kim et al. [5], predicted x- and y-coordinates of landmarks, lengths, and angles used in orthodontics at age 13 using values from ages 6 to 12. Zakhar et al. [6], provided 2 and 4-year forecasts of mandibular lengths and angles in individuals with Class II Malocclusion at age 16, and Zhang et al. [7], conducted a classification study predicting normal or overdeveloped mandibles at post-18 in children with anterior crossbite based on values from ages 8-14. Wood et al. [8], followed the same approach for Class I Malocclusion individuals. Asiri et al. [9], predicted maxillomandibular relationships of Class I/II individuals at age 15 based on radiographs taken at age 10 using decision trees. Jiwa et al. [10], focused on a 2-year prediction of X and Y coordinates of mandibular landmarks at age 19.

Various AI models were used across these studies, including traditional machine learning algorithms (e.g., Multiple Regression Analysis, LASSO, Ridge, Elastic Net, Random Forest, XGBoost, Decision Trees) and deep learning models (e.g., ResNet50, Customized Deep Learning Algorithms).

3.4 Results of AI Predictions

Detailed results of AI models in predicting mandibular growth and the most important predictor factors for each study are presented in TABLE 2. The Mean Average Error (MAE) for xy coordinates of landmarks varied from 1.41mm to 8.34mm. The accuracy for predicting mandibular lengths varied from 98.35% to 95.26%. The accuracy for predicting mandibular growth angles varied from 98.76% to 96.02%. For decision trees predicting maxillomandibular relationships, the accuracy was 85.4% for unpruned and 83.2% for pruned models. In classifying normal or overdeveloped mandibles in children with anterior crossbite, sensitivity was 0.95 and specificity was 0.75.

3.5 Comparison of AI with Non-AI Methods

Most studies did not include a direct comparison with other prediction methods. However, Jiwa et al. [10], compared the deep learning algorithm with Ricketts's growth prediction model using Dolphin Imaging$^{\mathrm{TM}}$ 11.9 software. The AI model had lower accuracy compared to Ricketts's growth prediction (MAE was 4.21mm for the AI model and 3.28mm for Ricketts's growth prediction). Zhang et al. [7], also compared their AI model with human predictors. The deep-learning model showed higher accuracy (85.0%) compared to three junior orthodontists with less than 5 years of experience (54.2%).

3.6 Risk of Bias Assessment

Risk of bias assessment was conducted according to QUADAS-2 tool (TABLE 4). All studies performed dental radiography interpretation accomplished by CNN techniques. There was no risk of bias in terms of patient's selection in none of mentioned studies. One study (Kim et al.) have mitigate unclear explanation of index test and so, there was a risk of bias. Also another study (SAFEER) failed to clearly clarify the reference standard test employed. Single observation was the main reason for fail in standard reference test both in risk of bias and applicability concerns in mentioned study. Altogether all studies have low risk of bias according to mentioned tool.

Table 4: Risk of Bias and Applicability Concerns.

Study	Risk of Bias				Applicability Concern		
	Patient Selection	Index Test	Reference Standard	Flow and timing	Patient Selection	Index Test	Reference Standard
Kim et al. (2023) [5]	LOW	HIGH	LOW	LOW	LOW	HIGH	LOW
Zakhar (2023) [6]	LOW	LOW	LOW	LOW	LOW	LOW	LOW
Zhang et al. (2023) [7]	LOW	LOW	LOW	HIGH	HIGH	LOW	LOW
Wood et al. (2023) [8]	LOW	LOW	LOW	LOW	LOW	LOW	LOW
Asiri et al. (2021) [9]	LOW	LOW	LOW	LOW	LOW	LOW	LOW
Jiwa et al. (2020) [10]	LOW	LOW	LOW	HIGH	LOW	LOW	LOW

4. DISCUSSION

The integration of AI and ML in predicting mandibular bone growth represents a significant advancement in orthodontics and maxillofacial surgery. This systematic review critically evaluates the performance of various AI and ML models in forecasting mandibular growth, comparing them with traditional prediction methods. The findings of this review demonstrate that AI and ML can significantly enhance the accuracy and reliability of predictions, although certain challenges and limitations still need to be addressed.

4.1 Model Performance and Predictive Accuracy

The studies included in this review utilized a range of AI and ML models, such as neural networks, support vector machines, decision trees, and deep learning algorithms. The results indicate that these models generally provide high levels of accuracy in predicting mandibular growth. For instance, the LASSO model used by Kim et al. [5], achieved an average error of 1.41 mm for predicting skeletal landmarks, outperforming other models like Radial Basis Function Network and Gradient-Boosted Decision Tree. Similarly, Zakhar et al. [6], reported that their LASSO model achieved over 98% accuracy in predicting mandibular lengths and angles, highlighting the model's robustness and effectiveness in clinical applications.

However, not all AI models outperformed traditional methods. Jiwa et al. [10], found that their deep learning model was less accurate than Ricketts's growth prediction model, with a mean average error (MAE) of 4.21 mm compared to 3.28 mm for Ricketts's model. This suggests that while AI and ML offer promising tools for growth prediction, their performance can vary depending on the specific algorithm and dataset used. Moreover, Zhang et al. [7], demonstrated that AI models could surpass human experts in certain scenarios, as their deep learning model showed higher accuracy (85.0%) compared to junior orthodontists (54.2%).

4.2 Challenges and Limitations

Despite the promising results, several challenges were identified in the application of AI and ML for mandibular growth prediction. One major limitation is the variability in datasets and study designs across the included studies. The datasets varied significantly in size, demographic composition, and inclusion/exclusion criteria, which may have influenced the models' performance. For example, some studies focused on specific age groups or malocclusion classes, limiting the generalizability of the findings to broader populations.

Another challenge is the need for standardized methodologies to compare AI and ML models' performance effectively. The studies used different metrics for evaluating accuracy, such as mean average error (MAE) and sensitivity/specificity, making it difficult to draw direct comparisons between models. Additionally, the complexity of AI and ML models can make them less interpretable than traditional methods, posing a challenge for clinicians who need to understand and trust the predictions made by these algorithms.

4.3 Clinical Implications

The clinical implications of using AI and ML for mandibular growth prediction are significant. Improved prediction accuracy can lead to better treatment planning and outcomes, particularly in cases involving congenital anomalies, trauma, or complex orthodontic cases. AI models can also assist clinicians in making more informed decisions, potentially reducing the reliance on subjective judgment and experience. However, for AI and ML models to be fully integrated into clinical practice, it is essential to address the challenges mentioned above. Standardizing datasets and methodologies, improving model interpretability, and ensuring continuous model validation with new data are crucial steps toward achieving this goal. Moreover, collaboration between AI specialists and clinicians is necessary to ensure that the models are tailored to meet the specific needs of clinical practice.

5. CONCLUSION

In conclusion, AI and ML models hold significant potential for improving the accuracy and reliability of mandibular growth predictions. While some traditional models remain competitive, the adaptability and learning capabilities of AI offer a distinct advantage in handling complex and multifaceted data. However, to fully realize the benefits of AI in clinical settings, further research is needed to standardize methodologies, expand datasets, and enhance model interpretability. The successful integration of AI and ML into clinical practice will require ongoing collaboration between researchers, clinicians, and AI developers, ensuring that these technologies are used effectively to improve patient outcomes.

6. Acknowledgment

None.

7. FUNDING

None.

8. COMPETING INTEREST

None.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this work the M.D. and N.Z. used [ChatGPT 4 software program] to paraphrase, improve the readability and enhance the language. After using this tool/service, all of the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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