Review Article

Artificial Intelligence in Oral Cancer Diagnosis: Current applications, challenges, and future Perspectives

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Abstract

Artificial intelligence (AI) is rapidly evolving into a pivotal diagnostic adjunct in oral oncology, particularly for the early identification of oral squamous cell carcinoma (OSCC). Recent advancements in machine learning (ML) and deep learning (DL) algorithms demonstrate high efficacy in automated screening, mucosal lesion classification, histopathological grading, and prognostic risk stratification. These models extract complex features from diverse diagnostic modalities, including clinical photographs, smartphone-acquired images, whole-slide digital histopathology, and advanced optical imaging. While current diagnostic accuracies, sensitivities, and specificities are high in controlled environments, routine clinical translation remains restricted. Key translational bottlenecks include low multi-center external validation, high risk of dataset bias, and a lack of algorithmic explainability ("black-box" models). This review synthesizes current AI applications within the past 2–3 years, evaluates performance metrics across varying data inputs, addresses critical implementation barriers, and outlines next-generation paradigms, including explainable AI (XAI), privacy-preserving federated learning, multimodal data fusion, and low-cost digital screening networks.

Keywords :

Introduction

Oral cancer, predominantly presenting as oral squamous cell carcinoma (OSCC), remains a major global public health challenge due to a high proportion of patients presenting at advanced clinical stages[(1)]. Delayed detection significantly limits therapeutic success, resulting in a five-year survival rate of below 50% for advanced presentations, while escalating patient morbidity and financial burdens. Conversely, early-stage diagnosis significantly improves prognosis, driving survival rates up to 80–90%[(1)]. While scalpel biopsy followed by histopathological evaluation represents the diagnostic gold standard, the process is subject to inter-observer variability, subjective assessment, and structural turnaround delays, particularly in distinguishing borderline epithelial dysplasia or early microscopic invasive lesions.

To reduce these clinical constraints, computational oncology has shifted toward AI-driven diagnostic pipelines. Modern deep learning architectures have transitioned from experimental structures to robust clinical decision support frameworks. By leveraging high-throughput image recognition and automated feature engineering, these systems assist clinicians across multiple workflows, including tele-dentistry screening and automated digital pathology[(2)]. Crucially, the current consensus emphasizes that AI systems are designed to function as intelligent diagnostic adjuncts rather than autonomous replacements for expert clinical or pathological judgment.

Current applications of AI in Oral Cancer Diagnosis

Computational workflows are now applied across the entire diagnostic spectrum of oral oncology. The primary clinical focus centers on automating the identification of oral potentially malignant disorders (OPMDs) and malignant transformations through various imaging paradigms[(2)].

Clinical and Smartphone-Based Photography

Because standard clinical photographs are non-invasive and easily acquired, they form the cornerstone of primary care triaging and tele-dentistry networks. Deep convolutional neural networks (CNNs) can differentiate benign conditions from frank invasive carcinomas with high sensitivity[(1)]. Handheld and smartphone-assisted AI screening frameworks are particularly valuable for resource-limited settings where specialized oral and maxillofacial clinics are sparse, enabling localized primary detection before advanced lesions progress[(3)].

Digital Histopathology and Advanced Optical Technologies

In digital pathology, deep learning models process whole-slide images (WSIs) to perform automated cellular segmentation, tissue microarchitecture profiling, and automated tumor grading. Concurrently, AI is being

integrated with optical imaging modalities, such as optical coherence tomography (OCT) and autofluorescence-based systems, to resolve real-time tissue microstructures and guide targeted surgical biopsies with computational accuracy.

Data Sources and Diagnostic Performance Metrics

AI models use an expanding matrix of clinical inputs to achieve precise classification. Performance varies heavily across these modalities, reflecting distinct structural resolution and image preprocessing requirements:

- **Clinical and Smartphone Imaging:** High accessibility; uses transfer learning on pre-trained networks (e.g., VGG, DenseNet, EfficientNet) to flag atypical mucosal patterns.
- **Whole-Slide Histopathology:** High-resolution microscopic datasets that evaluate cellular atypia, architectural changes, and invasive fronts.
- **Radiographic and Advanced Optical Data:** CT, MRI, and OCT data processed to quantify deep structural invasion and microvascular alterations.

Benchmarked Diagnostic Performance

Recent systematic and meta-analytic evaluations confirm that deep learning models demonstrate high diagnostic parameters in image-based classification tasks.

Modality / Architecture	Diagnostic Metrics	Primary Clinical Application	Key References
Handheld / DSLR Imaging (DenseNet121, VGG19, Efficient Net)	Accuracy: up to 97.5% Specificity: up to 99.0%	Primary care screening, community-level triaging, and tele-dentistry networks[3]	Thakuria et al., 2024
OralNet Framework (Fused Deep & Handcrafted Features)	Accuracy: >99.5%	Automated binary classification of OSCC on 100× and 400× histopathology slides[4]	Mohan et al., 2023
Xception Architecture (Multiclass Grading Pipeline)	AUC (macro): 0.929 AUC (micro): 0.942	Automated grading of oral epithelial dysplasia and malignant structural layers[5]	Štifaniæ et al., 2025

Discussion: Barriers To Clinical Implementation

Data Overfitting and Validation Gaps

The most significant barrier to routine clinical adoption is lack of broad external validation. Most published models utilize the retrospective datasets from a single institution, making them prone to overfitting. When exposed to independent, multi-center datasets with different stain intensities, camera models, or demographic variations, algorithmic performance often drops. This is particularly relevant in high-burden countries like India, where regional variations in habits (e.g., betel quid chewing formats, tobacco compositions, and localized mucosal alterations) alter lesion appearances significantly, requiring localized tuning and diverse demographic inclusion[1].

The "Black-Box" Problem and Explainable AI (XAI)

Clinicians are understandably hesitant to rely on deep learning predictions due to the opaque nature of neural network layers. To address this, current research emphasizes Explainable AI (XAI) frameworks. Using post-hoc visualization tools like Grad-CAM (Gradient-weighted Class Activation Mapping), models generate visual saliency heatmaps[5]. These heatmaps highlight the specific pixel region such as cellular pleomorphism or disrupted basement membranes—that drove the classification decision, allowing pathologists and clinicians to verify the algorithmic logic natively.

Ethical and Infrastructure Considerations

Deploying diagnostic AI requires balancing data access with strict privacy preservation laws. Furthermore, geographic or demographic imbalances in training datasets can introduce bias, causing models to perform poorly on underrepresented populations. Emerging techniques like Privacy-Preserving Federated Learning (FL) allow multi-institutional models to be trained collaboratively on decentralized datasets without transferring sensitive patient records across hospital firewalls[6].

Visual Workflow Concept Outlines[7-10]

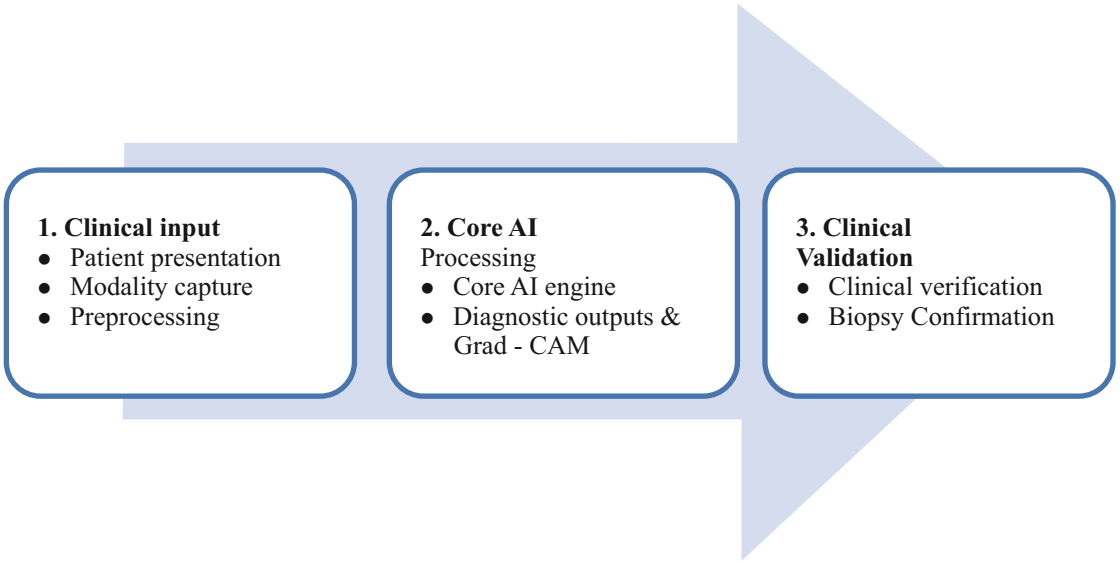


Figure 1: AI Diagnostic Workflow – Clinical Input → Preprocessing → AI Model → Lesion Classification → Clinical Decision Support.

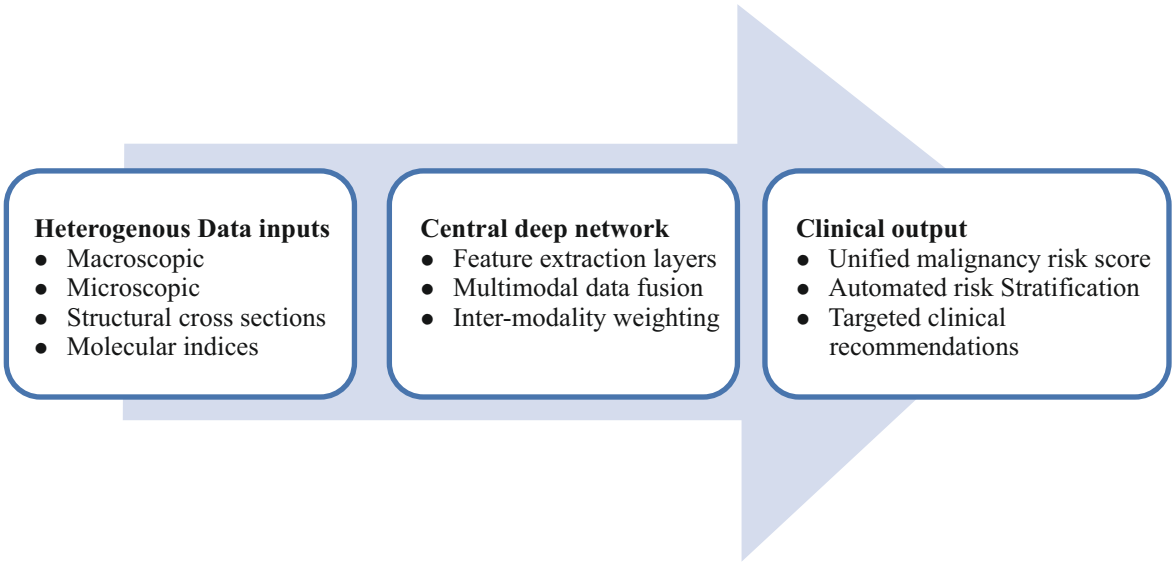


Figure 2: Multimodal AI Data Fusion – Clinical Images + Histopathology + Radiographs + OCT → AI Model → Diagnostic Output.

Conclusion

The integration of artificial intelligence into oral oncology represents a definitive paradigm shift from experimental computation to viable clinical decision support. As synthesized in this review, deep learning architectures have demonstrated remarkable diagnostic precision in processing both clinical screening images and digital histopathology. Automating this feature extraction offers a practical pathway to eliminate diagnostic delays, which is critical for shifting patient presentation toward early-stage detection where five-year survival rates reach 80–90%.

However, widespread clinical adoption requires overcoming clear translational bottlenecks. Future development must move past single-center retrospective datasets toward robust, multi-center external validation that accounts for regional demographic variations, such as localized betel quid and tobacco habits. Additionally, addressing the "black-box" dilemma through Explainable AI (XAI) and tools like Grad-CAM is non-negotiable for building clinical trust. Ultimately, AI should be utilized as an intelligent diagnostic adjunct rather than a standalone replacement for clinical expertise. By integrating privacy-preserving federated learning and multimodal data fusion, these systems can be safely deployed to democratize early screening and fundamentally improve patient outcomes.

Source of Support: Nil

Conflict of Interest: Nil

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