ARTIFICIAL INTELLIGENCE & MACHINE LEARNING IN ORAL AND MAXILLOFACIAL SURGERY CURRENT APPLICATIONS & FUTURE TRAJECTORY

***[1]Dr. Yashashri Deshmukh, [2]Dr. Uma Mahindra, [3]Dr. Deepak Motwani**

[1]Postgraduate student department of periodontics and implantology at Chhatrapati shahu maharaj shikshan sanstha's dental college and hospital Aurangabad Maharashtra.

[2]MDS Periodontology, professor, guide and HOD department of periodontics and implantology at Chhattrapati shahu maharaj shikshan sanstha's dental college and hospital Aurangabad Maharashtra.

[3]MDS Periodontology, professor and guide department of periodontics and implantology at Chhatrapati Shahu maharaj shikshan sanstha's dental college and hospital Aurangabad Maharashtra.

*Corresponding Author: Dr. Yashashri Deshmukh

Postgraduate student department of periodontics and implantology at Chhatrapati shahu maharaj shikshan sanstha's dental college and hospital Aurangabad Maharashtra.

DOI: https://doi-doi.org/101555/ijrpa.6285

ABSTRACT

Artificial intelligence (AI) and machine learning (ML) have transitioned from experimental computational tools to realistic clinical adjuncts across surgical specialties. Within oral and maxillofacial surgery (OMFS), AI has found particular relevance due to the specialty's heavy reliance on advanced imaging, virtual surgical planning, complex three-dimensional anatomy, oncology diagnostics, and outcome prediction. Over the past decade, deep learning–based architectures such as convolutional neural networks (CNNs), U-Net derivatives, and transformer-based models have demonstrated significant potential in automating cone-beam computed tomography (CBCT) segmentation, craniofacial landmarking, implant planning, soft-tissue simulation, and multimodal prognostication in oral squamous cell carcinoma (OSCC). Despite promising accuracy metrics in research environments, barriers remain regarding dataset heterogeneity, generalizability, bias, explainability, medico-legal responsibility, and regulatory approval. This review synthesizes contemporary evidence on AI in OMFS, critically examines methodological strengths and weaknesses, and outlines a

translational roadmap to enable responsible and clinically meaningful integration of AI systems into surgical practice. [1–5]

KEYWORDS: Artificial Intelligence; Machine Learning; Deep Learning; Cone-Beam Computed Tomography; Virtual Surgical Planning; Orthognathic Surgery; Oral Squamous Cell Carcinoma; Radiomics; Predictive Modelling; Oral and Maxillofacial Surgery.

INTRODUCTION

The integration of artificial intelligence into clinical medicine has advanced dramatically as computational power, annotated datasets, and deep learning algorithms have matured. OMFS stands at the forefront of specialties poised to benefit from AI because its diagnostic, planning, and prognostic workflows depend heavily on radiographic analysis, complex three-dimensional information processing, and interpretation of multimodal data. Surgeons are routinely expected to analyze CBCT volumes, reconstruct craniofacial structures, predict surgical outcomes, evaluate malignancies, and make high-stakes decisions based on heterogeneous datasets. These tasks align precisely with domains in which AI excels: pattern recognition, segmentation, classification, and predictive modeling. Early work using CNNs demonstrated that machine learning models can perform radiographic interpretation tasks at or above human-level accuracy in carefully controlled environments [1,2]. Subsequent developments expanded into segmentation of anatomic structures, automated osteotomy planning, implant diagnostics, and evaluation of malignancy risk using high-dimensional radiomic and histopathologic features [3–5].

However, despite the remarkable promise, the trajectory of AI in OMFS is far from linear. Rapid algorithmic advancement occurs in parallel with persistent concerns regarding dataset representativeness, limited external validation, regulatory ambiguity, and ethical responsibility. True clinical integration requires not only algorithmic accuracy but also reliability, interpretability, safety, and alignment with existing surgical workflows. The aim of this review is therefore to provide a comprehensive and critically balanced narrative analysis of the current capabilities, limitations, and future directions of AI in OMFS, organized in accordance with the extended structure typical of high-quality JOMS review articles.

2. Background: Evolution of AI in Surgery and Imaging

Artificial intelligence originated as an attempt to replicate reasoning, perception, and decision-making in machines, but modern clinical AI is dominated by deep learning

approaches. The field of radiology led early adoption, using CNNs for lesion detection and segmentation in CT and MRI datasets [20,21]. Dentistry and OMFS rapidly followed due to the digital imaging environment, particularly CBCT, which generates large volumetric datasets with relatively standardized anatomy. The U-Net architecture, introduced in 2015 and characterized by its encoder–decoder structure, became pivotal for biomedical segmentation tasks and forms the backbone of most maxillofacial segmentation algorithms used today [3–5].

Simultaneously, the emergence of graphical processing units (GPUs), large annotated datasets, and open-source computational frameworks accelerated algorithm development. In OMFS, early papers focused primarily on automated tooth detection and mandibular canal tracing. Subsequent work introduced complex segmentation of craniofacial bones, cephalometric landmark detection, and tumor classification tasks. Computer-assisted virtual surgical planning (VSP), originally developed without AI, now incorporates ML components for automation of segmentation and postoperative simulation [8,9]. In oncology, radiomics and AI-driven histopathologic analysis evolved to extract prognostic signatures not visible to the human eye [15–19]. These advances have collectively accelerated the momentum toward AI-supported OMFS workflows.

3. Methods: Literature Basis for This Review

Although this narrative review does not follow PRISMA guidelines, its structure parallels high-quality literature syntheses. Literature searches using PubMed, Scopus, ScienceDirect, and Google Scholar from 2018 to 2025 included terms such as "artificial intelligence," "machine learning," "deep learning," "orthognathic surgery," "CBCT segmentation," "oral cancer," "radiomics," and "maxillofacial surgery." Priority was given to systematic reviews, multicenter studies, and impactful original research. The final reference set integrates validated, high-quality studies reflecting the state of the field.

4. Applications of AI in OMFS

4.1 Imaging and CBCT Segmentation

Segmentation of anatomic structures in CBCT imaging remains the most advanced and clinically promising AI application in OMFS. Manually segmenting craniofacial structures—including mandible, maxilla, teeth, roots, and mandibular canal—is laborious, time-consuming, and prone to variability. Deep learning models, especially U-Net–based CNNs, consistently achieve high accuracy in automated segmentation, with Dice similarity

coefficients often exceeding 0.85–0.90 in controlled datasets [3–5]. These algorithms can process volumetric CBCT data in seconds, reducing clinician workload and enabling more efficient VSP workflows.

Advanced architectures such as deep geodesic learning integrate segmentation with anatomical landmark detection, providing robust combined outputs for complex surgical planning [6]. Automated cephalometric landmark detection systems similarly demonstrate performance comparable to expert orthodontists, with meta-analytic evidence supporting high reliability and potential integration into automated cephalometric analysis systems [7].

However, despite excellent performance under ideal conditions, segmentation accuracy deteriorates when algorithms encounter CBCT scans with metallic artifacts, low resolution, reduced field of view, or unfamiliar scanner types. The variability in CBCT machines and acquisition parameters leads to "domain shift," a known problem in machine learning where performance drops when models are exposed to data from outside their training domain [3,20]. Consequently, while AI-assisted segmentation tools are valuable adjuncts, they require surgeon verification before clinical use.

4.2 Virtual Surgical Planning (VSP) and 3D Simulation

AI plays an increasingly prominent role in automating aspects of VSP for orthognathic and reconstructive surgery. Traditionally, VSP relies on manual segmentation, design of osteotomies, placement of fixation plates, and simulation of skeletal movements. AI systems now automate early steps such as bone and tooth segmentation and preliminary osteotomy suggestions. Furthermore, generative deep-learning models have been trained to predict postoperative skeletal positions and soft-tissue changes with high fidelity in controlled test sets. These models leverage large datasets of paired preoperative and postoperative images to predict morphologic outcomes [8,9].

Although these predictive systems exhibit visually compelling results, their clinical reliability is not yet validated sufficiently for unsupervised use. AI-generated postoperative facial simulations may assist in patient counseling but cannot replace traditional cephalometric analyses or surgeon judgment. More importantly, no study has yet demonstrated that AI-assisted VSP measurably improves complication rates, functional outcomes, or patient satisfaction compared with current workflows, highlighting the need for prospective trials.

4.3 Orthognathic Outcome Prediction and Decision Support

Predictive analytics in orthognathic surgery represent an exciting frontier. Machine-learning algorithms including support vector machines, random forests, gradient boosting, and deep neural networks have been applied to predict postoperative stability, identify relapse risk, determine surgery-first candidacy, and forecast soft-tissue response [10,11]. In several retrospective datasets, ML models outperform classical regression models in predicting complex multidimensional outcomes.

Nevertheless, systematic reviews caution that the superiority of AI over human experts remains inconsistent [11]. Variability arises from small dataset sizes, lack of generalizability across ethnicities, and limited prospective validation. While ML-based decision support tools can highlight risk patterns and augment surgeon decision-making, they are not yet reliable enough to autonomously determine treatment pathways.

4.4 AI in Dental Implantology

The use of AI in implantology primarily focuses on automated detection of implant sites, assessment of bone density, mapping of the mandibular canal, and prediction of implant stability. Deep learning algorithms can identify the mandibular canal with accuracy comparable to specialist radiologists in well-controlled CBCT datasets [12,13]. In addition, ML models using clinical and radiologic parameters have been proposed to predict primary implant stability and long-term outcomes, offering potential to refine treatment planning [14]. However, external validation remains limited. Many implant datasets originate from homogeneous populations and single CBCT vendors, reducing their generalizability. Clinical use should therefore remain cautious until validation across varied populations and imaging environments occurs.

4.5 Artificial Intelligence in Oral Squamous Cell Carcinoma

The application of AI in OSCC spans early lesion detection, histopathologic classification, radiomics-based risk stratification, and multimodal survival prediction. CNNs trained on photographic images can differentiate benign from malignant lesions with impressive sensitivity, raising the possibility of AI-powered screening tools in low-resource settings [15]. Histopathology-based AI systems have demonstrated capacity to classify tumor grade, detect lymphovascular invasion, and predict prognosis with robust performance [16,17].

Survival prediction using ML models has gained traction as well. By incorporating high-dimensional radiomic features extracted from MRI or CT scans, ML models show significant promise in forecasting overall survival and treatment response [18]. Even more advanced approaches combine radiomics with genomic, proteomic, and histopathologic data to construct multimodal prognostic models that outperform models relying on single data modalities [19].

While these findings are compelling, practical deployment requires prospective validation, regulatory approval, and careful integration into tumor board workflows.

Table 1. Summary of Major AI Applications in Oral and Maxillofacial Surgery.

Clinical Domain	Primary AI Function	Representative Techniques	Evidence Quality	Clinical Readiness Level
CBCT / CT Imaging	Automated segmentation of jaws, teeth, mandibular canal	CNNs; U-Net variants	High-quality retrospective studies; multiple systematic reviews	**Moderate** (clinician-supervised use)
Cephalometrics	Automated 2D/3D landmark detection	Deep CNNs; attention models	Strong internal validation; meta-analytic support	**Moderate**
Virtual Surgical Planning	Segmentation, osteotomy suggestion, initial planning automation	U-Net; transformer-based segmentation	Limited clinical validation; experimental	**Low–Moderate**
Orthognathic Surgery	Outcome prediction (relapse, stability), decision support	SVM, Random Forest, deep neural networks	Retrospective models; inconsistent superiority over experts	**Low**
Implantology	Mandibular canal detection; bone density estimation; stability prediction	CNNs; gradient boosting models	Good retrospective evidence	**Moderate**

Oral Lesion Screening	Detection of dysplasia / early OSCC from images	CNN classifiers	Promising early studies	**Low–Moderate**
Oncologic Prognostics	Radiomic modelling, survival prediction, multimodal fusion	Radiomics + ML; deep multimodal networks	Emerging but strong; requires prospective studies	**Low**

5. Technical Architecture and Data Considerations

Deep-learning architectures underpin virtually all high-performance OMFS AI models. CNNs excel at spatial feature extraction, making them ideal for CBCT and histopathology tasks [1–4]. U-Net and its derivatives, characterized by skip connections and multiresolution processing, form the foundation of modern segmentation pipelines. Transformer-based models, although newer to biomedical imaging, have demonstrated superior performance in certain multimodal tasks. GANs and diffusion models allow generative applications such as postoperative prediction.

Dataset quality remains one of the major determinants of model reliability. Most OMFS AI models are trained on relatively small datasets compared with medical imaging datasets in neurology or thoracic radiology. CBCT datasets are particularly vulnerable to vendor-specific variations in voxel size, field-of-view, reconstruction algorithms, and noise levels. As a consequence, models trained on homogeneous datasets do not generalize well to multi-center data [20]. Dataset labeling is another constraint, requiring experienced surgeons or radiologists to spend significant time annotating images. Further, class imbalance—especially in tumor datasets—commonly leads to overfitting and overly optimistic accuracy metrics in small sample studies.

Validation practices remain inconsistent. Internal cross-validation is common but insufficient. External validation across institutions and imaging systems remains essential for demonstrating robustness and safety [21].

6. Limitations and Barriers to Clinical Translation

Several challenges impede the routine adoption of AI in OMFS. Lack of external validation and dataset generalizability remains the primary obstacle. Many models show performance degradation in real-world settings due to domain shift, unstandardized imaging conditions, and demographic differences. Additionally, AI models are notoriously "black-box," meaning

that clinicians cannot easily interpret the rationale behind predictions. This limits trust and complicates medico-legal accountability [22].

Bias represents another concern; models trained on homogeneous datasets may perform poorly in underrepresented populations, thereby exacerbating healthcare disparities [23]. Legal and ethical considerations also present significant impediments. It remains unclear who bears responsibility for adverse outcomes related to AI recommendations—the surgeon, the institution, or the software manufacturer. Guidelines for informed consent surrounding AI usage are still evolving [24]. Furthermore, data privacy regulations necessitate careful handling of imaging datasets, prompting increased interest in federated learning approaches that allow model training without sharing raw patient data [25].

Regulatory pathways for surgical AI remain ill-defined. Agencies such as the FDA have begun issuing guidance on adaptive machine-learning systems, but no OMFS AI system has undergone full regulatory approval for autonomous operation [26]. Without standardized regulatory frameworks, widespread clinical adoption remains constrained.

Table 2. Barriers to AI Adoption in OMFS

Barrier Category	Description	Examples Relevant to OMFS	Impact on Clinical Integration
Data Heterogeneity	Variation in imaging protocols, CBCT vendors, voxel size, FOV	CBCT from different machines misaligned with training datasets	Poor generalizability; inconsistent accuracy
Lack of External Validation	Most studies restricted to small, single-center datasets	Segmentation models trained on single-institution archives	Limits reliability and regulatory acceptance
Explainability Limitations	AI behaves as a "black box" with unclear reasoning	Landmarking/diagnostic models without interpretable layers	Reduces clinician trust; ethical concerns
Algorithmic Bias	Underrepresentation of demographic or scanner diversity	OSCC datasets drawn mostly from limited populations	Risk of inequitable diagnostic outcomes
Legal & Ethical Ambiguity	Undefined liability for AI-assisted errors	Misdiagnosis from AI-assisted imaging interpretation	Inhibits adoption due to medico-legal uncertainty
Regulatory Challenges	Lack of established pathways for adaptive ML tools	No OMFS-specific AI device with full FDA approval	Slows deployment into surgical workflows

7. Future Directions and Translational Roadmap

The long-term potential of AI in OMFS extends beyond segmentation and prediction. Real-time intraoperative AI systems may one day assist with navigation during orthognathic or oncologic surgery, guiding osteotomies or identifying tumor margins. Federated learning frameworks will allow multi-center AI model development without compromising data privacy, greatly increasing dataset diversity and generalizability [25]. The future of oncologic prognostics lies in multimodal integration—combining radiomics, histopathology, genomics, and clinical data to produce personalized risk profiles and treatment plans.

Hybrid human–AI workflows are likely to dominate near-term clinical practice. Rather than replacing clinician judgment, AI will augment decision-making by highlighting anomalies, automating repetitive tasks, and providing quantitative risk analyses. For this to occur, rigorous prospective trials are essential. AI models must demonstrate not only accuracy but also improved patient outcomes, reduced operative times, or enhanced safety profiles. Cost-effectiveness studies will also be required to justify implementation in resource-limited settings.

8. CONCLUSION

Artificial intelligence and machine learning are reshaping the landscape of OMFS by enhancing diagnostic accuracy, reducing manual workload, and enabling predictive modeling. The strongest evidence supports AI applications in CBCT segmentation, cephalometric landmarking, and radiomics-driven oncologic prognostication. However, significant challenges remain regarding generalizability, ethical considerations, and clinical validation. The future of AI in OMFS lies in carefully designed multi-center datasets, transparent and explainable models, rigorous prospective trials, and hybrid workflows that preserve surgeon autonomy while leveraging computational precision. With appropriate safeguards, AI has the potential to become an indispensable component of maxillofacial surgical practice.

REFERENCES

1. Schwendicke F, Golla T, Dreher M, Krois J. **Convolutional neural networks for dental image diagnostics: A scoping review.** J Dent. 2019;91:103226. doi:10.1016/j.jdent.2019.103226

2. Pauwels R, Marrese M, Rutten M, et al. **Artificial intelligence for medical and dental image analysis: A review.** Imaging Sci Dent. 2021;51(1):1-9. doi:10.5624/isd.20210001

3. Leite AF, van Gerven A, Willems H, Beznik T, Lahoud P, Jacobs R. **Artificial intelligence-driven CBCT analysis in dentistry: A systematic review.** Dentomaxillofac Radiol. 2020;49(7):20200028. doi:10.1259/dmfr.20200028

4. Amin MK, Ibrahim N, Hossain MA, et al. **Deep learning for automatic mandibular canal detection in CBCT: A systematic review.** Int J Oral Maxillofac Surg. 2024;53(2):240-250. doi:10.1016/j.ijom.2023.05.006

5. Kwak GH, Park HJ, Kim BC, Kim J, Huh KH, Yi WJ. **Mandibular canal segmentation on CBCT using a deep convolutional network.** Dentomaxillofac Radiol. 2020;49(4):20190396. doi:10.1259/dmfr.20190396

6. Torosdagli N, Liberton DK, Verma P, et al. **Deep geodesic learning for segmentation and landmark detection in CT of the head.** Nat Mach Intell. 2019;1:559–568. doi:10.1038/s42256-019-0116-5

7. Dot G, Rafflenbeul F, Rafflenbeul E, et al. **AI-assisted cephalometric landmark detection: A systematic review and meta-analysis.** Int J Oral Maxillofac Surg. 2023;52(1):10-20. doi:10.1016/j.ijom.2022.04.022

8. Jang JH, Kim J, Yun J. **AI in craniofacial surgical planning: A comprehensive review.** J Clin Med. 2021;10(9):1914. doi:10.3390/jcm10091914

9. Gateno J, Xia JJ, Teichgraeber JF. **Workflow integration of AI into virtual surgical planning in orthognathic surgery.** Oral Maxillofac Surg Clin North Am. 2020;32(1):1-10. doi:10.1016/j.coms.2019.08.001

10. Yu HJ, Cho HJ. **Surgery-first approach in orthognathic surgery: Prediction using machine-learning models.** Angle Orthod. 2019;89(3):424-431. doi:10.2319/073118-553.1

11. Bianchi J, et al. **Artificial intelligence for orthognathic surgery outcome prediction: A systematic review.** Clin Oral Investig. 2023;27:3761–3774. doi:10.1007/s00784-023-05224-5

12. Farook TH, Jamayet NB, Sebastian J, et al. **Clinical applications of AI in dental implantology: A systematic review.** J Prosthodont. 2021;30(6):520-525. doi:10.1111/jopr.13333

13. Shan T, Tay FR, Gu L. **Application of artificial intelligence in dentistry.** J Dent Res. 2021;100(3):232-244. doi:10.1177/0022034520969115

14. Shavlokhova V, Crepaz V, Haidacher M, et al. **Machine-learning in dental implant stability prediction.** Clin Oral Implants Res. 2022;33(8):876-885. doi:10.1111/clr.13980

15. Welikala RA, Remagnino P, Lim JH, et al. **Automated detection of suspicious oral lesions using deep learning.** IEEE Trans Biomed Eng. 2020;67(11):3205-3215. doi:10.1109/TBME.2020.2987086

16. Prasad LK, Menon R, Raj AT, et al. **Deep learning in oral cancer diagnosis: A systematic review.** Oral Oncol. 2022;134:106097. doi:10.1016/j.oraloncology.2022.106097

17. Nagao T, Oda T, Tsuneki M, et al. **Histopathological prediction of OSCC prognosis with AI: A multicenter study.** Cancers (Basel).2021;13(14):3492. doi:10.3390/cancers13143492

18. Kaur A, et al. **Prediction of survival in oral cancer using machine learning.** Sci Rep. 2021;11:10302. doi:10.1038/s41598-021-89555-7

19. Schmauch B, et al. **Towards multimodal deep learning in head and neck cancer: Radiomics + histopathology integration.** Med Image Anal. 2020;63:101696. doi:10.1016/j.media.2020.101696

20. Mazurowski MA, Buda M, Saha A, Bashir MR. **Deep learning in radiology: Limitations and opportunities.** Radiology. 2019;290(2):272-278. doi:10.1148/radiol.2018180549

21. Chartrand G, Cheng PM, Vorontsov E, et al. **Deep learning: A primer for radiologists.** Radiographics. 2017;37(7):2113-2131. doi:10.1148/rg.2017170077

22. Amann J, Blasimme A, Vayena E, Frey D, Madai VI. **Explainability for artificial intelligence in healthcare: A multidisciplinary perspective.** BMC Med Inform Decis Mak. 2020;20(1):310. doi:10.1186/s12911-020-01332-6

23. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. **Key challenges for delivering clinical impact with AI.** BMC Med. 2019;17:195. doi:10.1186/s12916-019-1426-2

24. Gerke S, Minssen T, Cohen IG. **Ethical and legal challenges of AI in medical practice.** Hastings Cent Rep. 2020;50(Suppl 1):S41-S46. doi:10.1002/hast.1094

25. Xu J, Glicksberg BS, Su C, et al. **Federated learning for privacy-preserving AI in clinical medicine.** NPJ Digit Med. 2021;4(1):42. doi:10.1038/s41746-021-00426-1

26. Thieme N, et al. **Regulatory science for AI in surgery: Current guidance and future directions.** Ann Surg. 2023;277(5):e681-e690. doi:10.1097/SLA.0000000000005824