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# Digital Revolution in Healthcare: Applications of Artificial Intelligence in Cleft Lip and Palate Care

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**Abstract**

The purpose of this study was to identify the sub-areas of Artificial Intelligence that have been most utilized as well as their applications in individuals with cleft lip and palate. The electronic search was conducted using the following keywords: Artificial Intelligence; Machine Learning; Deep Learning; Neural Networks, Computer; Data Mining; Data Accuracy; Cleft Lip and Cleft Palate. The databases utilized were PubMed, Scopus, and Web of Science. The initial search yielded 756 articles, and after applying the eligibility criteria, 15 scientific studies were selected for the final sample. These articles were published between 2017 and 2024, with a peak in publications in 2023. Among the selected studies, 60% were conducted on the Asian continent. Additionally, 40% applied artificial intelligence for diagnostic and automated detection purposes, while 60% utilized images as a key component of their datasets. Notably, 66.7% of the studies employed exclusively deep learning algorithms. Overall, the vast majority of the studies (93.35%) reported satisfactory performance of the AI tools implemented. It can be concluded that artificial intelligence-particularly through deep learning, and machine learning-has been widely employed in the diagnosis and, to a lesser extent, in the treatment of individuals with cleft lip and palate, with emphasis on the use of imaging exams and good accuracy.

**Keywords:** Cleft Lip, Cleft Palate, Artificial Intelligence, Machine Learning, Deep Learning

## Introduction

Artificial intelligence (AI) has transformed various areas of knowledge, driving significant advances in education, engineering, and healthcare (Topol, 2019) [1]. Within this broad toolkit, distinct AI subfields—such as deep learning, neural networks, and machine learning-have been extensively researched and applied to optimize processes and enhance decision-making (Choi *et al*., 2020; Kufel *et al*., 2023) [2, 3]. Deep learning relies on deep neural networks that simulate human brain functionality. These networks comprise multiple processing layers that progressively refine data interpretation, enabling the identification of elements previously requiring human intervention (Choi *et al*., 2020; Kufel *et al*., 2023) [2, 3]. Neural networks, foundational to deep learning, draw inspiration from the biological structure of neurons and are deployed across diverse applications—from image recognition to medical diagnostics (Choi *et al*., 2020; Kufel *et al*., 2023) [2, 3]. Machine learning, in turn, is a broader concept encompassing algorithms capable of learning from data and improving their performance over time (Krishnan *et al*., 2023) [4].

In the healthcare field, one of the most promising applications of artificial intelligence lies in assisting the diagnosis and treatment of conditions like cleft lip and palate—the most prevalent craniofacial anomaly (Almoammar *et al*., 2024) [5]. This congenital malformation, characterized by an opening in the lip (unilaterally or bilaterally) and/or palate, significantly impacts quality of life by compromising anatomical and physiological functions such as feeding, speech, breathing, and hearing (Almoammar *et al*., 2024) [5]. The development of AI in healthcare has enabled remarkable advances in patient quality of life, providing more precise tools for personalized diagnostics and treatments (Alowais *et al*., 2023; Ambrosio *et al*., 2025) [6, 7]. The ability of artificial intelligence to analyze large volumes of data and identify patterns contributes significantly to modern medicine, enabling healthcare professionals to make evidence-based decisions (Khairullah *et al*., 2025) [8]. These advances reinforce AI's crucial role in the future of healthcare, promoting accessibility and effectiveness in medical care (Khairullah *et al*., 2025) [8].

Conducting a literature review on artificial intelligence (AI) and cleft lip and palate is essential to understand the potential of this technology in the care and health assistance of individuals affected by this craniofacial anomaly. The purpose of this study was to identify the sub-areas of Artificial Intelligence that have been most utilized as well as their applications in individuals with cleft lip and palate.

## Material and Methods

### Search Strategy

In the electronic search, the following keywords were used: Artificial Intelligence; Machine Learning; Deep Learning; Neural Networks, Computer; Data Mining; Data Accuracy; Cleft Lip and Cleft Palate. All terms are indexed in the Medical Subject Headings (MeSH - https://www.ncbi.nlm.nih.gov/mesh/). Additionally, the Boolean operator AND was applied to the searches. The databases utilized were PubMed (https://pubmed.ncbi.nlm.nih.gov), Scopus (https://www.scopus.com/search/form.uri?display=basic#basic), and Web of Science (https://www.webofscience.com/wos/woscc/smart-search). Studies published between January 1, 2004, and September 1, 2024, were included.

The inclusion criteria for the literature review were defined as follows:

- Application scope: studies applying AI in the diagnosis and/or treatment of individuals with cleft lip and palate;
- Algorithm specification: articles must report the specific AI algorithm used and its accuracy metrics;
- Study design: original research, case-control studies, longitudinal observational studies, and retrospective cross-sectional studies;
- Accessibility: full-text availability.

The exclusion criteria established for this literature review were as follows:

- Study types: case series, case reports, reviews, pilot studies, methodology protocols, conference proceedings, editorials, and errata;
- Software dependency: articles analyzing data through AI-powered software without novel algorithmic development or validation;
- Comorbidity focus: studies examining cleft lip and palate alongside associated pathologies (e.g., syndromic conditions);
- Language restriction: articles published in languages other than English.

The following elements were systematically extracted from each included study:

- Authors and year;
- Study objective: primary research goals or hypotheses;
- Sample;
- AI algorithm: specific techniques and architectures;
- Findings: key quantitative/qualitative results (e.g., accuracy, sensitivity);
- Authors' analysis: interpretation of results.

## Results

### Study Selection

The initial sample of the study consisted of 756 articles identified in the databases (PubMed, Web of Science, and Scopus) after searching with the selected keywords. 381 studies were excluded due to duplication; subsequently, 335 were removed after abstract screening. As a result, 40 articles underwent full-text review, and after applying the eligibility criteria, the final sample comprised 15 scientific studies. Fig 1, Table 1.

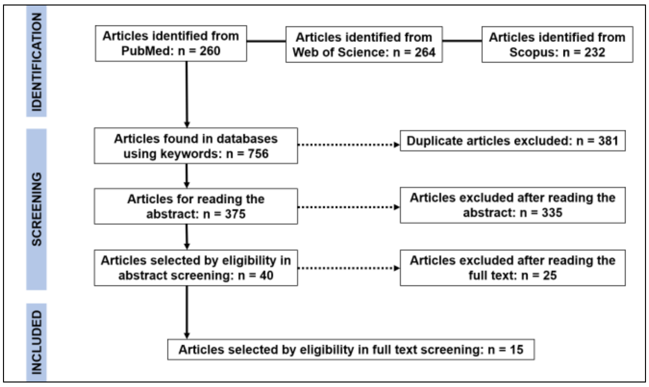


**Fig 1:** Flow diagram for articles searched

### Overview of Studies

In general, the selected articles were published between 2017 and 2024, with the peak of publications occurring in 2023.

In total, 60% (n=9) of the studies were conducted on the Asian continent (3 in China; 3 in Japan; 2 in South Korea; 1 in South Korea and China) (Ha *et al*., 2023, Kang *et al*., 2023, Lin *et al*., 2021, Wang *et al*., 2019, Zhang *et al*., 2018, Xu *et al*., 2023, Kuwada *et al*., 2023, Kuwada *et al*., 2023, Kuwada *et al*., 2021) [9-17], 26.66% (n=4) in the Americas (2 in Brazil; 1 in the United States; 1 in the United States, Argentina, Brazil, and Colombia) (Ragodos *et al*., 2022, Sayadi *et al*., 2022, Silva *et al*., 2023, Machado *et al*., 2021) [18-21], 6.67% (n=1) in Europe (1 in Sweden) (Cornefjord *et al*., 2024) [22], and another 6.67% (n=1) involved all three continents mentioned previously (1 in the United States, Brazil, Italy, France, and Saudi Arabia) (Miranda *et al*., 2023) [23], Table 1.

### Individual Study Characteristics

Concerning the aim of the studies, 40% (n = 6) applied AI for diagnostic and automated detection purposes (Ha *et al*., 2023; Wang *et al*., 2019; Kuwada *et al*., 2023; Kuwada *et al*., 2021; Ragodos *et al*., 2022; Cornefjord *et al*., 2024) [9, 12, 15, 17, 18, 22], 20% (n = 3) for risk prediction and genetic modeling (Kang *et al*., 2023; Zhang *et al*., 2018; Machado *et al*., 2021) [10, 13, 21], 13.35% (n = 2) for treatment planning and severity classification (Lin *et al*., 2021; Miranda *et al*., 2023) [11, 23], 13.35% (n = 2) for detection and annotation of anatomical landmarks in examinations (Xu *et al*., 2023; Sayadi *et al*., 2022) [14, 19], 6.65% (n = 1) for analysis of associated factors and data mining (Silva *et al*., 2023) [20], and 6.65% (n = 1) for assessment of AI model performance (Kuwada *et al*., 2023) [16], Table 1.

Among them, it was found that 60% (n=9) of the studies used images in their samples, including 4 radiographs (Lin *et al*., 2021; Kuwada *et al*., 2021; Kuwada *et al*., 2023; Kuwada *et al*., 2021) [11, 15-17]; 2 photographs (Ragodos *et al*., 2022 and Sayadi *et al*., 2022) [18, 19]; 2 computed tomography scans (Xu *et al*., 2023 and Miranda *et al*., 2023) [14, 23] (CBCT); 1 videofluoroscopy (Ha *et al*., 2023) [9], 20% (n=3) used single-nucleotide polymorphism (SNP) data (Kang *et al*., 2023; Zhang *et al*., 2018; Machado *et al*., 2021) [10, 13, 21], 13.33% (n=2) used voice data (Wang *et al*., 2019; Cornefjord *et al*., 2024) [12, 22], and 6.67% (n=1) used medical record data (Silva *et al*., 2023) [20], Table 1.

**Artificial Inteligence and Findings**

Regarding algorithms, it was found that 66.7% (n = 10) of the studies used exclusively deep learning algorithms (Ha *et al*., 2023; Kuwada *et al*., 2023, Kuwada *et al*., 2023, Xu *et al*., 2023, Ragodos *et al*., 2022, Sayadi *et al*., 2022, Kuwada *et al*., 2021, Wang *et al*., 2019; Cornefjord *et al*., 2024; Miranda *et al*., 2023) [9, 22, 23], 13.3% (n = 2) employed machine learning (Silva *et al*., 2023, Lin *et al*., 2021), and 20% (n = 3) combined multiple AI methods (Kang *et al*., 2023; Zhang *et al*., 2018; Machado *et al*., 2021) [10, 13, 21]. In terms of performance analysis, only one study (6.65%) reported suboptimal tool performance compared to other studies (Cornefjord *et al*., 2024) [22], Table 1.

**Table 1:** Articles selected according to inclusion and exclusion criteria

| Authors | AIM | Sample | AI Model | Findings | Analysis of the Authors Regarding the Findings |
|---|---|---|---|---|---|
| **Cornefjord *et al*., 2024** [22] | Assess velopharyngeal function. | Audio recordings from 162 children diagnosed with unilateral cleft lip and palate, bilateral cleft lip and palate, or isolated cleft palate. | Convolutional neural network (CNN) and a pre-trained CNN (VGGish). | VGGish demonstrated superior performance over CNN, achieving an accuracy of 57.1% compared to 39.8%. | The overall performance was inferior to that demonstrated in previous studies. |
| **Ha *et al*., 2023** [9] | Comparative analysis of diagnostic performance between artificial intelligence algorithms and experienced plastic surgeons in identifying velopharyngeal insufficiency. | 714 images from videofluoroscopy. | VGGNet, ResNet, Xception, ResNext, DenseNet, and SENet | The algorithms achieved Area Under the Receiver Operating Characteristic curve (AUC-ROC) values ranging from 0.8758 to 0.9468. | The algorithms demonstrated performance equivalent to that of plastic surgeons. |
| **Kang *et al*., 2023** [10] | Risk prediction modeling for nonsyndromic cleft lip with or without cleft palate (NSCL/P). | Ninety-two single nucleotide polymorphisms (SNPs) were genotyped across 143 children with NSCL/P and 119 healthy controls. | Genetic-algorithm-optimized neural networks ensemble (GANNE), support vector machine (SVM), random forest (RF), extreme gradient boosting (XGBoost), logistic regression (LR), light gradient boosting model (LGBM), and adaptive boosting (ADA). | Accuracy and predictive power (AUC) peaked when using only 10 selected SNPs, achieving an AUC of 88.2% – a 23% gain over polygenic risk score (PRS) and 17% over artificial neural networks (ANN). The deep learning model GANNE demonstrated superior performance for predicting genetic risk of NSCL/P. | Classification accuracy peaked at 10 SNPs, with performance declining as the number of input SNPs increased. |
| **Kuwada *et al*., 2023** [15] | Diagnostic assessment of cleft palate presence in patients with unilateral or bilateral cleft alveolus. | Panoramic radiographs from 491 patients. | DetetecNet and VGG-16 | DetectNet achieved perfect detection of the upper incisor region (recall, precision, F1 = 1.00) and an AUC of 0.95 for cleft palate classification (sensitivity 96%, specificity 93%). VGG-16 obtained an AUC of 0.93 (sensitivity 100%, specificity 86%). Radiologists showed significantly lower performance, with AUCs of 0.70 and 0.63. | The models developed in this study demonstrate potential as decision-support tools for detecting cleft palate in panoramic radiographs. |
| **Kuwada *et al*., 2023** [16] | Assess how image classes and training data volume influence deep-learning models for unilateral cleft alveolus (UCA)/bilateral cleft alveolus (BCA) detection on panoramic radiographs, to build a clinical model. Performance compared with human observers. | Panoramic radiographs from 353 patients with UCA and 93 patients with BCA were analyzed. | Four DetectNet-based deep learning models, Model U: trained on UCA and normal images (NI); Model B: Trained on BCA and NI; Model C1: Combined UCA, BCA, and NI; Model C2: Combined UCA, BCA, and NI. | Model C2 achieved optimal performance in detecting alveolar clefts on panoramic radiographs, with a precision of 0.98 and an F-measure of 0.92. Its results were comparable to those of human radiologists, who achieved a recall of 0.93, precision of 0.98, and an F-measure of 0.95. | The DL models trained with both UCA and BCA data (Models C1 and C2) demonstrated high detection performance. Additionally, the results indicate that the amount of training data can significantly impact the effectiveness of a deep learning model. |
| **Miranda *et al*., 2023** [23] | To create and test an artificial intelligence algorithm capable of automatically classifying the severity of the alveolar bone defect in patients with cleft lip and palate (CLP). | Cone-beam computed tomography (CBCT) scans from 194 patients with CLP were analyzed. | CNN | The AI classifier achieved a precision of 0.823, recall of 0.816, and accuracy of 81.6% for classifying alveolar bone defect severity. | A consistently high overall precision. |
| **Silva *et al*.,** | To use data mining techniques | Medical records of 222 | Decision Tree, DT | The DT model correctly classified | Data mining techniques |

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|---|---|---|---|---|---|
| **2023** [20] | to identify variables associated with the occurrence of fistulas after primary palatoplasty in patients with unilateral cleft lip and palate. | patients. | (J48/C4.5 algorithm) and Apriori algorithm. | 95.9% of cases. | were effective in identifying relevant predictor variables associated with the occurrence of fistulas. |
| **Xu *et al*., 2023** [14] | Develop and test an AI-based automated system for precise identification of anatomical landmarks. | CBCT scans from 117 patients with cleft lip and palate. | Graph convolutional neural network (GCN) - PointNet++ | Precision: Mean Distance Error (MDE) of 1.33 mm for 27 craniofacial landmarks; Detection Rate (SDR): 9 landmarks (30%) achieved SDR >90% at 2 mm error tolerance; Efficiency: Processing time of 16 seconds per dataset. | High accuracy, robustness, and clinical potential of the applied method. |
| **Ragodos *et al*., 2022** [18] | Create and test a deep learning model capable of automatically identifying dental anomalies in intraoral photos. | 38,486 intraoral photographs from 4,084 individuals (765 children with orofacial cleft and 3,319 controls). | ResNet-18 | Mean AUC-ROC ranged from 0.683 to 0.872, with the best performance for agenesis (AUC 0.678) and the lowest for rotated teeth (AUC 0.562). Precision (PPV) ranged from 0.374 to 0.534, and sensitivity (recall) ranged from 0.619 to 0.868. | The developed model shows great potential to rapidly identify dental anomalies. |
| **Sayadi *et al*., 2022** [19] | Develop and test an artificial intelligence model capable of automatically recognizing the main anatomical landmarks of the lip and nose region. | A total of 345 two-dimensional photographs of infants and children with unilateral cleft lip were used in this study. | High-Resolution Net architecture. | The model detected 21 anatomical landmarks with a normalized mean error (NME) ranging from 0.029 to 0.055. | The model was successful in automatically identifying and marking the anatomical landmarks. |
| **Kuwada *et al*., 2021** [17] | Develop and validate a diagnostic system to detect and classify cleft alveolar (CA). | 593 panoramic radiographs. 383 patients with CA and 210 patients without CA. | DetectNet. | Overall accuracy: 82.2% in the detection and classification of CA. Precision: 0.85–0.88 for CA. | The model created in this study appeared to have the potential to detect and classify CAs on panoramic radiographs, and might be useful to assist the human observers |
| **Lin *et al*., 2021** [11] | Determine which cephalometric variables can early predict the future need for orthognathic surgery. | Lateral cephalograms of 56 individuals with non-syndromic unilateral cleft lip and palate. | XGBoost algorithm | Accuracy of 87.4%, with sensitivity of 97.83% (the ability to correctly identify patients who would not require surgery) and specificity of 90%. | The results of the study are positive and relevant for clinical practice. |
| **Machado *et al*., 2021** [21] | Genetic risk evaluation for nonsyndromic cleft lip with or without cleft palate (NSCL ± P). | 1,588 individuals (722 patients with NSCL ± P and 866 without NSCL ± P). 72 SNPs previously associated with NSCL ± P; Single Single Nucleotide Polymorphism (SNP) | Random forest (RF) and artificial neural network (ANN). | RF: Identified 13 SNPs with high predictive importance for NSCL ± P risk; accuracy of 99%. ANN: Validated the same 13 SNPs, achieving 94.5% overall accuracy. | The results obtained are innovative and promising for the prediction of genetic risk. |
| **Wang *et al*., 2019** [12] | Develop an automatic system based on a deep recurrent neural network to detect hypernasality in the speech of children with cleft palate (CP). | Voice recordings from 144 children (72 with CP and hypernasality and 72 children without speech disorders as the control group). | Long Short Term Memory - Deep Recurrent Neural Network (LSTM-DRNN) | Maximum accuracy of 93.35% in the automatic detection of hypernasality. | High accuracy, robustness, and capacity for acoustic feature classification for hypernasality detection. |
| **Zhang *et al*., 2018** [13] | Develop and evaluate models for the genetic risk assessment of NSCL/P. | 382 patients with NSCL/P and 709 without NSCL/P. | Logistic Regression (LR) Support Vector Machine (SVM) Random Forest (RF) Naive Bayes (NB) K-Nearest Neighbor (KNN) Decision Tree (DT) Artificial Neural Network (ANN). | LR, AUC = 0.90 (best performance for genetic risk assessment). SVM and RF, AUC = 0.89. NB, KNN, DT, ANN, AUC ranging from 0.83 to 0.88. | The models are promising for the genetic risk assessment of NSCL/P. |

**Discussion**

Artificial intelligence has proven to be a promising tool in the healthcare field and has been utilized in the multidisciplinary management of individuals with cleft lip and palate (Almoammar KA, 2024) [5]. For professionals working with craniofacial anomalies, it is essential to understand the applications, the AI algorithms that have been used, and the accuracy of these tools—factors that are becoming increasingly indispensable and represent a key distinction of the present study, given that this information is still scarce in the scientific literature.

Overall, studies on cleft lip and palate and AI have been conducted worldwide, yet this review highlights that 60% of the research originated from the Asian continent. While some reviews (e.g., Almoammar KA, 2024) [5] did not evaluate study localities, others similarly reported over 50% Asian contributions (Dhillon *et al*., 2021; Huqh *et al*., 2022) [24, 25]. A possible explanation for this Eastern predominance may relate to the higher prevalence of cleft lip and palate in Asian populations, as epidemiological studies indicate (Salari *et al*., 2022; Zhou *et al*., 2023) [26, 27]. Another hypothesis, requiring further validation, suggests that Southeast Asian countries are actively incentivized to develop AI-driven tools, potentially accelerating research in this region.

Among the applications of AI tools in healthcare, a key highlight is their capacity to assist professionals in decision-making for diagnosis, prognosis, and treatment planning (Crossnohere *et al*., 2022) [28], as well as in workplace management tasks. In the selected studies, most utilized AI for diagnostic purposes in individuals with craniofacial anomalies. Specific applications included: cleft risk diagnosis (Kang *et al*., 2023; Zhang *et al*., 2018) [10, 13], cleft presence detection (Kuwada *et al*., 2023; Kuwada *et al*., 2023; Kuwada *et al*., 2021) [15-17], bone defect assessment (Miranda *et al*., 2023) [23], predictors for future surgeries (Lin *et al*., 2021) [11], hypernasality evaluation (Wang *et al*., 2019) [12], velopharyngeal function analysis (Cornefjord *et al*., 2024) [22], dental anomaly identification (Ragodos *et al*., 2022) [18], anatomical landmark mapping (Xu *et al*., 2023) [14], and variables linked to fistula occurrence (Silva *et al*., 2023) [20]. This demonstrates AI's versatile role in addressing multifaceted clinical challenges in cleft care.

Another key observation is that among the selected studies, 7 utilized two-dimensional (2D) imaging exams such as radiographs (Lin *et al*., 2021; Kuwada *et al*., 2023; Kuwada *et al*., 2023; Kuwada *et al*., 2021) [11, 15-17], photographs (Ragodos *et al*., 2022; Sayadi *et al*., 2022) [18, 19], and videofluoroscopy (Ha *et al*., 2023) [9]. Two other studies employed computed tomography (CT)—a three-dimensional (3D) imaging technique (AAPD, 2024) [29]—but with divergent approaches: one study captured 2D images from CT scans to train a 2D Convolutional Neural Network (Miranda *et al*., 2023) [23], and another processed CT data into 3D point clouds using PointNet++ AI (Xu *et al*., 2023) [14]. This finding underscores AI's adaptability in analyzing tomographic data but also reveals a critical gap: future research must prioritize true 3D object analysis (e.g., dental arches, facial structures, and anatomical scans) to fully leverage volumetric data in craniofacial diagnostics.

The analysis of the selected articles reveals the rapid evolution and sophistication of artificial intelligence applications in orofacial clefts, with a clear division between approaches based exclusively on deep learning, traditional machine learning, and hybrid models. Studies such as those by Cornefjord *et al*. 2024 [22], Ha *et al*. 2023 [9], Kuwada *et al*. (2021 and 2023) [15-17], Miranda *et al*. 2023 [23], Xu *et al*. 2023 [14], Ragodos *et al*. 2022 [18], and Sayadi *et al*. 2022 [19] illustrate the dominance of deep learning in image-based diagnostics and automatic recognition tasks, often surpassing human specialists in both accuracy and speed. Conversely, authors like Silva *et al*. 2023 [20] and Lin *et al*. 2021 [11], demonstrate that classic machine learning algorithms still play a relevant role in clinical data analysis and outcome prediction, especially when interpretability and simplicity are desired. Studies by Kang *et al*. 2023 [10], Machado *et al*. 2021 [21] and Zhang *et al*. 2018 [13] highlight the strength of integrated approaches, combining different techniques to achieve maximum accuracy in complex scenarios such as genetic risk prediction. This methodological diversity not only expands the clinical application potential but also reinforces the need for tailored strategies for different contexts and data types in orofacial cleft care.

Among the studies included in this review, most of them employed algorithms neural network-based algorithms, such as convolutional neural networks (CNNs), deep learning architectures (e.g., DetectNet, VGG, ResNet), and artificial neural networks (ANNs) (Ha *et al*., 2023; Kang *et al*., 2023; Wang *et al*., 2019; Zhang *et al*., 2018; Xu *et al*., 2023; Kuwada *et al*., 2023; Kuwada *et al*., 2023; Kuwada *et al*., 2021; Ragodos *et al*., 2022; Sayadi *et al*., 2022; Machado *et al*., 2021; Cornefjord *et al*., 2024; Miranda *et al*., 2023) [9, 10, 12-19, 21-23]. This explicit quantification of AI methodologies-an aspect not addressed in previous reviews (Almoammar KA, 2024; Dhillon *et al*., 2021) [5, 24]-poses challenges for direct comparison with earlier literature. Nonetheless, detailing the specific AI techniques utilized in cleft lip and palate research is essential for advancing the field. The frequent use of neural networks observed in these studies likely reflects their strong diagnostic capabilities, offering improved efficiency and accuracy in clinical tasks (Ossowska *et al*., 2022) [30]. In line with these findings, the present review demonstrates that the majority of included studies applied AI models primarily for diagnostic purposes in the context of cleft lip and palate care (Ha *et al*., 2023; Wang *et al*., 2019; Kuwada *et al*., 2023; Kuwada *et al*., 2021; Ragodos *et al*., 2022; Cornefjord *et al*., 2024) [9, 12, 15, 17, 18, 22].

Artificial inteligence have demonstrated promising applicability in enhancing diagnostic efficiency and precision—an outcome supported by several of the studies analyzed (Ossowska *et al*., 2022) [30]. Many researchers leveraged AI models explicitly for diagnostic purposes, suggesting a strong alignment between neural network capabilities and clinical objectives. Additionally, the present review explored not only the use of AI but also critically assessed the reported accuracy of these tools and the evaluative rigor applied by the authors. Although accuracy assessment methods varied among the studies, the majority reported satisfactory outcomes (Ha *et al*., 2023; Kang *et al*., 2023; Lin *et al*., 2021; Wang *et al*., 2019; Zhang *et al*., 2018; Xu *et al*., 2023; Kuwada *et al*., 2023; Kuwada *et al*., 2023; Kuwada *et al*., 2021; Ragodos *et al*., 2022; Sayadi *et al*., 2022; Silva *et al*., 2023; Machado *et al*., 2021; Miranda *et al*., 2023) [9-21, 23]. This reinforces the importance of performance validation when considering AI for clinical translation. Importantly, an AI model's accuracy is deeply tied to the quality of its input data (e.g., imaging records) and, more significantly, the robustness of its training protocols (Dhillon *et al*., 2021) [24]. For healthcare professionals, understanding these factors is essential when evaluating whether such tools can be feasibly integrated into real-world practice.

The limitations of this literature review include the diversity of sample types comprising the database (radiographs, photographs, CT scans, videofluoroscopy, SNP data, voice recordings, and medical records) and the varied methodologies applied to evaluate artificial intelligence tool accuracy. Future research must prioritize clinical validation across all specialties involved in rehabilitation protocols. This represents a critical gap requiring assessment to determine whether AI models can effectively support diagnosis and treatment planning for professionals managing craniofacial anomalies—particularly cleft lip and palate

## Conclusion

It can be concluded that artificial intelligence—particularly through deep learning and machine learning—has been widely employed in the diagnosis and, to a lesser extent, in the treatment of individuals with cleft lip and palate, with emphasis on the use of imaging exams and good accuracy.

Despite these promising results, the heterogeneity of methodologies and the need for clinical validation highlight the importance of further studies to establish AI as an auxiliary tool in the multidisciplinary care of these patients.

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