(International Print/Online Journal)

SJIF IMPACT FACTOR: 6.829
PUBMED-National Library of Medicine ID-101739732

ISSN (Print): 2209-2870
ISSN (Online): 2209-2862

International Journal of Medical Science and Current Research (IJMSCR)
Available online at: www.ijmscr.com
Volume 8, Issue 4 , Page No: 386-390
July-August 2025

IJMSCR

Evaluation of Artificial Intelligence-Based Diagnostic Tools for Accurate Detection and Classification of Oral Lesions

[1]Dr. Parul Dixit , [2]Dr. R Rajeev, [3]Dr. S.K Padmakumar , [4]Dr. Leelakrishnan C
[1,4]Junior Resident, [2]Associate Professor, [3]HOD & Professor,
Government Dental College, Thiruvananthapuram

***Corresponding Author:**
Dr. Parul Dxit
Department of Oral Pathology and Microbiology, Fourth floor,
GDC Trivandrum, Kerala

Type of Publication: Original Research Paper
Conflicts of Interest: Nil

Abstract

Artificial Intelligence (AI) has emerged as a transformative tool in oral pathology, offering innovative solutions for the detection and classification of oral lesions, including oral potentially malignant disorders (OPMDs) and oral squamous cell carcinoma (OSCC). This review critically evaluates the current status of AI-based diagnostic tools, detailing their technological foundation, clinical applications, diagnostic workflow, and comparative advantages over conventional diagnostic methods. In addition, the review addresses current limitations, ethical and regulatory challenges, and explores future directions such as explainable AI, federated learning, and integration into telemedicine and mobile platforms. AI demonstrates significant potential to improve early detection, diagnostic accuracy, and accessibility in oral healthcare settings.

Keywords: Artificial Intelligence, Oral Squamous Cell Carcinoma, Deep Learning, Oral Potentially Malignant Disorders, Digital Pathology

Introduction

Oral cancer is a major global health concern, with oral squamous cell carcinoma (OSCC) comprising over 90% of cases[1]. Late-stage diagnosis remains a key factor behind poor survival rates and clinical outcomes[1]. While conventional diagnostic methods like clinical examination, biopsy, cytology, and histopathology are standard, they heavily rely on clinician expertise and are subject to inter-observer variability[2]. In this context, artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), offers significant potential to improve diagnostic accuracy and consistency[3]. These technologies can analyze clinical, histological, and imaging data to detect patterns beyond human perception, enabling earlier and more objective detection of OSCC. AI-based tools have shown promise in identifying subtle precancerous changes, classifying lesion types, and predicting malignant transformation[3]. Integration of AI with digital pathology and intraoral imaging enhances real-time screening capabilities[4]. Moreover, AI can assist in decision-making and triaging, particularly in low-resource or high-volume clinical settings[4].

Discussion

AI Technologies in Oral Pathology

Despite their promise, AI-based diagnostic tools face several limitations. One major challenge is the quality and diversity of training data. Many models are trained on small or homogeneous datasets, which can limit generalizability to diverse populations[26]. Another concern is the "black box" nature of deep learning models, which often lack explainability, making it difficult for clinicians to interpret or trust their outputs[27].

Regulatory and legal barriers also hinder the adoption of AI in clinical practice. AI systems require extensive validation and approval from regulatory agencies such as the FDA, and ethical concerns regarding data privacy, patient consent, and algorithmic bias must be addressed[28]. Moreover, technical infrastructure requirements may limit deployment in low-resource settings, and overreliance on AI may risk diminishing clinicians' diagnostic skills over time[28].

Diagnostic Workflow of AI-Based Tools

The diagnostic workflow of AI-based systems in oral pathology follows a structured and systematic pipeline, beginning with the collection of high-quality datasets. These datasets typically consist of large volumes of annotated clinical images—such as intraoral photographs, histopathology slides, and radiographs—accompanied by essential metadata, including patient demographics, lesion location, and histological diagnosis[10]. The accuracy of this phase heavily depends on precise annotation by expert clinicians or pathologists, as these annotations serve as the ground truth for model training and directly impact performance[10].

Following data acquisition, the preprocessing phase is critical. This stage involves techniques such as normalization, noise reduction, contrast enhancement, and various data augmentation methods (e.g., image rotation, scaling, and flipping) to enhance dataset variability and mitigate overfitting[11]. The processed data is then utilized to train AI models, primarily using supervised learning techniques like convolutional neural networks (CNNs), which learn to classify lesions based on distinct morphological, textural, and optical features[12].

Once trained, these models undergo rigorous validation and testing using independent datasets to assess their generalizability. Key performance indicators—such as accuracy, sensitivity, specificity, precision, and the area under the receiver operating characteristic (ROC) curve (AUC)—are employed to evaluate model effectiveness, especially in distinguishing between potentially malignant disorders (OPMDs) and invasive carcinomas[13].

Upon achieving clinically acceptable performance levels, these validated AI models are integrated into clinical decision support systems (CDSS). These systems are deployed through various platforms, including:

- Mobile applications (e.g., *OralScreen*, mHealth platforms for remote lesion triaging),
- Cloud-based diagnostic portals (e.g., *PathAI*, *Aiforia* for histopathological analysis),
- Intraoral imaging systems embedded with AI modules (e.g., *VELscope AI*, *Identafi*, and prototype AI-enhanced autofluorescence devices)[14].

Numerous ongoing clinical trials and pilot studies are currently evaluating the real-world application of these tools in early oral cancer detection and screening. Prominent examples include:

- Trials incorporating deep learning on autofluorescence and reflectance imaging data for OPMD risk stratification (e.g., *NCT05689240*)[15],
- Implementation of AI-assisted cytology and telepathology systems in rural screening programs across India and Southeast Asia[15],
- Multi-center validation of AI algorithms trained on WHO-graded dysplasia to predict malignant transformation[15].

The overarching aim of this AI-driven workflow is to enable real-time, reproducible, and scalable diagnostic support, particularly in high-throughput or resource-limited environments. When used in conjunction with expert clinical evaluation, these tools hold considerable promise in enhancing early detection, minimizing diagnostic delays, and supporting population-wide surveillance strategies for oral cancer[16].

Applications in Detection and Classification

AI technologies show strong potential in the early detection of OPMDs and OSCC, with CNN models accurately distinguishing lesions like leukoplakia, erythroplakia, oral lichen planus, and submucous fibrosis from normal mucosa[17]. In histopathology, AI effectively identifies features such as cellular atypia and tumor invasion, aiding in dysplasia grading and distinguishing carcinoma in situ from invasive cancer, with performance comparable to expert pathologists[18],[19].

Advanced imaging modalities are increasingly being integrated with AI to enhance diagnostic precision in

Volume 8, Issue 4; July-August 2025; Page No 386-390

oral oncology. Techniques such as autofluorescence, reflectance imaging, and hyperspectral imaging (HSI) enable AI models to detect subclinical tissue changes and differentiate lesion types based on spectral patterns[20]. Optical coherence tomography (OCT) provides non-invasive, real-time visualization of epithelial architecture, aiding in lesion monitoring and depth assessment[20]. AI-assisted cytology offers automated analysis of exfoliated cells, identifying atypical features as a non-invasive alternative to biopsy[20]. Additionally, multiphoton microscopy and Raman spectroscopy, combined with deep learning, allow molecular-level tissue characterization before morphological changes occur[20]. These technologies are being deployed through chairside tools and mHealth applications—such as OralID, MOMs App, and VELscope with AI—and are under evaluation in multicenter trials across high-risk regions[20]. Collectively, these innovations support scalable, objective, and early detection strategies, complementing clinical decision-making in oral cancer diagnostics.

Comparison with Conventional Methods

Conventional diagnostic methods in oral pathology are often limited by subjectivity and require considerable time and expertise. Visual-tactile examinations are influenced by examiner experience, while histopathological analysis, though the gold standard, can be time-consuming and subject to inter-observer variability[21]. In contrast, AI-based tools provide rapid, objective, and reproducible analyses. Studies have shown that CNN models outperform general dentists in detecting early-stage lesions from photographic images[22] and can assist pathologists by pre-screening slides, allowing them to focus on diagnostically challenging cases[23].

Advantages of AI-Based Tools

AI tools bring several advantages to oral diagnostics. They eliminate inter-observer variability by providing objective assessments and offer scalability, enabling high-throughput analysis of thousands of images simultaneously[24]. Additionally, the processing speed of AI allows results to be delivered within seconds, compared to hours or days with traditional methods[24]. The reproducibility of AI decisions supports longitudinal monitoring and standardization across healthcare settings[24]. Furthermore, the integration of AI with mobile health (mHealth) applications and cloud-based systems enables remote screening and diagnostic support, especially in underserved areas[25]. AI also serves as a valuable educational resource, providing simulation-based learning platforms for training clinicians and students[25].

Challenges and Limitations

Despite their promise, AI-based diagnostic tools face several limitations. One major challenge is the quality and diversity of training data. Many models are trained on small or homogeneous datasets, which can limit generalizability to diverse populations[26]. Another concern is the "black box" nature of deep learning models, which often lack explainability, making it difficult for clinicians to interpret or trust their outputs[27].

Regulatory and legal barriers also hinder the adoption of AI in clinical practice. AI systems require extensive validation and approval from regulatory agencies such as the FDA, and ethical concerns regarding data privacy, patient consent, and algorithmic bias must be addressed[28]. Moreover, technical infrastructure requirements may limit deployment in low-resource settings, and overreliance on AI may risk diminishing clinicians' diagnostic skills over time[28].

Future Directions

To address current limitations, research is increasingly focused on developing explainable AI (XAI) systems that can visually illustrate decision-making processes[29]. Federated learning is gaining traction as a privacy-preserving approach to training AI models using data from multiple institutions without centralizing sensitive patient information[29]. Future diagnostic tools may combine AI outputs with clinician input, molecular markers, and patient history to form hybrid systems with enhanced accuracy[30]. Additionally, the integration of AI into telemedicine platforms and electronic health records (EHRs) will expand access to diagnostics and support real-time decision-making in both urban and rural healthcare settings[30].

Conclusion

AI-based diagnostic tools have demonstrated considerable potential in transforming oral pathology by enabling early, accurate, and reproducible detection of lesions. As the technology continues to evolve, improvements in model interpretability, dataset

Volume 8, Issue 4; July-August 2025; Page No 386-390

diversity, and regulatory frameworks will be critical for their widespread adoption. Collaborative efforts among clinicians, researchers, policymakers, and technologists are essential to ensure the safe, effective, and ethical deployment of AI in routine oral healthcare.

References

1. Warnakulasuriya S. Global epidemiology of oral and oropharyngeal cancer. Oral Oncol. 2009;45(4–5):309–16.
2. Lingen MW, Kalmar JR, Karrison T, Speight PM. Critical evaluation of diagnostic aids for the detection of oral cancer. Oral Oncol. 2008;44(1):10–22.
3. Jeyaraj PR, Samuel N. Artificial intelligence in oral oncology: The dawn of a new era. J Oral Maxillofac Pathol. 2020;24(1):121–9.
4. Ariji Y, et al. Deep learning models for diagnostic support in oral cancer screening. J Dent Res. 2021;100(7):748–55.
5. Liu Y, et al. Artificial intelligence in medical imaging: threat or opportunity? Radiology. 2019;290(2):281–4.
6. Esteva A, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115–8.
7. Liang Y, et al. Deep learning-based imaging analysis for diagnosis of oral diseases. IEEE Rev Biomed Eng. 2020;13:342–56.
8. Houssein EH, et al. Medical image classification using deep learning: A survey. Comput Biol Med. 2021;139:104927.
9. Singh P, et al. Image preprocessing in medical imaging: concepts and applications. Biomed Eng Lett. 2020;10(2):267–80.
10. Dey P, et al. Role of artificial intelligence in cytology: a review. Diagn Cytopathol. 2020;48(5):470–5.
11. Chicco D, Jurman G. The advantages of the Matthews correlation coefficient over F1 score and accuracy in binary classification evaluation. BMC Genomics. 2020;21(1):6.
12. Litjens G, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017;42:60–88.
13. Acharya UR, et al. Automated identification of normal and oral cancer CT images using hybrid texture deep learning algorithm. Pattern Recognit Lett. 2020;129:138–44.
14. Krithiga M, et al. Computer-aided diagnosis in oral cancer using artificial intelligence: A systematic review. J Oral Pathol Med. 2021;50(3):207–14.
15. ClinicalTrials.gov. NCT05689240: Deep Learning for Oral Cancer Screening.
16. Uthoff RD, et al. Point-of-care autofluorescence imaging for oral cancer detection. J Biomed Opt. 2019;24(2):025002.
17. Sharma N, et al. Deep learning-based classification of oral lesions using photographic images. J Dent Res. 2021;100(5):492–9.
18. Shaban M, et al. A deep learning approach for automatic diagnosis in oral histopathology. Sci Rep. 2020;10(1):11779.
19. Fatima S, et al. AI in histopathological image analysis: Potentials and limitations. Pathol Res Pract. 2022;236:153963.
20. Sampaio H, et al. Hyperspectral imaging and AI for oral lesion classification. J Biomed Opt. 2021;26(7):076001.
21. Speight PM, et al. Screening for oral cancer—a perspective from the UK. Oral Oncol. 2010;46(6):429–30.
22. Chugh R, et al. Deep learning for oral lesion detection in community-based settings. PLoS One. 2020;15(6):e0234753.
23. Bejnordi BE, et al. Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in breast cancer. JAMA. 2017;318(22):2199–210.
24. Hosny A, et al. Artificial intelligence in radiology. Nat Rev Cancer. 2018;18(8):500–10.
25. Rieke N, et al. The future of digital health with federated learning. NPJ Digit Med. 2020;3:119.

26. Kelly CJ, et al. Key challenges for delivering clinical impact with artificial intelligence. BMC Med. 2019;17(1):195.
27. Tjoa E, Guan C. A survey on explainable artificial intelligence (XAI): Toward medical XAI. IEEE Trans Neural Netw Learn Syst. 2021;32(11):4793–813.
28. Gerke S, et al. Ethical and legal implications of AI in healthcare. Am J Bioeth. 2020;20(5):6–11.
29. Yang Q, et al. Federated machine learning: Concept and applications. ACM Trans Intell Syst Technol. 2019;10(2):1–19.
30. Shortliffe EH, et al. Artificial intelligence in medicine: Computer-based clinical decision support. Elsevier; 2019.

Volume 8, Issue 4; July-August 2025; Page No 386-390