SCIENTIFIC ARTICLE

Artificial Intelligence in the Early Detection of Oral Potentially Malignant Disorders: Current Evidence and Clinical Challenges

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ABSTRACT

Oral potentially malignant disorders (OPMDs) encompass clinically diverse mucosal conditions associated with an increased risk of oral squamous cell carcinoma. Early recognition is essential, yet conventional examination is influenced by lesion heterogeneity, practitioner experience and access to specialist assessment. This narrative review evaluates artificial intelligence (AI) in the detection of OPMDs, focusing on photographic imaging, convolutional neural networks, smartphone screening, diagnostic accuracy and implementation barriers. Published studies and evidence syntheses suggest that image-based AI can identify suspicious oral lesions with promising sensitivity and specificity in selected datasets. However, differences in case selection, reference standards, validation approaches and imaging conditions complicate comparisons. High retrospective accuracy does not demonstrate improved referral decisions or reduced cancer incidence. Smartphone applications may extend access to screening but require quality-controlled image acquisition, privacy safeguards and clinician oversight. Future studies should prioritize independent external validation, prospective multicenter testing, appropriate diagnostic thresholds and patient-centered outcomes. AI should complement clinical examination and histopathological assessment rather than replace them.

KEYWORDS: Artificial intelligence; Oral potentially malignant disorders; Deep learning; Oral cancer; Clinical photography; Early detection.

INTRODUCTION

Oral squamous cell carcinoma (OSCC) is a serious disease whose treatment may impair speech, swallowing and appearance. Earlier recognition of suspicious mucosal changes can support timely referral and biopsy. Oral potentially malignant disorders (OPMDs) include oral leukoplakia, erythroplakia, oral submucous fibrosis and proliferative verrucous leukoplakia. Their clinical features and malignant potential differ, making accurate terminology and careful assessment important [1].

Conventional examination depends on inspection, palpation, medical and behavioral history and, when indicated, histopathology. Early lesions may resemble frictional keratosis, inflammatory conditions or other benign abnormalities. Conversely, a lesion with a relatively subtle appearance can still contain epithelial dysplasia. Clinical uncertainty is therefore unavoidable, particularly in primary care where suspicious lesions may be encountered infrequently.

Artificial intelligence (AI) offers computational tools that can recognize patterns in images and support decisions about whether lesions merit further evaluation. Deep learning has attracted attention because it can learn image features without relying entirely on manually selected measurements. Systematic reviews indicate encouraging diagnostic performance, but important methodological differences limit direct translation into practice [3,4]. This article examines AI-assisted imaging for OPMD detection, with emphasis on evidence quality, practical deployment and clinical challenges.

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MATERIALS AND METHODS

A narrative review approach was used to discuss published studies of AI-based oral lesion detection, relevant diagnostic accuracy syntheses, and research on malignant transformation of OPMDs. The selected literature includes clinical photographic studies, systematic reviews and meta-analyses, and methodological publications relevant to reporting and validation. Particular attention was given to photographic acquisition, machine-learning approaches, diagnostic reference standards and the interpretation of sensitivity and specificity.

The review is a critical narrative synthesis. Database search was conducted across Pubmed, Scopus, Web of Science and Embase, Accordingly, the included references should be regarded as a focused evidence base rather than an exhaustive inventory of all eligible publications. No original patient records, clinical photographs or experimental datasets were analyzed.

ORAL POTENTIALLY MALIGNANT DISORDERS

The category of OPMDs reflects increased population-level risk rather than certainty of progression in an individual patient. Oral leukoplakia is particularly heterogeneous: lesions may be homogeneous or nonhomogeneous, solitary or multifocal, and may occur at sites associated with different levels of concern. Erythroplakia and proliferative verrucous leukoplakia also require careful specialist evaluation [1].

Malignant transformation estimates vary with lesion definition, study design and follow-up duration. Aguirre-Urizar and colleagues reviewed recent evidence on leukoplakia transformation [2]. A later comprehensive meta-analysis reported a pooled transformation proportion of 6.64%, with increased risk associated with nonhomogeneous appearance, larger size, tongue location and epithelial dysplasia [5]. These findings show why visual recognition alone is not equivalent to prognostic assessment.

An algorithm identifying a white lesion may provide useful screening information, but cannot determine dysplasia grade from a surface photograph with the certainty of tissue examination. Similarly, detecting an existing carcinoma is not the same as predicting transformation of a premalignant lesion. Research should explicitly separate detection, classification, referral triage and long-term prediction.

AI TECHNIQUES AND CLINICAL IMAGING

Machine learning uses examples to learn relationships between inputs and outcomes. Convolutional neural networks (CNNs) are frequently used for photographic image classification because successive computational layers detect edges, colors, textures and more complex patterns. Model development typically includes image labeling, preprocessing, training, tuning and validation. The quality of the reference diagnosis is fundamental: an inaccurate label can lead to a confidently wrong prediction.

Fu et al. investigated deep learning for OSCC detection from photographic images [6]. Warin et al. explored automated oral cancer classification [7] and subsequently evaluated CNN-based detection of OPMDs [8]. These studies support feasibility but do not establish that one architecture will perform equally well with different devices, patient groups or lesion distributions.

Image segmentation can highlight the region used for classification, while quality-control algorithms may identify blur, poor illumination or incomplete mucosal coverage. Yet visually persuasive heat maps are not proof that a model has learned biologically meaningful features. Spurious associations with camera settings, backgrounds or clinical instruments may contribute to apparent performance. Development datasets should therefore include variation in anatomy, lesion types, image acquisition and clinical setting.

DIAGNOSTIC PERFORMANCE

Published reviews generally report encouraging diagnostic performance, although pooled estimates must be interpreted in context. Li et al. reported sensitivity of 89.9% and specificity of 89.2% for AI-assisted clinical imaging in the detection of OPMDs and oral cancer [4]. Sahoo et al. found approximately 87% sensitivity and 81% specificity across imaging approaches [9]. Another imaging-based meta-analysis reported sensitivity of approximately 91.9% and specificity of 87.9% [10]. These estimates are not interchangeable because the underlying studies differ in population, reference standard, lesion spectrum and model selection.

Horvath et al. reported high performance for selected intraoral-photography architectures [11]. Nevertheless, estimates obtained from best-performing models or curated images may overstate real-world effectiveness. Repeated testing on development data, small samples and the absence of independent external validation can produce optimistic results. A study should distinguish patient-level from image-level separation to prevent photographs of the same patient appearing in both training and test sets.

Sensitivity describes the proportion of relevant cases correctly identified, whereas specificity describes the proportion of noncases correctly classified. Predictive values also depend on prevalence. A system evaluated in a specialist clinic with many suspicious lesions may generate more false alarms when deployed in low-prevalence community screening. Reporting should therefore include confusion matrices, confidence intervals, decision thresholds and clinically meaningful error analysis. Diagnostic accuracy alone cannot demonstrate reduced diagnostic delay or mortality.

SMARTPHONE SCREENING AND TELE-DENTISTRY

Smartphones offer a relatively accessible means of documenting oral lesions, particularly when dedicated imaging equipment is unavailable. AI-assisted mobile photography could support screening, longitudinal documentation and secure referral to oral medicine specialists. A systematic review by Cao et al. examined AI-assisted smartphone detection of oral cancer and OPMDs and reported promising pooled estimates [12]. An umbrella review also discussed the developing evidence for AI-integrated mobile photographs [13].

Practical performance depends on more than the algorithm. Images of the posterior tongue, floor of mouth or soft palate may be difficult to obtain. Shadows, saliva, motion, variable camera distance and inconsistent focus can obscure clinically important features. Standardized positioning, lighting and image-quality checks should be integral to any workflow. An inadequate photograph should trigger repeat imaging or direct examination rather than an automatically reassuring result.

Tele-dentistry may extend specialist input to underserved facilities, but it also requires secure transfer, appropriate consent and a reliable mechanism for follow-up. A photograph cannot replace palpation, assessment of induration or evaluation of symptoms. Screening pathways should specify who reviews AI outputs, how urgent referrals are prioritized and what happens when the algorithm and clinician disagree.

CLINICAL DECISION SUPPORT

The most defensible near-term role of AI is adjunctive decision support. A clinician can document risk factors, inspect and palpate the oral mucosa, obtain standardized photographs and consider the algorithm's output alongside the clinical findings. A

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suspicious lesion should be referred or biopsied when indicated regardless of a low-risk AI classification. Conversely, a positive AI flag requires professional interpretation rather than automatic diagnosis.

AI could assist with lesion documentation, triage of referrals and education of less experienced dental personnel. However, clinical responsibilities must remain within professional scopes of practice. Dental assistants and imaging technicians may contribute to acquisition and documentation under approved protocols, while diagnostic decisions remain with qualified clinicians. Training should cover image quality, false-negative risk, patient communication and appropriate escalation.

Longitudinal risk prediction is a separate objective requiring follow-up datasets with reliable transformation outcomes. Combining photographs with tobacco exposure, anatomical site, lesion duration and histopathology might eventually improve risk stratification. Such multimodal models should be compared with conventional clinical assessment rather than assumed to offer incremental benefit.

DISCUSSION

The literature indicates a consistent technical opportunity: computational analysis can recognize visual features associated with suspicious oral lesions. The unresolved question is whether this recognition improves care when used by general dental teams. Specialist-derived datasets often contain a greater proportion of obvious disease than community practice. This spectrum difference can produce performance estimates that are difficult to reproduce in routine screening.

Another issue is the distinction between lesion-level classification and patient-level decision-making. A patient may have several lesions, only one of which warrants biopsy. Image-based systems must therefore define how multiple findings, image uncertainty and clinical risk factors influence the recommendation. Algorithms should also be evaluated for their impact on referral volume, time to diagnosis and missed lesions, not merely percentage accuracy.

Implementation in Saudi dental services could be explored through prospective multicenter studies involving primary care, specialist dental centers and hospital-based oral medicine clinics. Such studies should recruit consecutive eligible patients, document lesion characteristics and use independent reference assessment. They should also examine acceptability, training requirements, privacy and the ability to maintain reliable follow-up. These are proposed research priorities, not outcomes established by the current review.

Transparency in model development and evaluation is necessary for reproducibility. Reporting frameworks for AI research continue to evolve; the TRIPOD-LLM statement illustrates this broader movement but addresses language-model research and should not substitute for design-appropriate guidance for diagnostic imaging studies [14].

CHALLENGES AND LIMITATIONS

The principal barriers include limited training diversity, class imbalance, inconsistent diagnostic labels, weak external validation and variable image quality. Algorithms may also perform unevenly across patient populations or devices. Such differences require direct testing rather than assumptions of fairness or generalizability.

False negatives can delay recognition of important disease, while false positives may cause anxiety and unnecessary referral. Threshold selection should therefore reflect the intended use and the consequences of error. Privacy, informed consent, cybersecurity, storage of identifiable oral images and accountability for clinical decisions must be addressed before deployment.

This review is limited by its narrative approach and selected reference base. No exhaustive search or formal appraisal was performed, and reported diagnostic estimates come from heterogeneous investigations. The synthesis cannot establish comparative superiority of a particular algorithm or quantify the effect of AI screening on long-term patient outcomes.

CONCLUSION

AI-assisted photographic imaging is a promising adjunct for recognizing oral potentially malignant disorders. Current studies suggest useful diagnostic discrimination under selected research conditions, and mobile imaging could expand access to preliminary assessment. However, independent validation, standardized acquisition and prospective evaluation remain essential. Clinical examination, appropriate referral and histopathological diagnosis must continue to guide patient care. Future work should determine whether AI actually reduces missed lesions and diagnostic delay while maintaining equitable, safe and accountable practice.

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