



Machine Learning and Computer Vision in Maxillofacial Surgery: Advances in Prediction, Planning, and Automation

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Abstract. Through machine learning (ML) and computer vision (CV) advances are taking shape in maxillofacial surgery that are revolutionising diagnosis, automation of laborious imaging tasks, and data-driven surgical planning and intraoperative support. New deep learning architectures have been used in three-dimensional imaging modalities including cone-beam computed tomography (CBCT) and CT to segment bone, teeth, mandibular canals, and implants and report similar performance to expert manual labelling and a significant reduction in processing time. In orthognathic and reconstructive workflows, ML-based shape estimation, reference model generation, and virtual surgical planning tools are used for reproducible planning and simulation. Computer-vision-based analysis of surgical videos and instrument tracking are very promising for intraoperative guidance and automated charting while their clinical implementation is constrained by diverse available data and regulatory obstacles. In this narrative review, we summarise new technical breakthroughs, clinical applications, important datasets and benchmarks, and key barriers towards translation from ML/CV to everyday maxillofacial surgical use.

Keywords: artificial intelligence, surgical planning, automated diagnostics, imaging, Oral and maxillofacial surgery

1 Introduction

Digital imaging and 3D modelling are fundamental to contemporary oral and maxillofacial surgery (OMFS) - diagnosis, implant planning, orthognathic surgery, trauma reconstruction and oncologic resections [2]. The volume and intricacy of 3D imaging (CBCT/CT) is why ML and CV solutions have been proposed to automate segmentation, classification, localisation and outcome prediction. Due to the progress

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achieved in convolutional neural networks (CNNs), transformer-based vision models, as well as ensemble methods, accuracy and robustness in pre-conditional tasks that were previously labour-intensive and time-dependent have been obtained with great speed [1].

2 Core Technical Approaches

Convolutional neural networks (U-Net variants and 3D U-Nets) and several attention mechanisms along with multi-stage pipelines have been the predominant architectures for volumetric CBCT/CT segmentation tasks. Recently, transformer-style backbones and hybrid CNN-transformer models have been implemented for tooth- and multi-structure segmentation, providing superior long-range context capture in 3D volumes [4]. The shortage of fully labelled 3D datasets has been combatted through self-supervised and semi-supervised learning methods. Ensemble learning and post-processing (morphological corrections, graph-based refinement) still provide clinical-grade outputs [3].

3 Segmentation: Teeth and Bone, Mandibular Canal, Implants

Automated tooth and dental structure segmentation from CBCT has gained ground quickly, with several approaches achieving high Dice similarity coefficients and strong instance identification. Multi-class segmentation such as cortical bone, cancellous bone, teeth, and neurovascular canals allows downstream processing applications like planning implants and risk assessment. A critical task for implant safety, mandibular canal segmentation, has been addressed by dual-stage, attention-guided 3D networks demonstrating high accuracy in large CBCT cohorts. Several validations in deep-learning pipelines for identifying and segmenting dental implants and prosthetic components have been performed allowing faster evaluation and postoperative assessment [5]. Table 1. Shows the Dental CBCT Segmentation Tasks and Applications

Table 1. Dental CBCT Segmentation Tasks and Applications

Structure Segmented	Method Used	Typical Accuracy (Dice Score)	Clinical Use
Teeth	Deep learning-based segmentation	0.90 – 0.96	Tooth identification and treatment planning
Bone (cortical & cancellous)	Multi-class CNN	0.85 – 0.94	Bone quality assessment

Structure Segmented	Method Used	Typical Accuracy (Dice Score)	Clinical Use
Mandibular Canal	Attention-guided 3D CNN	0.87 – 0.95	Implant safety and nerve protection
Neurovascular Canal	3D U-Net-based model	0.86 – 0.93	Surgical risk evaluation
Dental Implants	CNN-based segmentation	0.92 – 0.97	Postoperative assessment
Prosthetic Components	Deep learning detection models	0.90 – 0.95	Treatment monitoring

4 Virtual Surgical Development and Shape Modelling

ML practices for estimation of reference bony shape and generation of “normal” templates have been used for orthognathic planning and craniofacial reconstruction. Derived from a deformed bony model, self-supervised models can estimate reference anatomy and propose osteotomy targets and implant shapes for reconstruction [6]. These models have been integrated into virtual surgical planning (VSP) systems in an attempt to minimise subjectivity and increase reproducibility of preoperative planning decisions. Fig. 1. shows the DL and SA mandibular models with surface deviation overlay.

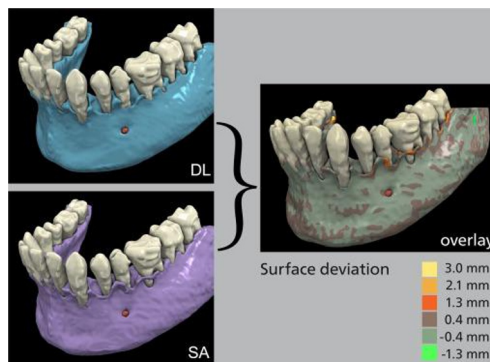


Fig. 1. DL and SA mandibular models with surface deviation overlay.

5 Prediction and Decision Support

Machine-learning-based models have been established for prognostic and outcome prediction of OMFS tasks such as complication risk, implant success, and postoperative occlusal outcomes following orthognathic surgery [14]. Predictive models integrating imaging features and clinical metadata can assist in case selection and personalised planning, but external validation and prospective trials remain sparse [7]. Surgical video analysis, instrument tracking, intraoperative CV and so on. Computer vision in surgical video (endoscopic or open-field) can segment anatomy, detect instruments and give real-time alerts or guidance. [22] Many instrument segmentation and tracking models developed for minimally invasive surgery are adapted for maxillofacial contexts yet intraoperative image variability, occlusions and lighting changes remain challenging [15]. Automatic video documentation and workflow recognition will enhance training, quality assurance, and research but demand annotated surgical video datasets [8].

6 Clinical Domains of Impact

6.1 Orthognathic surgery

AI has been applied to automate cephalometric landmarking, skeletal classification, and simulated surgical outcomes to reduce planning time and enhance repeatability. Deep frameworks to generate patient-specific “reference” bony shapes help to plan objectively in jaw corrections [9].

6.2 Implantology

AI-optimised CBCT segmentation and the analysis of the implant site and site assessment accelerate the implant planning process and screen for anatomic potential risks like nearness of the mandibular canal and sinus cavities. Commercial and academic systems have similar recommendations for implant placement to expert clinicians on retrospective evaluations (i.e., recommendations of the individual systems in comparison to expert clinicians, but the potential utility is also a more research question in a prospective clinical setting) [10].

6.3 In trauma and reconstructive surgery

The recent introduction of machine learning (ML) in fracture diagnosis and fragment segmentation on facial CT helps expedite the timely triage and preoperative planning for zygomaticomaxillary complex (ZMC) and orbital fractures. For reconstructive workflows, automated defect characterisation/3D implant (patient-specific implant) design by applying generative models is feasible in preclinical and clinical proof-of-concept studies [11].

6.4 Oncology and pathology

Computer vision provided to radiologic and histopathologic images supports tumour identification, margin estimation, and risk stratification in oral cancers; ML can be used to inform surgical margin planning and reconstruction strategy as well [12].

6.5 Datasets, benchmarks, and reproducibility

This field has benefited from several curated CBCT/CT datasets and dedicated annotation works on multi-structure segmentation. Recent open datasets and benchmark challenges have facilitated comparative models, which have accelerated development. However, diversity in datasets (scanners, voxel size, field-of-view), annotation standards and limited sample sizes generalise a hard task [13].

7 Result and Discussion

This narrative review illustrates that machine learning (ML) and computer vision (CV) algorithms have made significant advances to many areas of oral and maxillofacial surgery. In the reviewed literature, deep learning-based segmentation models when applied to CBCT and CT imaging have generally reported high levels of accuracy with a Dice similarity coefficient often found to be above 0.90 when segmenting the teeth, jawbone, and mandibular canal. The results can be comparable to manual annotations by expert workers and greatly decrease the time spent on processing, which also lowers to minutes. Transformer and hybrid CNN-transformer designs demonstrated greater resilience in areas with complex anatomy with representations of the long-range spatial dependency, especially in multi-structure segmentation. Attention-guided and dual-stage networks were shown to show better performance in mandibular canal detection, which is considered paramount in decreasing iatrogenic nerve injury during implant placement.

ML-based shape modeling and reference anatomy estimation allowed the reproducible and objective planning of surgery in orthognathic and reconstructive surgeries. Research indicated better uniformity in osteotomy development and restoration of symmetry as compared to the traditional manual techniques of planning. In reconstructive and trauma cases, automated fracture detection and fragmentation were used to provide faster diagnosis and preoperative evaluation, particularly in zygomaticomaxillary and orbital fractures. A combination of predictive models that combine imaging characteristics and clinical variables showed promising results in predicting implant success, postsurgery, and stability of the occlusal and the occurrence of complications. Most of the studies, however, were retrospective and single-center based studies. Applications of computer vision intraoperative settings were found to be encouragingly feasible but limited by inter-surgical variability and

unavailability of large annotated video datasets, such as instrument tracking and surgical workflow recognition. Fig. 2 shows the Automated CBCT-based mandibular segmentation (a–d).

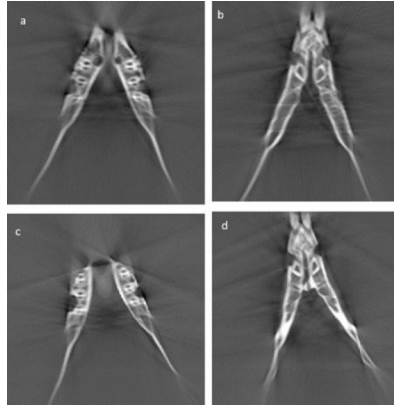


Fig. 2. Automated CBCT-based mandibular segmentation (a–d).

7.1 Discussion

The evidence reviewed points to the fact that the transition of ML and CV technologies is to the tools of clinically relevant decision-support in maxillofacial surgery. The most mature and clinically deployable application is automated segmentation, which offers a consistent level of accuracy and workflow efficiency in the fields of implantology, orthognathic surgery and reconstructive planning. These functions support the growing number and complexity of 3D imaging data that is experienced in contemporary OMFS practice. Although it has good technical performance, there are a number of issues that restrict its clinical usage. The heterogeneity in datasets, scanner variability, and failure to use consistent annotation protocols, all cause poorer interinstitutional generalizability. Majority of the models do not have prospective validation that is necessary in terms of regulatory approval and clinical trust. Moreover, black-box decision-making in deep learning networks presents issues to explainability, especially in life or death surgical planning.

Predictive and decision-support models have important potential to give individualized surgical care with the incorporation of multimodal data, but due to the lack of long-term outcome linked data, their clinical reliability is limited. In the same fashion, although intraoperative computer vision systems promise real-time guidance and automatic documentation, the problem of occlusion and variations in lighting and also the calculation needs are still not achieved. Future studies must focus on multicenter prospective studies, standard benchmarks, and frameworks of clinician-in-the-loop validation. Explainable AI combined with federated learning and real-time

intraoperative systems can be further integrated to provide improved safety, transparency, and scalability. In general, ML and CV technologies are a groundbreaking development in maxillofacial surgery, and only when carefully validated and ethically implemented can bring long-lasting clinical outcomes.

8 Future directions

It will probably focus more heavily on multimodal models, with imaging, clinical records, and intraoperative video merging for end-to-end decision support as a starting point for next steps. Federated and privacy-preserving learning may help mitigate the limitations of data sharing yet still allow multi-centre model training. Real-time intraoperative CV with navigation and robotics may support semi-automated tasks like osteotomy guidance, fragment positioning and robotic-assisted implant placement. Conventional benchmarking, the emergence of prospective trial design and clinician-focused deployment studies will be required to transition from the prospect into routine clinical impact from innovative research.

9 Conclusion

In maxillofacial surgery, machine learning and computer vision are emerging rapidly, with precise automated segmentation, newly available tools for decision support and innovative planning tools that might speed up the processing and standardise medical care. Translational success will hinge on intense testability, scrutiny of ethics & explainability, and close deployment in clinical contexts.

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