ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

Beyond the Cleft: Can Artificial Intelligence Redefine the Future of Cleft Care

Dr. Vitika Rawal[1]; Dr. Renuka Pawar[2]; Dr. Chanamallappa R. Ganiger[3]; Dr. Sandesh Phaphe[4]; Dr. Yusuf A. Ronad[5]; Dr. Pratap Mane[6]; Dr. Seema Patil[7]

[1;2;3;4;5;6;7]School of Dental Sciences, Krishna Institute of Medical Sciences, Karad, Maharashtra, India

Publication Date: 2026/11/07

Abstract: Cleft lip and palate (CLP) represent a major group of congenital craniofacial conditions that require coordinated, long-term care involving multiple healthcare specialties. The increasing adoption of artificial intelligence (AI) in dentistry and orthodontics has opened new avenues for addressing the diagnostic and therapeutic complexities associated with cleft management. This narrative review examines the evolving applications of AI throughout the CLP treatment pathway, highlighting its potential contributions to clinical assessment, treatment planning, and outcome evaluation. The review considers seven key areas in which AI-based technologies may support cleft care. These include the identification of cleft anomalies from prenatal ultrasound and photographic images using deep learning algorithms; computer-assisted planning and digital fabrication of nasoalveolar molding appliances; automated localization of cephalometric landmarks in patients with atypical craniofacial structures; three-dimensional assessment and segmentation of alveolar bone grafts using cone-beam computed tomography (CBCT); radiographic identification of dental abnormalities frequently associated with CLP; predictive modelling of orthognathic surgical requirements and postoperative facial soft-tissue changes; and computerized analysis of speech patterns associated with velopharyngeal dysfunction. Research in these areas suggests that AI may improve the efficiency and consistency of diagnostic procedures, facilitate quantitative analysis, and assist clinicians in complex treatment decisions. However, the translation of these technologies into routine clinical practice remains challenging. Important barriers include limited sample sizes, inadequate representation of patient populations, insufficient validation across independent clinical settings, the possibility of algorithmic bias, and ethical issues related to patient data protection and professional accountability. For orthodontists involved in cleft care, AI offers opportunities to enhance clinical decision-making and streamline selected aspects of treatment. Nevertheless, its outputs must be interpreted in conjunction with comprehensive clinical examination, patient-specific findings, and multidisciplinary expertise. Future research should prioritize larger and more diverse datasets, independent clinical validation, transparent reporting, and evaluation of real-world patient outcomes to establish the reliability and clinical value of AI-assisted approaches in CLP management.

Keywords: *Cleft Lip and Palate, Alveolar Bone Grafting, Artificial Intelligence (AI), Cleft Lip & Palate, Cleft Orthodontics, Cleft Pediatric Oral Health, Craniofacial Growth and Development, Nasoalveolar Molding (Nam), Orthognathic Surgey, Plastic Surgergy, Prenatal Detection.*

How to Cite: Dr. Vitika Rawal; Dr. Renuka Pawar; Dr. Chanamallappa R. Ganiger; Dr. Sandesh Phaphe; Dr. Yusuf A. Ronad; Dr. Pratap Mane; Dr. Seema Patil (2026) Beyond the Cleft: Can Artificial Intelligence Redefine the Future of Cleft Care. *International Journal of Innovative Science and Research Technology*, 11(10), 3121-3130. https://doi.org/10.38124/ijisrt/26oct1612

I. INTRODUCTION

The treatment of cleft lip and palate (CLP) presents a significant challenge in craniofacial care because of the complexity of the condition and the need for coordinated treatment across several stages of growth. Management often begins during infancy and continues into early adulthood, involving collaboration among orthodontists, surgeons, and other specialists. Cleft-related orthodontic treatment differs considerably from conventional orthodontics because patients may present with altered craniofacial anatomy, maxillary deficiency, alveolar bone defects, dental malposition, and asymmetrical facial development. Throughout this prolonged treatment journey, clinicians must make important decisions at specific developmental stages, including presurgical infant orthopedics, secondary alveolar bone grafting (ABG), orthodontic preparation during adolescence, and orthognathic surgery when indicated [1].

Conventional diagnostic approaches in cleft care have primarily depended on two-dimensional (2D) radiographs, three-dimensional (3D) imaging, manual cephalometric analysis, and clinical expertise. Although these methods remain essential, the considerable anatomical variation observed in patients with syndromic and non-syndromic clefts can complicate accurate diagnosis and treatment

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

planning. The displacement, distortion, or absence of conventional anatomical landmarks may affect the reliability of cephalometric measurements and increase variability between examiners. Similarly, segmenting teeth, alveolar structures, and surrounding craniofacial tissues can be particularly challenging when anatomical boundaries are irregular or disrupted by the cleft defect. Another major concern is the difficulty of accurately anticipating craniofacial growth, treatment-related skeletal changes, and soft-tissue responses following orthodontic or surgical intervention.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has introduced new possibilities for improving diagnostic and planning procedures in digital dentistry. These computational approaches can process large volumes of clinical and imaging data, identify complex anatomical patterns, and automate tasks that traditionally require considerable clinician time. Convolutional neural networks (CNNs), for example, have been investigated for applications such as cephalometric landmark identification, tooth segmentation, and the analysis of craniofacial morphology [2]. However, applying these technologies to cleft orthodontics requires more than simply adapting algorithms developed for patients with typical craniofacial anatomy. AI systems must also account for the distinctive anatomical features associated with cleft deformities, including displaced teeth adjacent to alveolar defects, irregular bone contours, and asymmetrical maxillary development. Their clinical reliability therefore depends on the availability of representative training datasets and adequate validation in patients with different cleft presentations [3].

As AI continues to advance in dental and craniofacial practice, its potential role in addressing the specific challenges of cleft orthodontics warrants closer examination. This narrative review aims to explore the current applications of AI throughout the different stages of cleft orthodontic management, with particular attention to diagnostic performance, imaging analysis, treatment planning, and the prediction of treatment outcomes. It also examines the limitations that may affect clinical implementation, including data scarcity, algorithmic bias, limited generalizability, and the need for robust clinical validation. By evaluating these developments and unresolved challenges, the review seeks to clarify the potential contribution of AI to more consistent, individualized, and evidence-informed care for patients with cleft lip and palate.

- *Historical Perspective: Evolution from Manual Assessment to AI-Driven Analysis*

For much of the twentieth century, the diagnosis and treatment planning of patients with cleft lip and palate (CLP) depended largely on clinicians' experience and conventional diagnostic methods. Orthodontists commonly used manually traced lateral cephalometric radiographs, plaster study models, and clinical photographs to evaluate craniofacial structures and plan treatment. However, these conventional approaches were not always well suited to the anatomical complexities of cleft patients, whose craniofacial structures may be altered by congenital defects, previous surgical procedures, and subsequent growth changes. Differences in diagnostic protocols and treatment approaches among cleft centres also made it difficult to establish consistent methods for evaluating treatment outcomes. Consequently, clinical decision-making often relied substantially on individual expertise, highlighting the need for more standardized and reproducible assessment techniques [4].

The introduction of three-dimensional imaging represented an important advancement in craniofacial diagnosis. With the increasing use of cone-beam computed tomography (CBCT) in orthodontics, clinicians gained a more detailed understanding of the spatial relationships between teeth, alveolar bone, and surrounding anatomical structures. This technology enabled improved assessment of cleft morphology, estimation of alveolar bone volume, and preoperative planning for secondary alveolar bone grafting [3]. Despite these advantages, interpreting three-dimensional datasets continued to require considerable clinical expertise and manual effort. The identification of anatomical landmarks, delineation of relevant structures, and measurement of craniofacial parameters remained vulnerable to observer variability, fatigue, and the time-intensive nature of image analysis.

The emergence of deep learning subsequently introduced new possibilities for automating the interpretation of medical and dental images. In particular, the success of deep convolutional neural networks in large-scale image classification demonstrated the potential of deep learning for visual recognition tasks. These developments accelerated interest in applying AI to medical imaging, followed by its growing adoption in dentistry and orthodontics [2]. By the late 2010s, AI-based systems for automated cephalometric landmark identification had begun to undergo clinical evaluation, creating opportunities to reduce the manual workload associated with conventional radiographic analysis [5].

Since then, research has increasingly explored the potential application of AI to different aspects of cleft care, including prenatal detection, identification of dental anomalies, assessment of alveolar bone defects, prediction of surgical outcomes, and analysis of speech-related characteristics. Nevertheless, progress in algorithm development does not necessarily translate into immediate clinical readiness. Many proposed applications still require validation using larger and more diverse CLP populations, standardized evaluation methods, and independent clinical datasets. Therefore, although the transition from manual assessment to intelligent computational analysis represents a promising development in cleft orthodontics, establishing the reliability, generalizability, and clinical usefulness of these technologies remains essential before their widespread implementation.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

➢ *Why Cleft Lip and Palate Presents Unique Diagnostic Challenges*

Cleft lip and palate (CLP) presents diagnostic challenges that extend beyond the identification of a congenital defect. The condition affects craniofacial development, dental formation, skeletal relationships, and facial symmetry, creating a complex clinical picture that changes throughout growth. These challenges also help explain why artificial intelligence (AI) may have a meaningful role in cleft orthodontics, particularly in improving the consistency of image interpretation and supporting clinical decision-making.

The effects of CLP on craniofacial development begin during early embryogenesis and may continue to influence facial growth throughout childhood and adolescence [6]. In addition to the original developmental defect, surgical interventions performed at different stages of treatment can influence subsequent growth. Procedures such as primary lip repair, palatal closure, and secondary alveolar bone grafting may be associated with scar formation and restrictions in maxillary growth. The extent of these effects varies according to the severity of the cleft, the surgical techniques used, and individual growth patterns. Consequently, many patients develop distinctive skeletal and dental relationships that differ from those observed in individuals without clefts. Standard orthodontic reference values must therefore be interpreted cautiously, particularly when clinicians are deciding whether a patient can be managed with orthodontic treatment alone or may require orthognathic surgery.

Cephalometric assessment presents another important difficulty in this population. Anatomical landmarks commonly used to evaluate maxillary position and craniofacial relationships, including Point A, the anterior nasal spine, and the alveolar process, may be altered by the cleft defect, previous surgical intervention, or associated skeletal asymmetry [7]. Their identification on radiographic images can therefore be less straightforward than in patients with typical craniofacial anatomy. Differences in landmark interpretation between examiners may affect the accuracy of cephalometric measurements and, consequently, the assessment of skeletal discrepancies. When treatment decisions depend on small differences in maxillary position or the severity of a skeletal deformity, measurement errors may influence the interpretation of treatment needs. This makes reliable landmark identification particularly important when distinguishing between orthodontic camouflage and combined orthodontic-surgical management.

Dental anomalies further complicate the diagnostic process. Patients with CLP have an increased likelihood of missing teeth, supernumerary teeth, abnormal tooth morphology, and disturbances in eruption, particularly in the region adjacent to the cleft. Agenesis of the maxillary lateral incisor on the affected side is frequently reported, although its prevalence varies across patient populations and cleft types. Supernumerary teeth may also occur within or near the cleft region [8]. Additional findings, including root dilaceration, ectopic eruption, and enamel developmental defects, can influence treatment planning and the long-term prognosis of individual teeth. During the mixed dentition stage, clinicians must evaluate tooth number, eruption sequence, root development, available arch space, and the relationship of the dentition to the alveolar defect. They must also establish whether alveolar bone grafting has been performed and assess the adequacy of the resulting bone support. Considering these factors together requires careful interpretation of clinical findings and multiple imaging modalities.

Beyond dental and skeletal abnormalities, CLP may produce three-dimensional facial asymmetry and characteristic changes in nasal form, including deviation of the nasal septum and distortion of the alar base. These features may not be adequately represented by conventional two-dimensional radiographs, which provide limited information about the three-dimensional relationships of facial structures. Accurate evaluation may therefore require a combination of clinical examination, standardized photography, digital surface imaging, and, where clinically justified, three-dimensional radiographic assessment [9]. These findings are important not only for surgical planning and postoperative evaluation but also because facial appearance and symmetry can substantially influence patients' perceptions of treatment outcomes.

Taken together, these challenges demonstrate why the application of AI in cleft orthodontics requires a different approach from its use in routine orthodontic diagnosis. Algorithms developed using predominantly non-cleft populations may not perform consistently when confronted with altered anatomical landmarks, missing or displaced teeth, irregular alveolar structures, and pronounced facial asymmetry. AI systems intended for this population must therefore be evaluated using representative CLP datasets and validated against appropriate clinical reference standards. If adequately developed and validated, such systems may help standardize image analysis, improve the reproducibility of selected diagnostic measurements, and support clinicians in managing complex treatment decisions. However, their role should remain complementary to clinical expertise, with particular attention to the anatomical variability and individual treatment requirements of patients with cleft lip and palate.

II. CURRENT APPLICATIONS OF ARTIFICIAL INTELLIGENCE ACROSS THE CLEFT CARE CONTINUUM

➢ *Prenatal Detection and Genetic Risk Prediction*

The potential contribution of artificial intelligence (AI) to cleft lip and palate (CLP) management begins during the prenatal period. Early identification of a cleft can help parents understand the condition, access appropriate counselling, and prepare for delivery at a centre equipped to provide multidisciplinary craniofacial care. It also facilitates timely planning for postnatal interventions, including presurgical infant orthopedics when indicated. Conventional two-dimensional obstetric ultrasonography remains the primary method for prenatal detection; however, its diagnostic performance varies considerably according to the type of cleft, fetal position, image quality, and operator expertise.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

Reported detection rates for cleft lip range widely, while isolated cleft palate is particularly difficult to diagnose before birth [3]. The complex orientation of the fetal palate and acoustic shadowing from adjacent bony structures can make reliable visualization challenging.

Recent advances in deep learning have created opportunities to improve the interpretation of prenatal ultrasound images. Convolutional neural networks (CNNs) can be trained to identify image patterns associated with facial discontinuities and other morphological features suggestive of cleft abnormalities. Rather than depending entirely on predefined anatomical criteria, these systems learn relevant features from annotated imaging datasets [10]. Researchers have also explored multimodal approaches that combine different forms of information to improve classification. Such multimodal models, which jointly analyse anatomical imaging features and acoustic speech data, have reported improvements over single-modality approaches in the settings studied [3]. However, the applicability of such findings to routine prenatal CLP screening requires further clarification and independent clinical validation.

AI-assisted screening may also be useful after birth, particularly in regions where access to specialist diagnostic services is limited. Smartphone-based image analysis has shown potential for identifying visible cleft lip abnormalities from photographs, offering a possible means of supporting early referral in underserved communities [10]. This approach may be relevant in India, where geographical barriers and shortages of specialist services can delay access to appropriate cleft care. Nevertheless, photographic screening cannot reliably exclude isolated cleft palate or replace a comprehensive clinical examination.

Beyond anatomical screening, AI is being investigated as a tool for understanding the genetic factors associated with CLP. Machine learning methods applied to genome-wide association study data may help identify complex relationships among multiple genetic variants that contribute to susceptibility to non-syndromic clefts [11]. Such approaches could complement conventional genetic association analyses by identifying interactions that may be difficult to detect using simpler statistical models. At present, however, these findings should be regarded as research developments rather than established clinical prediction tools. Larger, genetically diverse datasets and independent validation are necessary before AI-derived risk estimates can be incorporated into routine genetic counselling.

- *Nasoalveolar Molding and Presurgical Infant Orthopedics*

Presurgical infant orthopedics, particularly nasoalveolar molding (NAM), is an important component of early management for selected infants with cleft lip and palate. The technique aims to improve the alignment of the alveolar segments, reduce the width of the cleft, and guide the development of the nasal cartilage before primary surgical repair. Its use is supported by the relative malleability of neonatal cartilage, which is influenced in part by hormonal and biochemical factors during early infancy [12]. By taking advantage of this period of increased tissue plasticity, clinicians can gradually modify the relationship between the alveolar segments and improve selected aspects of nasal form before surgery.

Despite its potential benefits, conventional NAM treatment involves several practical challenges. Appliance fabrication typically requires impressions or casts, laboratory procedures, repeated clinical adjustments, and regular follow-up appointments. The clinician must assess changes in the infant's alveolar anatomy, nasal symmetry, and soft-tissue contours at each visit before modifying the appliance. These decisions require considerable clinical experience, while the frequent attendance required can place a substantial burden on families who live far from specialist cleft centres.

Digital technologies are beginning to address some of these limitations. The development of RapidNAM by Schiebl and colleagues introduced a workflow that uses three-dimensional palatal scanning to facilitate the design and fabrication of customized appliances through digital manufacturing [13]. By reducing dependence on conventional stone models and associated laboratory procedures, this approach offers an alternative method for producing patient-specific presurgical orthopedic appliances.

The integration of AI into digital NAM workflows could provide additional advantages. Image-processing algorithms may assist in measuring changes in alveolar cleft width, evaluating nasal symmetry, and monitoring columellar dimensions across successive appointments. When developed and validated appropriately, automated measurements could improve consistency in treatment monitoring and help clinicians identify changes that warrant appliance adjustment. These systems would support, rather than replace, the clinical judgment required to determine the direction and extent of orthopedic correction.

Remote monitoring is another promising area of development. Smartphone photography combined with photogrammetry and AI-based image analysis could potentially allow clinicians to document visible changes in facial morphology between scheduled visits [3]. For families living in rural or geographically isolated areas, this approach may reduce some unnecessary travel and help identify situations requiring earlier clinical review. However, the reliability of remote assessment depends on standardized image acquisition, adequate image quality, and validation across different cleft presentations. Remote monitoring should therefore complement regular clinical assessment rather than replace in-person evaluation when appliance adjustment, tissue examination, or other direct interventions are required.

Overall, AI-assisted prenatal screening and digital presurgical orthopedics represent two emerging areas in which computational technologies may contribute to earlier identification, improved measurement, and more individualized care. Their long-term value will depend on demonstrating meaningful clinical benefits, ensuring

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

equitable performance across patient populations, and integrating these tools into existing multidisciplinary cleft care pathways.

➢ *Cephalometric and Radiographic Diagnosis*

Automated cephalometric landmark detection is among the most established applications of artificial intelligence (AI) in orthodontics. Its use in patients with cleft lip and palate (CLP) is particularly relevant because anatomical alterations can make landmark identification more difficult and increase the clinical consequences of measurement errors. Patel et al., in a study published in the *British Dental Journal* in 2025, evaluated the WebCeph AI platform in patients with CLP and reported performance comparable to conventional digital manual tracing, alongside a considerable reduction in analysis time [7]. However, the findings also highlighted an important limitation: the identification of maxillary landmarks remained less accurate in cleft patients than in non-cleft reference populations. This suggests that, although AI can streamline cephalometric assessment, clinician-led verification remains necessary, particularly when measurements influence decisions regarding skeletal correction or orthognathic surgery.

AI-assisted dental analysis has also shown potential for improving the interpretation of panoramic radiographs in patients with CLP. Arslan et al. assessed the Diagnocat platform for automated tooth detection and numbering in 100 cleft patients representing two age groups. The system achieved a sensitivity of 0.98 and a precision of 0.96, with no statistically significant difference in performance between the younger and older groups within the mixed-dentition population studied [14]. These findings indicate that automated dental identification may assist clinicians in evaluating tooth presence and position, although further validation across different cleft types and clinical settings is necessary.

CNN-based models have also been developed to identify unilateral cleft alveolus on routine panoramic radiographs [11]. This approach suggests that AI-based image analysis could eventually support the recognition of alveolar cleft defects during conventional dental radiographic assessment. If validated in broader patient populations, such systems may serve as supplementary screening tools, helping clinicians identify findings that warrant more detailed clinical examination or additional imaging when indicated. Nevertheless, automated detection should not be regarded as a substitute for comprehensive diagnostic assessment, particularly when determining the extent of an alveolar defect or planning secondary bone grafting.

➢ *Alveolar Bone Graft Assessment*

Secondary alveolar bone grafting (ABG) is a critical stage in the multidisciplinary management of cleft lip and palate (CLP), as the quality and volume of the grafted bone influence subsequent orthodontic treatment and dental rehabilitation. Reliable evaluation of graft outcomes is therefore essential for determining whether adequate bone support has been achieved and whether further intervention is required [15]. Cone-beam computed tomography (CBCT) and other three-dimensional imaging techniques allow clinicians to assess the morphology and volume of alveolar defects in considerable detail. However, manual segmentation and volumetric measurement remain time-consuming procedures, often requiring approximately 30–60 minutes per patient and potentially producing variations between examiners [16]. Such variability can make comparisons between preoperative and postoperative assessments more difficult.

To address these challenges, Zhang et al. investigated the use of a three-dimensional U-Net deep learning architecture to automatically segment alveolar cleft defects using preoperative and postoperative CT datasets. Their approach demonstrated performance comparable to expert manual assessment while reducing the time required for image analysis [16]. Automated segmentation of this kind could help standardize the evaluation of alveolar defects and facilitate more efficient assessment of bone graft outcomes. Nevertheless, its clinical usefulness depends on validation across different defect morphologies, imaging protocols, and patient populations.

Another important development involves improving the interpretability of AI-based diagnostic systems. Miranda et al. incorporated saliency map visualizations into an AI classification framework for alveolar bone defects, enabling clinicians to identify the image regions that contributed most strongly to the model's predictions [17]. This feature offers a visual means of examining the basis of an algorithm's output rather than relying solely on its final classification. Such transparency may help clinicians assess whether the system is focusing on anatomically relevant features and identify potentially misleading predictions. However, saliency maps do not independently establish that an AI decision is correct, and their clinical value must be evaluated alongside diagnostic accuracy and expert interpretation.

Overall, AI-assisted segmentation and interpretable image analysis may improve the efficiency and consistency of alveolar bone graft assessment in patients with CLP. These technologies could support postoperative monitoring and subsequent orthodontic planning, provided that their performance is established through rigorous clinical validation and that final treatment decisions remain guided by comprehensive clinical and radiographic evaluation.

➢ *Orthognathic Surgical Planning*

Maxillary hypoplasia is a common skeletal complication in patients with complete cleft lip and palate (CLP), and a proportion of these individuals eventually require maxillary advancement through Le Fort I osteotomy. The reported prevalence varies across studies, reflecting differences in cleft severity, surgical history, and patient characteristics [4]. Planning orthognathic surgery in this population can be particularly challenging because the skeletal deformity often coexists with altered soft-tissue anatomy and the effects of previous surgical procedures. Scar formation following palatal repair may influence the soft-tissue response to skeletal advancement, making postoperative facial changes more difficult to predict using

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

conventional linear ratios alone [18]. Furthermore, some patients require segmental osteotomies to address complex maxillary discrepancies, adding further considerations to three-dimensional surgical planning.

Artificial intelligence may offer additional support by helping clinicians anticipate future skeletal discrepancies and identify patients who could eventually require orthognathic intervention. Machine learning models developed using longitudinal cephalometric records from childhood have demonstrated the potential to predict later surgical treatment requirements. In the reported studies, these approaches showed improved predictive performance compared with criteria based on individual variables or predefined thresholds [19]. Such findings suggest that AI-assisted growth assessment could contribute to earlier identification of patients at risk of developing clinically significant maxillary deficiency. However, these predictions must be interpreted cautiously because craniofacial growth, treatment history, and individual biological variation can influence the eventual need for surgery.

Recent advances in generative AI have also expanded the possibilities for simulating surgical outcomes. AI models have been developed to predict postoperative skeletal and soft-tissue changes, and more recent approaches, including those combining graph neural networks with diffusion-based modelling, aim to generate simulated postoperative lateral cephalograms from preoperative patient data [18, 20]. These approaches represent a developing direction in AI-assisted orthognathic planning, in which computational models attempt to reproduce the expected anatomical changes following surgery. For cleft patients, such technologies may eventually support the visualization of potential skeletal outcomes and facilitate discussions between clinicians and patients. Nevertheless, generated images should be regarded as predictive simulations rather than definitive representations of postoperative results. Their clinical application requires further validation in CLP-specific populations, particularly to establish whether the predicted skeletal changes correspond reliably to actual surgical outcomes.

- *Speech Assessment*

Velopharyngeal dysfunction (VPD) and the resulting hypernasality are among the most common speech-related concerns in individuals with cleft lip and palate (CLP), as they can significantly affect speech intelligibility and influence decisions regarding further surgical or therapeutic intervention. Assessment of these conditions traditionally relies on perceptual speech evaluation performed by speech-language pathologists. Although this remains a fundamental component of clinical assessment, the interpretation of speech characteristics may vary between examiners, particularly when the degree of hypernasality is mild or borderline [11]. This variability highlights the need for complementary assessment methods that can provide more objective and reproducible information.

Artificial intelligence (AI) has emerged as a potential tool for supporting speech assessment in patients with CLP. AI-based acoustic analysis systems can examine recorded speech samples and identify features associated with abnormal resonance. These features may include mel-frequency cepstral coefficients (MFCCs) and other acoustic parameters that help characterize speech patterns. Studies evaluating such systems have reported promising results in the automated classification of nasality, with some approaches achieving performance comparable to clinical assessments [10]. However, diagnostic accuracy can vary according to the speech tasks used, the characteristics of the patient population, recording quality, and the language represented in the training data. Consequently, AI-based speech analysis should complement, rather than replace, comprehensive assessment by qualified speech-language pathologists.

The potential application of these technologies is particularly relevant in India, where access to specialized cleft speech assessment services may be limited in rural and geographically remote communities. AI-assisted analysis of speech recordings could support telehealth consultations by enabling preliminary screening and helping clinicians identify patients who may require detailed velopharyngeal evaluation. Such systems could also facilitate longitudinal monitoring of speech outcomes following surgical or therapeutic intervention. Nevertheless, successful implementation will require validation across India's diverse linguistic populations, standardized recording protocols, and appropriate safeguards for patient data. With these considerations addressed, AI-assisted remote speech assessment may help improve access to timely evaluation and support more coordinated care for individuals with CLP.

- *Comparative Efficacy: An Evidence-Based Perspective*

An overall assessment of the available research reveals that the effectiveness of artificial intelligence (AI) in cleft orthodontics varies according to the clinical task being performed. Automated cephalometric analysis has demonstrated promising results in patients with cleft lip and palate (CLP), although reduced accuracy in identifying certain anterior maxillary landmarks remains a recurring concern [5, 7]. This limitation is particularly relevant because anatomical alterations associated with the cleft and previous surgical interventions can make these landmarks more difficult to identify. Consequently, AI-generated measurements may be useful for routine analysis, but careful clinical verification remains necessary when the results could influence major treatment decisions.

Among the applications examined, automated alveolar bone segmentation and volumetric assessment appear particularly promising for improving workflow efficiency. Deep learning approaches have demonstrated the potential to reduce the time required to evaluate alveolar cleft defects while achieving results comparable to expert manual segmentation in the populations studied [16, 21]. Reported reductions in processing time may reach approximately 80–90% in some workflows, although these figures should be interpreted in the context of the specific algorithms, imaging

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

protocols, and validation methods used. Such improvements could facilitate postoperative graft assessment and longitudinal monitoring, provided that diagnostic reliability is maintained across different defect morphologies and patient groups.

AI-based prediction of future orthognathic surgical requirements also represents an emerging area of clinical interest. Machine learning models have shown potential to identify patients at risk of developing significant maxillary deficiency, sometimes performing better than conventional approaches based on predefined clinical thresholds [19, 20]. However, predicting skeletal changes alone does not fully capture the complexity of surgical outcomes in CLP patients. Soft-tissue responses may be influenced by previous operations, scar formation, individual anatomical differences, and the extent of skeletal movement. Accordingly, the reliability of AI-generated postoperative simulations remains dependent on the representativeness of the training data and the ability of the models to account for these patient-specific factors.

Despite these encouraging developments, an important limitation is shared by much of the current evidence: many studies rely on relatively small patient samples, retrospective data, or populations drawn from individual clinical centres [10, 11]. These characteristics can limit the generalizability of the findings and make it difficult to determine how consistently a system will perform in different clinical environments. Furthermore, differences in imaging protocols, outcome measures, and validation methods complicate direct comparisons between AI platforms.

Overall, AI has considerable potential to support diagnosis, treatment planning, and outcome assessment in cleft orthodontics. Nevertheless, promising technical performance should not be equated with established clinical effectiveness. Larger prospective studies, independent multicentre validation, standardized evaluation criteria, and research involving diverse CLP populations are needed before these technologies can be adopted confidently in routine practice. A balanced interpretation of the evidence is therefore essential: AI offers valuable opportunities to improve efficiency and consistency, but its integration into cleft care must be guided by demonstrated clinical benefit, transparent reporting, and continued professional oversight.

III. LIMITATIONS, ETHICAL CONSIDERATIONS AND RESPONSIBLE CLINICAL INTEGRATION

Despite the growing interest in artificial intelligence (AI) for cleft orthodontics, several limitations must be addressed before these technologies can be incorporated confidently into routine clinical practice. One major concern is the limited size and diversity of the datasets used to develop and evaluate many existing models. A substantial proportion of published studies rely on small, single-centre patient cohorts, sometimes comprising fewer than 200 individuals [3, 10]. Although these studies may demonstrate promising results under specific conditions, their findings cannot automatically be extended to patients with different cleft types, degrees of anatomical deformity, surgical histories, or patterns of craniofacial growth. Broader validation is therefore necessary to establish whether these systems maintain reliable performance across the diverse clinical presentations encountered in everyday practice.

The possibility of algorithmic bias presents another important challenge. The demographic composition of training datasets can influence how well an AI system performs in populations that differ from those represented during its development [9]. If certain ethnic groups or geographical regions are inadequately represented, the resulting models may produce less reliable predictions for those populations. This issue is particularly relevant to India, where the need for accessible cleft care is substantial and patients present with considerable anatomical and demographic diversity [22]. However, the extent to which South Asian populations are underrepresented must be established through systematic evaluation of individual datasets rather than assumed across all AI platforms. Developing representative training cohorts and conducting population-specific validation are essential steps towards improving the fairness and reliability of AI-assisted diagnosis.

Another concern relates to the interpretability of AI-generated results. Although some systems provide diagnostic measurements or predictions with high reported accuracy, clinicians may find it difficult to understand the factors responsible for a particular output. This becomes especially important when AI recommendations could influence decisions regarding alveolar bone grafting, orthodontic camouflage, or orthognathic surgery. Explainable AI methods, including visual overlays and feature-importance maps, may help clinicians examine how a model reaches its conclusions. Nevertheless, these explanations do not necessarily establish that a prediction is clinically correct. AI outputs must therefore be assessed alongside the patient's clinical findings, radiographic evidence, treatment history, and individual needs.

Regulatory oversight and professional accountability also require careful consideration. Standards governing AI-assisted healthcare are evolving, and the requirements applicable to a particular system may depend on its intended clinical use and regulatory classification [2]. For AI applications in orthodontics, it is important to establish clear expectations regarding clinical validation, data privacy, cybersecurity, performance monitoring, and responsibility for decisions informed by algorithmic recommendations. Clinicians and healthcare institutions should evaluate the evidence supporting a tool before adopting it and should remain alert to changes in its performance when it is used with different patient populations or imaging protocols.

At present, the most appropriate approach is to use AI as a supportive component of clinical decision-making rather than as an independent replacement for professional judgment. When appropriately validated, these systems may help reduce repetitive workload, improve measurement

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

consistency, and organize complex diagnostic information. However, their outputs should always be interpreted within the broader context of multidisciplinary cleft care. Collaboration among orthodontists, craniofacial surgeons, radiologists, speech-language pathologists, and other relevant specialists remains essential to developing individualized treatment plans. Responsible integration of AI will ultimately depend not only on technological progress but also on clinical validation, ethical implementation, transparent communication, and continued human oversight.

IV. DISCUSSION

This review highlights the rapid evolution of artificial intelligence (AI) in cleft orthodontics and its growing relevance to clinical practice. AI-based technologies are increasingly being explored and incorporated into diagnostic imaging, surgical planning, and speech assessment, creating new opportunities to improve the management of patients with cleft lip and palate (CLP). However, the pace of technological development has not always been matched by equally strong clinical evidence. Although the results reported to date are encouraging, further investigation is necessary to establish whether these tools can deliver consistent, reliable benefits across the diverse patient populations encountered in routine cleft care.

The studies included in this review highlight the potential of AI to assist with several diagnostic and treatment tasks across the CLP care pathway. Unlike dedicated technologies that address a specific issue with treatment, AI can be used to implement applications that cover the entire CLP trajectory, from prenatal screening and cephalometric prediction to alveolar bone assessment, prediction of the surgical result, and assessment of the speech function. One potentially very promising application of AI is the automated measurement of alveolar cleft defects. Deep learning-based segmentation can be used to make measurements that could be equivalent to those made by experts through manual analysis but in a much reduced amount of time. Some workflows cited in the literature review suggest time savings of about 80–90%, making this a significant area of further clinical research [16, 21]. Similarly, ML models that rely on longitudinal records of cephalometric measures could be used to predict which children are at risk of developing skeletal discrepancies that would require orthognathic surgery [19, 20]. Such predictive models could offer something additional in terms of insight beyond what can be gleaned from an isolated clinical examination, but this is contingent on the accuracy with which they are able to predict.

Despite this progress, the existing literature still has several limitations. One persistent issue is that the detection of some anterior maxillary cephalometric landmarks can be less accurate in CLP patients [5, 7]. These landmarks are extremely useful when analyzing the amount of maxillary deficiency and thus guiding the subsequent orthodontic or surgical treatment planning, but their displacement and distortion by the cleft can impair automated detection, particularly when algorithms have been trained predominantly on non-cleft populations. Caution is therefore warranted in relying on AI to identify these landmarks until its accuracy has been shown to be equivalent to that of manual cephalometry in patients with CLP.

Methodological rigour and generalisability of existing evidence should be considered alongside this. Many published studies are retrospective, have small cohorts and are single-centre studies [10, 11]. Therefore, performance may not be generalisable in different clinical environments, imaging protocols and cleft characteristics. Another consideration is the under-representation of South Asian populations in AI training data, particularly in the context of India, where the burden of CLP is substantial and there is a clear need for reliable, accessible technologies [22].

However, the extent of this under-representation should be quantified through systematic examination of the datasets used in individual studies. Variation in the accuracy, clinical readiness and soft-tissue outcome prediction may be related to differences in study methodology and validation. Future research should therefore move beyond small-scale feasibility studies towards prospective, multicentre investigations involving larger and more representative CLP populations. Greater attention should be given to independent validation, consistent performance benchmarks, interpretable AI outputs, and the assessment of clinical outcomes rather than technical accuracy alone. The inclusion of diverse ethnic groups and different cleft phenotypes will also be essential to determine whether these systems can be applied equitably and reliably in everyday practice.

To summarise, AI technology has the capability to enhance diagnostic evaluation, optimise workflow efficiency and provide tailored treatment plans in the field of cleft orthodontics. To be effective, however, evidence-based design and standardisation, implementation integrity and effective monitoring must be assured, and effectiveness in meeting real clinical needs demonstrated. Currently, however, AI tools are best used as supplementary to the diagnosis and planning process, with healthcare professionals directing the treatment process. When applied as a collaborative tool with multidisciplinary input, AI can bring valuable analytics into cleft treatment planning.

V. CONCLUSION

This review demonstrates the promising potential for AI to assist in clinical decision-making across a broad spectrum of clinical applications within CLP management, encompassing prenatal screening, nasoalveolar molding, cephalometric analysis, evaluation of alveolar bone graft, orthognathic surgical planning, and speech analysis. Current evidence suggests that AI-based algorithms can attain promising diagnostic performance for many of these applications, along with significant improvements in the time efficiency of CBCT alveolar defect analysis and fully-automated dental identification. However, the translation of these technologies into clinical practice remains limited by small study cohorts, a lack of prospective multicentre validation, and the under-representation of several patient groups, including South Asian patients, in existing training

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

datasets. Greater research efforts will be required before AI can be confidently incorporated into routine cleft orthodontic care. The relatively low accuracy reported for some anterior maxillary cephalometric landmarks is of particular concern, as inaccuracy in their identification may impact multiple important orthodontic and surgical treatment decisions.

Therefore, validation of these parameters by a clinician is still required. In conclusion, AI should be considered as an adjunct to enhance diagnosis, processing speed, and repeatability of measurements and treatment planning, but clinical experience, multidisciplinary collaboration, and patient-centered approach will still be the basis of cleft management.

REFERENCES

[1]. Santiago PE, Grayson BH: Role of the craniofacial orthodontist on the cleft palate and craniofacial team .Semin Orthod. 2009, 15:225-43. 10.1053/j.sodo.2009.07.004

[2]. Thurzo A, Urbanová W, Novák B, et al.: Where is the artificial intelligence applied in dentistry? Systematic review and literature analysis. Healthcare :1269. 10.3390/healthcare10071269

[3]. Almoammar KA: Harnessing the power of artificial intelligence in cleft lip and palate: an in-depth analysis from diagnosis to treatment, a comprehensive review. Children :140. 10.3390/children11020140

[4]. Long RE Jr, Semb G, Shaw WC: Orthodontic treatment of the patient with complete clefts of lip, alveolus,and palate: lessons of the past 60 years. Cleft Palate Craniofac J. 2000, 37:533. 10.1597/15451569_2000_037_0533_ototpw_2.0.co_2

[5]. Alam MK, Alfawzan AA: Characteristics of Different Types of Cleft and Non-cleft Individuals. . Front Cell Dev Biol.. 2020, 8:789. 10.3389/fcell.2020.00789

[6]. Rossell-Perry P: Atlas of surgical repair for cleft lip, palate and associated nasal deformities . Berlin: Springer. 2020,

[7]. Patel P, El-Mangoush A, Amin A, Ahmad M: The accuracy and speed of artificial intelligent cephalometric software compared to computer and paper tracing in patients with cleft lip and palate. Br Dent J. 2025,10.1038/s41415-025-8877-y

[8]. Ravelo V, Acero J, Fuentes-Zambrano J, García Guevara H, Olate S. : Artificial intelligence used for diagnosis in facial deformities: a systematic review. J Pers Med. 2024, 14:647. 10.3390/jpm14060647

[9]. Akcam MO, Evirgen S, Uslu O, Memikoğlu UT. .: Dental anomalies in individuals with cleft lip and/or palate .Eur J Orthod. 2010, 32:207-13. 10.1093/ejo/cjp156

[10]. Huqh MZU, Abdullah JY, Wong LS, et al.: Clinical applications of artificial intelligence and machine learning in children with cleft lip and palate: a systematic review. Int J Environ Res Public Health. 2022, 19:10860.10.3390/ijerph191710860

[11]. Dhillon H, Chaudhari PK, Dhingra K, et al.: Current applications of artificial intelligence in cleft care: a scoping review. Front Med. 2021, 8:676490. 10.3389/fmed.2021.676490

[12]. Grayson BH, Cutting CB: Presurgical nasoalveolar orthopedic molding in primary correction of the nose, lip, and palate of infants with bilateral cleft lip and palate. Cleft Palate Craniofac J. 2001, 38:193-8.10.1597/1545-1569_2001_038_0193_pnomip_2.0.co_2

[13]. Schiebl J, Bauer FX, Grill F, et al.: RapidNAM: algorithm for the semi-automated generation of patient-specific nasoalveolar molding devices for patients with bilateral cleft lip and palate. IEEE Transactions on Biomedical Engineering. 2020, 67:1263-1271. 10.1109/tbme.2019.2934907

[14]. Arslan C, Yucel NO, Kahya K, Akturk ES, Cakan DG: Artificial intelligence for tooth detection in cleft lip and palate patients. Diagnostics :2849. 10.3390/diagnostics14242849

[15]. Bergland O, Semb G, Abyholm FE: Elimination of the residual alveolar cleft by secondary bone grafting and subsequent orthodontic treatment. Cleft Palate J. 1986, 23:175-205.

[16]. Zhang X, Qin N, Zhou Z, Chen S: Machine learning in 3D auto-filling alveolar cleft of CT images to assess the influence of alveolar bone grafting on the development of maxilla. BMC Oral Health. 2023, 23:16.10.1186/s12903-023-02706-8

[17]. Miranda F, Choudhari V, Barone S, et al.: Interpretable artificial intelligence for classification of alveolar bone defect in patients with cleft lip and palate. Scientific Reports. 2023, 13:15861. 10.1038/s41598-023-11 of 1243125-7

[18]. Park JA, Moon JH, Lee JM, Cho SJ, Seo BM, Donatelli RE, and Lee SJ. : Does artificial intelligence predict orthognathic surgical outcomes better than conventional linear regression methods?. Angle Orthod. 2024,94:549-56. 10.2319/111423-756.1

[19]. Lin G, Kim PJ, Baek SH, Kim HG, Kim SW, Chung JH: Early prediction of the need for orthognathic surgery in patients with repaired unilateral cleft lip and palate using machine learning and longitudinal lateral cephalometric analysis data. J Craniofac Surg. 2021, 32:616-20. 10.1097/SCS.0000000000006943

[20]. Kim, IH., Jeong, J., Kim, JS.: Predicting orthognathic surgery results as postoperative lateral cephalograms using graph neural networks and diffusion models. . Nat Commun . 2025, 16:2586. 10.1038/s41467-025-57669-x

[21]. Ezhov M, Gusarev M, Golitsyna M, et al.: Clinically applicable artificial intelligence system for dental diagnosis with CBCT. Sci Rep. 2021, 11:15006. 10.1038/s41598-021-94093-9

[22]. Kantar RS, Hamdan US, Muller JN, et al.: Global prevalence and burden of orofacial clefts: a systematic analysis for the Global Burden of Disease Study 2019. journal of Craniofacial Surgery. 2023,34:10.1097/SCS.0000000000009591

[23]. Nantha O, Sathanarugsawait B, Praneetpolgrang P. : Cleft lip and palate classification through vision transformers and Siamese neural networks. . journal of imaging . 2024,10:271.10.3390/jimaging10110271

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26oct1612

[24]. Murphy I, Taylor N. : The accuracy and speed of artificial intelligent cephalometric software compared to computer and paper tracing in patients with cleft lip and palate.. British dental journal . 2025, 10.1038/s41415-025-8877-y.
[25]. Kuwada C, Ariji Y, Kise Y, : Detection and classification of unilateral cleft alveolus with and without cleft palate on panoramic radiographs using a deep learning system.. Scientific Report . 2021, 11:16044. 10.1038/s41598-021-95653-9
[26]. Mathad VC, Scherer N, Chapman K et.al: A Deep Learning Algorithm for Objective Assessment of Hypernasality in Children With Cleft Palate. . IEEE Trans Biomed Eng. 2021, 68:2986-2996. 10.1109/TBME.2021.3058424