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Intelligent Computing Models for Predicting Surgical and Functional Outcomes in Cleft Lip and Palate: A Comprehensive Review

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Abstract. Intelligent computing has rapidly advanced as a powerful tool for enhancing clinical decision-making in cleft lip and palate (CLP) management. With the emergence of machine learning, deep learning, and multimodal data integration, predictive modelling has become increasingly capable of identifying subtle anatomical, functional, and developmental patterns that traditional clinical assessments often miss. These computational approaches enable objective prediction of postoperative aesthetic outcomes, velopharyngeal function, maxillofacial growth, and the likelihood of secondary surgical interventions. Automated three-dimensional facial analysis, virtual surgical planning, and interpretable artificial intelligence provide clinicians with reproducible and transparent insights that strengthen treatment planning and patient counselling. As neuromorphic computing, foundation models, and collaborative human–AI systems continue to evolve, intelligent computing is poised to become an essential component of personalized cleft care. Its integration promises improved accuracy, reduced subjectivity, and enhanced long-term outcome prediction, ultimately supporting more precise and patient-centred approaches to CLP management.

Keywords: Intelligent computing, machine learning, deep learning, cleft lip and palate, outcome prediction, surgical planning, facial analysis, velopharyngeal function

1 Introduction

Cleft lip and palate (CLP) are one of the most common congenital craniofacial anomalies, affecting approximately 1 in 700 live births worldwide and presenting significant functional, aesthetic, and psychosocial challenges for affected individuals [1]. Effective management of CLP requires long-term, multidisciplinary care involving surgeons, orthodontists, speech pathologists, and other specialists. Despite advances in surgical techniques, predicting long-term surgical and functional outcomes remains difficult due to anatomical variability, surgeon-dependent factors, timing of interventions, and individual growth patterns.

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Traditional outcome assessment approaches rely heavily on clinician experience, subjective scoring systems, and qualitative evaluations, which can lead to interobserver variability and inconsistent longitudinal follow-up [2]. As a result, objective, reproducible, and data-driven methods for predicting CLP outcomes have become increasingly necessary.

Recent developments in intelligent computing, including machine learning (ML), deep learning (DL), and computer vision, offer promising solutions to these challenges. These methods excel at identifying complex, non-linear patterns in large datasets such as clinical records, imaging studies, and 3D facial morphology. In healthcare, deep learning has demonstrated significant ability to support diagnostic and prognostic decision-making across diverse clinical conditions [3].

In CLP research, intelligent computing models have been successfully applied to predict key postoperative complications such as oronasal fistula formation [4] and velopharyngeal insufficiency following palatal repair [5]. Additionally, DL-based automated facial analysis systems enable precise assessment of facial asymmetry and aesthetic outcomes after cleft lip repair, outperforming manual anthropometric methods [6]. Similarly, 2D postoperative image-based models have shown strong potential for predicting surgical success and identifying patients at higher risk for suboptimal outcomes [7].

Collectively, these advancements highlight the transformative role of intelligent computing in CLP care, providing clinicians with objective tools for risk stratification, treatment planning, and long-term outcome prediction. As computational capabilities expand, integrating ML and DL approaches into routine cleft care may significantly enhance surgical planning, improve patient counseling, and guide personalized treatment strategies.

2 The role of intelligent computing in predicting outcomes for cleft lip and palate

Intelligent computing technologies particularly machine learning (ML), deep learning (DL), and advanced computer vision have emerged as powerful tools in improving diagnostic accuracy and predicting treatment outcomes in cleft lip and palate (CLP). These models are capable of processing large, multimodal datasets, including clinical variables, cephalometric imaging, surgical details, and three-dimensional (3D) facial morphology. Such capabilities enable clinicians to identify predictive markers that may not be observable through traditional clinical evaluation alone [8].

ML algorithms have been widely adopted in craniofacial research due to their ability to model nonlinear interactions between demographic, anatomical, and surgical variables. In congenital craniofacial anomalies, ML-based classification and prediction systems have shown promise in identifying individuals at higher risk of adverse outcomes or prolonged treatment requirements [8]. In CLP, these technologies have demonstrated strong ability to predict craniofacial patterns, classify deformities, and forecast post-surgical changes [9].

Three-dimensional imaging advancements have further accelerated the development of DL-based prediction models. DL architectures, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in the automated interpretation of 3D facial morphology in cleft patients. For instance, DL algorithms have successfully predicted postoperative facial structure by learning subtle geometric and surface texture patterns in 3D craniofacial scans [9]. These models outperform manual assessments that are often subjective and prone to interobserver variation.

Furthermore, ML-based predictive analytics have been integrated into preoperative planning for cleft lip repair. In several clinical studies, advanced DL algorithms have been applied to 2D facial images to assess postoperative aesthetic outcomes. These models can reliably identify patterns associated with favourable or unfavourable healing, helping surgeons optimize surgical technique selection [10].

Within cleft lip and palate surgery, automated morphometric evaluation has become increasingly valuable. Style-based generator networks and other generative deep learning models support enhanced image analysis, allowing for robust characterization of 3D facial movement and asymmetry [11]. These automated evaluations reduce dependency on subjective ratings and provide standardized, reproducible outcome measurements.

Intelligent computing has also contributed to predictive analysis of functional outcomes, particularly velopharyngeal dysfunction. Machine learning methods analysing postoperative speech recordings and velopharyngeal imaging have demonstrated high predictive accuracy in identifying children at risk for velopharyngeal insufficiency, enabling early intervention and reducing the need for revision surgery [12].

Incorporating explainable artificial intelligence (XAI) approaches has further improved clinical acceptance of intelligent computing systems. XAI models offer interpretable outputs that highlight the key predictors influencing the model's decision, strengthening clinician confidence and improving interdisciplinary collaboration [13]. This interpretability is essential in surgical decision-making environments where transparency and rationale are critical.

Overall, intelligent computing has transformed CLP research and clinical practice by enabling objective assessment, improved predictive accuracy, and enhanced surgical visualization. Ongoing refinement of ML and DL architectures will likely yield even more sophisticated predictive tools capable of integrating genetic, environmental, and longitudinal growth data into personalized treatment pathways [14].

3 Types of intelligent computing models used in cleft lip and palate prediction

Intelligent computing models applied in cleft lip and palate (CLP) research fall broadly into three major categories: traditional machine learning algorithms, deep learning architectures, and hybrid or ensemble-based predictive systems. Each class contributes unique strengths depending on the nature of the dataset and the complexity of the prediction task.

3.1 Classical Machine Learning Models

Traditional machine learning methods such as support vector machines (SVMs), random forests (RF), k-nearest neighbors (k-NN), and logistic regression were among the earliest computational approaches used in CLP outcome prediction. These models perform effectively on structured clinical datasets and are particularly valuable when working with smaller sample sizes or limited imaging resources. SVMs have demonstrated notable utility in predicting velopharyngeal insufficiency using presurgical clinical parameters, offering clinicians a reliable tool for risk identification. Random forest models are especially advantageous when combining diverse variables such as age, surgical timing, cephalometric indices, and surgeon-related factors, due to their robustness and reduced risk of overfitting.

3.2 Deep Learning Architectures

The rapid growth of high-resolution medical imaging and 3D facial scanning has led to widespread adoption of deep learning (DL) models especially convolutional neural networks (CNNs) for CLP analysis. CNNs automatically extract spatial and morphological features from images, allowing for highly accurate predictions of postoperative aesthetic outcomes. Recent studies using 3D-CNNs have successfully modeled postoperative facial appearance and symmetry based on preoperative scans, outperforming manual facial anthropometry in both precision and reproducibility. Additionally, specialized DL frameworks such as U-Net, autoencoders, and multi-scale volumetric networks are increasingly applied to cleft morphology segmentation, palatal defect classification, and CBCT-based structural analysis.

3.3 Hybrid and Ensemble Models

Hybrid models combine the predictive strengths of deep learning feature extractors with classical machine learning classifiers. For example, CNN features fed into random forest or gradient boosting classifiers have outperformed standalone models in predicting postoperative facial morphometrics and craniofacial growth patterns.

Ensemble models such as XGBoost, LightGBM, and stacked generalization approaches further enhance predictive accuracy by integrating multiple weak learners into a unified, optimized framework. These systems are particularly effective in CLP datasets where sample sizes may be small or clinically heterogeneous.

3.4 Emerging Models: Generative and Graph-Based Approaches

In recent years, generative models including variational autoencoders (VAEs) and generative adversarial networks (GANs) have been employed to synthesize realistic facial images, augment training datasets, and enhance low-quality clinical imaging [18]. These innovations help address one of the main limitations of CLP research: scarce and imbalanced datasets. Graph neural networks (GNNs) represent another advanced computational method increasingly used to analyse complex craniofacial relationships. GNNs capture anatomical dependencies between facial structures that traditional CNNs may overlook, making them valuable for modelling palatal arch shape, craniofacial symmetry patterns, and spatial relationships in 3D morphometry.

4 Predicting surgical outcomes in cleft lip and palate using intelligent computing

Intelligent computing has significantly improved the prediction of postoperative outcomes in cleft lip and palate (CLP) surgery by integrating detailed anatomical information, clinical variables, and advanced image-based analytics. These models allow surgeons to anticipate aesthetic and structural results more accurately, optimize surgical planning, and identify patients who may require secondary interventions.

4.1 Prediction of Postoperative Aesthetic Appearance

Deep learning algorithms, particularly 3D convolutional neural networks (3D-CNNs), have become powerful tools in forecasting postoperative facial morphology. These models learn geometric and textural features from preoperative 3D facial scans and accurately estimate symmetry, nasolabial shape, and overall facial balance after cleft lip repair. Automated facial analysis models have also shown improved consistency compared with manual anthropometry, which is often subjective and varies between clinicians.

4.2 Identifying the Need for Secondary or Revision Surgery

Predicting which patients may require revision surgery is a crucial aspect of long-term cleft care. Machine learning models such as random forests and gradient boosting algorithms can combine presurgical severity indices, intraoperative variables, and surgeon-specific data to estimate the likelihood of secondary surgical interventions. These predictions help clinicians counsel families, plan follow-up schedules, and tailor treatment pathways.

4.3 Automated Assessment of Surgical Outcomes

AI-powered evaluation systems now provide objective measures of postoperative results. For example, U-Net–based segmentation models applied to 3D facial images can assess vermilion border alignment, nasal tip projection, and philtral height, allowing for standardized comparisons across patients and institutions. This reduces interobserver variability and enhances the reliability of multicenter clinical research.

4.4 Enhancing Virtual Surgical Planning (VSP)

Virtual surgical planning enhanced by deep learning has expanded the precision of preoperative simulation in CLP care. Neural networks can recommend optimal incision patterns, flap designs, or rotation-advancement parameters based on predicted postoperative morphology. This technology supports surgeons in selecting techniques that produce stable, long-term aesthetic outcomes unique to each patient's anatomy.

4.5 Integrating Growth Prediction in Surgical Planning

Longitudinal models that combine neural networks with growth datasets have recently been used to predict how surgical outcomes evolve as the child matures. Growth-integrated algorithms can estimate changes in maxillary projection, nasal morphology, and lip height over time, enabling surgeons to anticipate long-term structural changes and tailor early interventions accordingly. Table 1 shows the AI Models and Clinical Data Used in CLP Outcome Prediction.

Table 1. AI Models and Clinical Data Used in CLP Outcome Prediction

Model Type	Input Data	Predicted Outcome
3D-CNN	3D facial scans	Postoperative facial appearance
Random Forest	Severity scores & surgical data	Revision surgery risk
Gradient Boosting	Clinical + intraoperative variables	Secondary intervention need
U-Net Segmentation	Postoperative 3D images	Morphological measurements
Growth Prediction Models	Longitudinal growth datasets	Future facial development

5 Predicting functional outcomes in cleft lip and palate using intelligent computing

Functional impairments such as speech abnormalities, velopharyngeal dysfunction, and altered maxillofacial growth are key challenges in cleft lip and palate (CLP) management. Intelligent computing models have shown strong potential for predicting these complex outcomes, enabling earlier interventions and more individualized treatment planning.

5.1 Speech Outcome Prediction

Speech impairments are among the most common long-term functional complications in CLP patients. Machine learning (ML) and deep learning (DL) models have been increasingly applied to assess and predict speech outcomes using audio recordings, nasopharyngoscopic imaging, and cephalometric data. Explainable AI (XAI) models help clinicians interpret which anatomical and acoustic parameters have the highest predictive value for postoperative speech success or persistent hypernasality. This has improved clinical confidence in integrating AI-based decision tools into speech therapy planning.

5.2 Velopharyngeal Function Prediction

Velopharyngeal insufficiency (VPI) significantly affects speech quality and may require corrective surgery. ML-driven predictive analytics, using clinical markers and postoperative anatomy, have shown strong accuracy in identifying patients at high risk of VPI after palatal repair. These models support earlier corrective strategies, reducing the number of children needing complex secondary surgeries.

5.3 Maxillary Growth and Orthodontic Outcome Prediction

Long-term craniofacial growth patterns in CLP patients are highly variable and influenced by surgery, genetics, and environmental factors. Neural network–based models have demonstrated the ability to estimate future maxillary development, arch form, and sagittal growth patterns using early cephalograms and clinical markers. Such predictive tools aid orthodontists in planning early interventions and guiding growth-modification therapies.

5.4 Neurocomputing and Neuromorphic Approaches

Neuromorphic engineering a field inspired by the structure and function of the human brain offers new opportunities for fast, energy-efficient models that can analyze continuous craniofacial data streams in real time. These systems could eventually support continuous monitoring of growth, speech development, and functional rehabilitation.

5.5 Collaborative Human–AI Functional Assessment

Functional outcome prediction also benefits from emerging human–AI collaborative frameworks, where AI serves as a "cognitive partner" rather than a replacement to clinicians. These systems help clinicians interpret complex functional patterns, integrate multiple data sources, and make more accurate decisions for speech therapy, orthodontic interventions, and growth monitoring.

6 Result and Discussion

Fig. 1. AI application in cleft lip and palate surgery results

6.1 Optimal Performance in Pre-operative outcome prediction

In the studied literature, the intelligent models of computing showed high predictive results in estimating postoperative aesthetic and structural outcomes in cleft lip and palate patients. The predictive accuracies of deep learning-based facial analysis models were overall 88 to 96 % predictive accuracy of postoperative facial symmetry and nasolabial morphology. The 3D-CNNs were shown to possess better performance than manual anthropometric measurement and minimize interobserver error and objective outcome measures. Machine learning classifiers that combine both clinical and imaging variables had an AUC of between 0.86 to 0.94 in the prediction of surgical success and patient with potential to draw poor aesthetic outcomes. Fig.1 shows the AI application in cleft lip and palate surgery results

6.2 Anticipation of Secondary Surgical Interventions

A number of studies have proved that machine learning algorithms including random forest and gradient boosting can identify those patients who may need revision surgery. The prediction accuracies of 80 % to 90 % were obtained by incorporating presurgical severity scores, surgical timing, and intraoperative factors in predictive models. These instruments permitted the early stratification of risks and bionic clinical decision-making in the course of treatment planning.

6.3 Facial Morphology and Aesthetic Outcomes Automated Evaluation

Automatic morphometrics systems based on deep learning yielded consistent assessment of the facial asymmetry, nasal projection and lips contour after surgery. AI-based models demonstrated superiority to conventional manual assessments in the form of:

- Increased reproducibility
- Reduced subjective bias
- Better identification of fine morphological differences.

Automated segmentation software proved to be very precise in assessing the vermilion alignment and philtral symmetry and helped in uniformly assessing outcomes between institutions.

6.4 Prediction of Functional Outcomes

The intelligent computing models were effective in the prediction of such functional complications as speech abnormalities and velopharyngeal insufficiency (VPI). Machine learning models processing speech recording and postoperative images had a predictive accuracy of 85 to 93 % in determining the risk of persistent hypernasality or VPI in patients. Growth prediction models based on neural networks were able to predict patterns of maxillary development and orthodontic outcomes, allowing one to plan any kind of intervention early on and minimize the number of complications later in life.

6.5 Effect of Virtual Surgical Planning and Explainable AI

Virtual surgical planning systems with AI support have increased the accuracy of preoperative simulation and the quality of the choice of the surgical technique. Planning tools that are built on neural network tools showed enhanced prediction of the postoperative facial morphology and functional outcomes than traditional planning methods. Explainable AI (XAI) systems and clinical predictions made clinicians more confident that their models consider anatomy and clinical factors and encourage interdisciplinary collaboration and better treatment transparency.

6.6 Compared to Traditional Professional Clinical Evaluation

Intelligent computing methods proved to be better than the traditional subjective scoring methods:

- Higher predictive accuracy
- Greater reproducibility
- Less variability in the observers.
- Better outcomes prediction through time.

Traditional clinical assessment procedures were weak in measuring nonlinear anatomic and developmental links, and AI models were compelling at incorporating multimodal data such as imaging, speech examination, and growth data. Table 2 shows the intelligent computing vs traditional clinical evaluation.

Table 2. Intelligent Computing vs Traditional Clinical Evaluation

Parameter	**Intelligent Computing**	**Traditional Clinical Methods**
Predictive Accuracy	High	Moderate
Reproducibility	High	Limited
Observer Variability	Low	High
Outcome Prediction	Long-term prediction possible	Limited prediction ability

Parameter	Intelligent Computing	Traditional Clinical Methods
Data Analysis	Multimodal & nonlinear analysis	Mainly subjective evaluation

7 Conclusion

Intelligent computing has emerged as a transformative tool in the prediction and evaluation of surgical and functional outcomes in cleft lip and palate (CLP). By integrating multimodal datasets—including clinical parameters, imaging studies, speech assessments, and longitudinal growth records—machine learning and deep learning models provide clinicians with objective, reproducible, and highly accurate predictive insights. These technologies address longstanding challenges in CLP care, such as subjective assessment methods, interobserver variability, and the difficulty of forecasting long-term outcomes based on early clinical findings. Across aesthetic, structural, and functional domains, intelligent computing models have demonstrated superior performance compared with conventional evaluation approaches. Predictive algorithms now assist in forecasting postoperative facial symmetry, identifying risk of velopharyngeal insufficiency, estimating maxillofacial growth trajectories, and determining the likelihood of revision surgery. In addition, advances in explainable AI have strengthened clinical trust in these systems by offering transparent and interpretable decision pathways. Looking ahead, the future of CLP management will increasingly rely on computational tools that are more generalizable, energy-efficient, and ethically aligned. The integration of foundation models, neuromorphic hardware, and human–AI collaborative frameworks will further enhance the precision and personalization of treatment planning. As intelligent systems evolve, they are expected to augment not replace clinical expertise, serving as reliable cognitive partners that support comprehensive, patient-centered care. In summary, intelligent computing represents a major advancement in cleft care, offering unprecedented opportunities for predictive accuracy, standardization, and personalized treatment. Continued innovation, interdisciplinary collaboration, and responsible model development will ensure that these technologies become integral components of future surgical planning, outcome assessment, and long-term functional management in patients with cleft lip and palate.

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