Integrating AI into Modern Strategies for Oral Cancer Screening and Diagnosis

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Abstract. Oral cancer is a major health problem worldwide, mainly because it is often detected at a late stage. Early diagnosis can greatly improve survival and quality of life, but traditional screening methods depend heavily on trained professionals and are limited in remote and low-resource areas. In recent years, artificial intelligence (AI) has emerged as a powerful tool in oral cancer screening and diagnosis. AI enhances clinical examination, imaging, cytology, molecular analysis, and biomarker detection by improving accuracy, speed, and objectivity. Techniques such as deep learning, machine learning, and image analysis help in identifying early dysplastic changes that may not be visible to the human eye. AI also supports smartphone-based screening and tele-medicine, making early detection possible even in underserved regions. By integrating AI with optical imaging,cytology, salivary biomarkers, molecular targeting, and nanotechnology, oral cancer diagnosis becomes more precise and accessible. This review highlights how AI transforms traditional and advanced diagnostic methods, enabling early detection of oral potentially malignant disorders and oral cancer, and supporting timely and patient-centered care.

Keywords: Artificial Intelligence, Oral Cancer, Early Detection, Oral Potentially Malignant Disorders, 1Optical Imaging, Cytology, Salivary Biomarkers, Molecular Diagnostics, Nanotechnology, Tele-screening

1 Introduction

Oral Cancer represents a worldwide public health problem and OSCC is the sixth most common cancer with the five-year survival rate of 50% and associated with high morbidity and mortality rates Increasing incidence rate of oral cancer malignancies and late-stage presentation have become global healthcare issues. The most reported risk factor that elevates oral cancer is the use of tobacco and alcohol. Another etiologic factor that has recently been reported to be linked with head and neck cancer (HNC) is HPV infection [1]. There has been an increase in prevalence of oral cancer among younger individuals with no traditional risk factors pointing to the need to screen even young individuals for OSCC.[1] Following therapy, patients frequently report speech and swallowing issues as well as declining oral health, highlighting the significance of early identification. Hence there is a critical need that can quickly, accurately, and non-

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invasively identify early oral dysplasia. Conventional screening relies on qualified professionals and is frequently restricted in remote or low-resource environments, which causes a delay in diagnosis. New possibilities for the early diagnosis of potentially malignant oral illnesses have been made possible by recent developments in artificial intelligence (AI) [2].

1.1 Risk factors

Many risk factors or potential causes of OC have been identified in India. OC has been found to be highly correlated with biological variables such as syphilis, human papillomavirus (HPV), nutritional inadequacies, chronic candidiasis, and infections, as well as chemical factors such as alcohol and smoke.

1.2 How long does oscc take to metastasize

Oral squamous cell carcinoma (OSCC) typically metastasizes within 10–12 months, though some metastases can appear within three months. The average time to diagnose oral cancer is about 105 days.

1.3 Traditional approaches to oral cancer screening and diagnosis

Conventional oral examination (COE), which involves careful visual inspection and palpation of the oral mucosa under sufficient illumination to identify suspicious lesions like leukoplakia, erythroplakia, non-healing ulcers, or induration, is the mainstay of traditional methods for detecting oral cancer. Although false positives are still a problem, vital staining with toluidine blue has long been used as an adjuvant to emphasize areas of elevated DNA and RNA content, assisting doctors in identifying high-risk lesions that require biopsy [8]. Table.1 shows the Comprehensive overview of diagnostic techniques of oral cancer detection. While computed tomography (CT), magnetic resonance imaging (MRI), ultrasonography with fine-needle aspiration cytology (FNAC), and positron emission tomography combined with CT (PET-CT) play critical roles in staging, evaluating soft tissue extension, lymph node involvement, and detecting metastasis, imaging techniques like panoramic radiographs and intraoral radiography aid in assessing bone involvement [9]. Fig.1 shows the Clinical and Adjunctive Techniques for Oral Cancer Screening. Despite their limitations, especially in the early stages of the disease, these traditional diagnostic techniques serve as the basis for the identification of oral cancer. Fig.2 shows the molecularly targeted methods [3].

1.4 Advanced techniques in oral cancer screening

1) Optical coherence tomography.
2) Tissue auto-fluorescence.
3) Identafi 3000a.
4) Chemiluminescence.

5) Vizilite plus
6) Microlux DL
7) Orascopiptuc DK
8) Ked Dental
9) Velscope
10) Illum scan.

- Oral cancer detection using nanoparticles.
- Alternative diagnostic aids used for detection of oral cancer.
- Cytological techniques (Oral CDX) even using liquid based cytology.
- Saliva protein detection techniques that have been shown in some studies to be increased in oral cancer patients (Il-6, Il-8, SCC-Ag2, Calcinin, 70 Kd heat shock protein, annexin I, cathepsin G, peroxiredoxin II, Thioredoxin, etc).

- miRNA study techniques and DNA quantification techniques.
- NON-TARGETED METHODS:

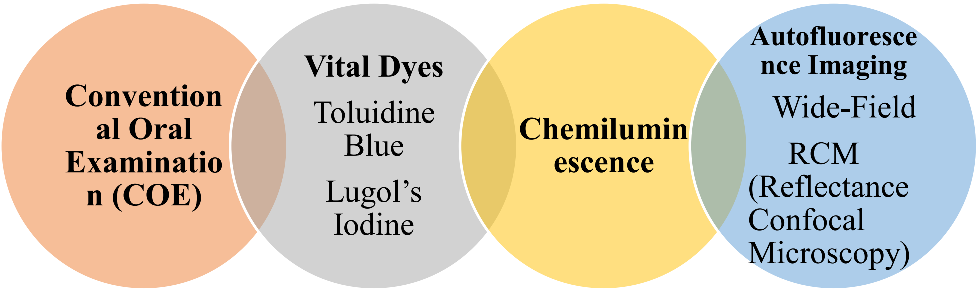

Fig. 1. Clinical and Adjunctive Techniques for Oral Cancer Screening

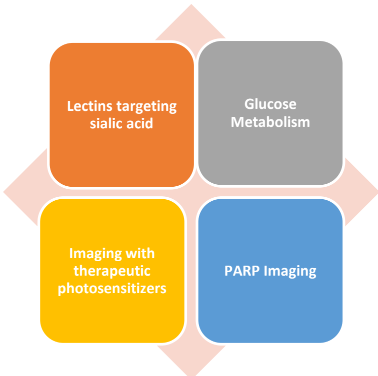

Fig. 2. Molecularly targeted methods

Table 1. Comprehensive overview of diagnostic techniques of oral cancer detection

MAIN CATEGORY	SUB-CATEGORY	TECHNIQUES / DEVICES
I. Non-Targeted Conventional Screening	Clinical Examination	Conventional Oral Examination (COE)
	Vital Dyes	1) Toluidine Blue 2) Lugol's Iodine
	Chemiluminescence Devices	1) Vizilite Plus 2) Microlux DL 3) Identafi 3000a 4) Orascoptic DK 5) Illum Scan 6) Ked Dental
	Autofluorescence Imaging	1) Tissue Autofluorescence 2) VELscope 3) Wide-field autofluorescence systems
II. Advanced Optical Imaging Techniques	High-Resolution Optical Tools	1) Optical Coherence Tomography (OCT) 2)Reflectance Confocal Microscopy (RCM)
	Multispectral & Fluorescence Systems	1) Identafi 3000a (multispectral) 2) VELscope 3) Illum Scan 4) Microlux DL 5) Orascoptic DK
	Chemiluminescence (Advanced)	Vizilite Plus and similar enhanced systems
III. Cytological & Cellular Techniques	Cytology	1)Oral CDx Brush Biopsy 2)Liquid-Based Cytology (LBC)
	Molecular Cellular Techniques	1) DNA Ploidy Assessment 2)DNA Quantification 3) miRNA Profiling Techniques
IV. Molecular & Biomarker-Based Diagnostics	Salivary Biomarkers	IL-6 , IL-8 , SCC-Ag2 , Calgranulin ,70 kDa Heat Shock Protein , Annexin I ,

		Cathepsin G, Peroxiredoxin II , Thioredoxin
	Molecular Targeted Imaging	1) Lectins targeting sialic acid 2) Glucose metabolism imaging 3) PARP imaging 4) Imaging with therapeutic photosensitizers
V. Nanotechnology-Based Diagnostics	Nanoparticle Applications	1)Gold nanoparticles (AuNPs) 2)Quantum dots 3) Magnetic nanoparticles 4) SERS nanoparticles 5) Nano-biosensors for saliva or tissue detection

2 Non-targeted conventional screening

2.1 Conventional Oral Examination (COE) in Clinical Examination

AI improves COE by automatically identifying dangerous lesions in photos taken with smartphones and intraoral cameras using deep learning image-analysis algorithms, especially CNNs [10]. These techniques offer consistent interpretation of mucosal abnormalities and lessen inter-examiner variability. AI is used by tele-screening tools to prioritize high-risk lesions in remote areas. Deep learning improves early detection by identifying early dysplastic alterations that are not readily apparent to the human eye [4].

2.2 Vital Dyes

AI uses computer-vision technologies to help measure staining intensity, optical density, and lesion borders. By distinguishing between inflammatory dye uptake and actual dysplasia, machine learning lowers the number of false positives. By classifying dye-positive areas into benign lesions, OPMDs, or cancers, pattern-recognition methods increase the precision of diagnosis which is shown in Fig. 3.

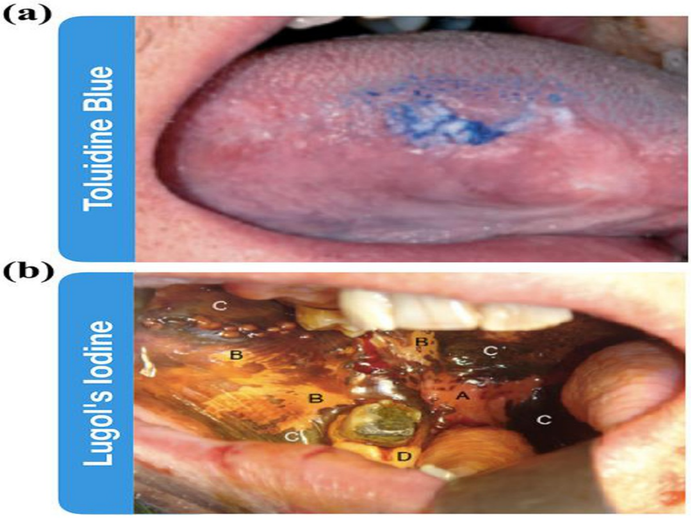

Fig. 3. Toluidine blue staining the oral cavity to identify leukoplakia lesion and Lugol's iodine staining to identify dysplastic tissue

2.3 Chemiluminescence

AI improves the interpretation of acetowhite variations under chemiluminescent light in Chemiluminescence Devices (Vizilite Plus, Microlux DL, Identafi 3000a, Orascoptic DK, Illum Scan, Ked Dental). AI based on real-time video automatically identifies small mucosal anomalies like epithelium thickness and shows aberrant patterns of epithelial reflectance. By differentiating hyperkeratosis from dysplasia, machine-learning models improve specificity and decrease false positives [5].

2.4 Autofluorescence Imaging

(Tissue autofluorescence, VELscope, wide-field fluorescence systems) Loss of autofluorescence (LOF) is more accurately measured by AI than by visual inspection. Deep learning algorithms differentiate between actual dysplastic patterns and fluorescence loss caused by inflammation. Clinicians are directed to high-risk areas by real-time AI that superimposes heatmaps on fluorescence images. Even possible malignant transformation can be predicted using clustering techniques [6].

3 Advanced optical imaging techniques

3.1 High-Resolution Optical Tools

AI detects nuclear crowding, basement membrane rupture, and epithelial disarray by automatically interpreting micro-resolution structural pictures. Segmentation models measure the thickness of the epithelium and delineate its layers. Classifier methods increase diagnostic reproducibility and shorten reading times (Fig.4)

3.2 Multispectral & Fluorescence Systems

(Identafi 3000a, VELscope, Illum Scan, Microlux DL, Orascoptic DK)
AI improves the visibility of vascular alterations, hemoglobin absorption, and metabolic variations in dysplastic tissue by integrating multi-wavelength data (white, violet, and amber light). OPMDs can be detected early and more accurately thanks to ML algorithms that enhance spectral contrast interpretation. (Fig 4)

3.3 Advanced Chemiluminescence

AI creates customized risk categorization by combining chemiluminescence imaging data with patient history. Subtle epithelial changes are easier to see with automated picture enhancement. Deep learning pattern recognition significantly increases specificity by lowering false positives[6] as shown in Fig. 4.

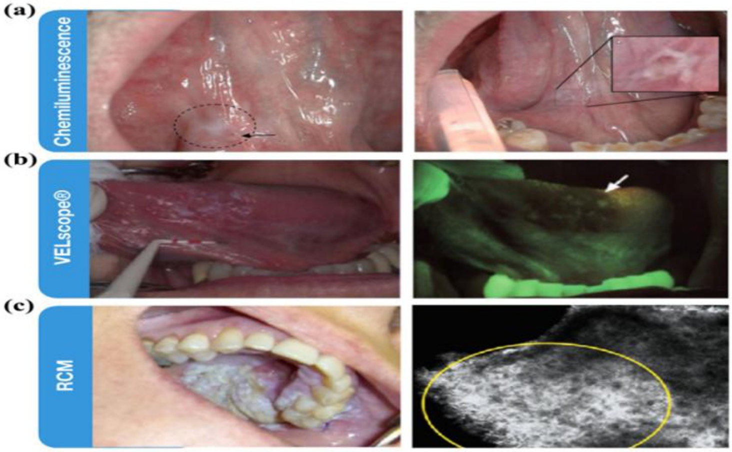

Fig. 4. Mild dysplasia, Severe dysplasia and Oral squamous cell carcinoma

4 Cytological & cellular techniques

AI uses pleomorphism, hyperchromatism, and nuclear–cytoplasmic ratios to automatically identify abnormal cells. By methodically analyzing whole slides, high-throughput slide-scanning AI lowers false negatives. ML scoring systems link results with established molecular markers and standardize cytological interpretation.

Based on the identification of circulating tumor cells (CTCs), circulating tumor DNA (ctDNA), circulating tumor RNA (ctRNA), proteins, and exosomes, liquid biopsy is a non-invasive diagnostic technique. Crucially, a liquid biopsy can be performed on physiological fluids other than blood, including urine, saliva, seminal plasma, pleural effusions, cerebrospinal fluid, sputum, and stool samples shown in the Fig. 5.

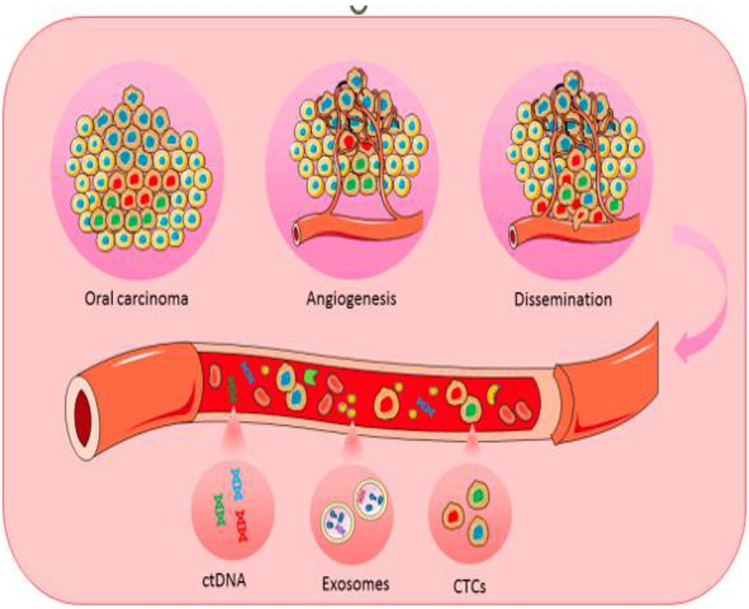

Fig. 5. Liquid biopsy in Oral cancer

4.1 Molecular Cellular Techniques

Large and complicated genomic datasets are analyzed by AI-powered algorithms to find signs of malignant transformation. Machine learning algorithms use multi-omics data (DNA, RNA, proteomics) for precision diagnostics and identify ploidy abnormalities linked to early carcinogenesis. Progression risk from OPMD to OSCC is estimated using predictive modelling [7].

5 Molecular & biomarker-based diagnostics

5.1 Salivary Biomarkers

(IL-6, IL-8, SCC-Ag2, Calgranulin, HSP-70, Annexin I, Cathepsin G, Peroxiredoxin II, Thioredoxin)

AI uses proteomic datasets to find distinctive biomarker expression patterns. ML improves sensitivity and specificity by combining several analytes to create high-accuracy diagnostic signatures. AI models facilitate the interpretation of multiplex biosensors for point-of-care diagnostics and classify patients into risk groups.

5.2 Molecular Targeted Imaging

By spotting minute variations in fluorescence or contrast between healthy and cancerous tissues, AI improves the detection of molecular probe uptake. Compared to traditional imaging, deep learning algorithms are able to identify metabolic alterations earlier. Additionally, AI enhances focused imaging picture reconstruction by lowering noise and raising specificity[7] which is shown in Fig. 6.

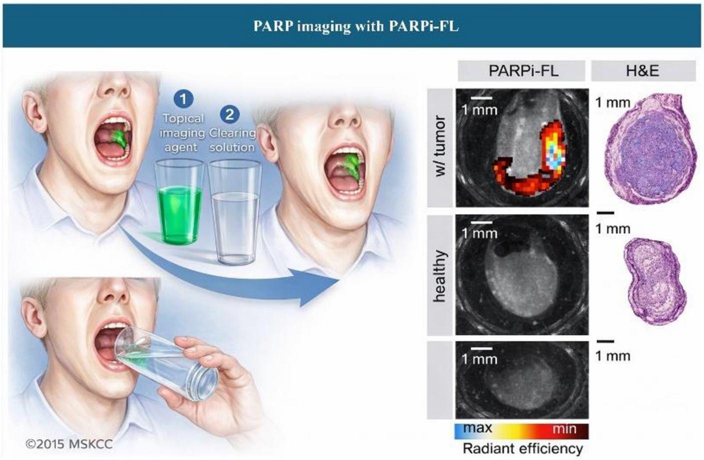

Fig. 6. Schematic of the imaging procedure for detection of Oral carcinoma using a PARPi-FL

6 Nanotechnology-based diagnostics

(Gold nanoparticles, Quantum dots, Magnetic nanoparticles, SERS nanoparticles, Nano-biosensors)

AI improves the interpretation of optical, magnetic, or Raman signals based on nanoparticles. Particularly in SERS-based systems, machine-learning algorithms identify distinct spectral signatures linked to dysplasia and cancer. To produce a combined diagnostic score, deep learning algorithms combine the results from several nanosensors. Additionally, AI increases signal-to-noise ratios, making it possible to identify extremely early carcinogenic alterations as shown in Fig. 7.

Gold nanoparticles (AuNPs) are widely explored in oral cancer diagnostics due to their biocompatibility, easy functionalization, stable optical properties, and precise size control. They can be synthesized in multiple shapes (nanospheres, nanorods, nanoshells, nanocages, nanoprisms), allowing versatile biomedical application as shown in the Fig. 8.

Tumor accumulation occurs mainly through the enhanced permeability and retention (EPR) effect (*passive targeting*), after which AuNPs enter cells via size-dependent endocytosis though this uptake is limited. Conjugating AuNPs with antibodies enables *active targeting*, greatly improving specificity. El-Sayed et al. demonstrated that anti-EGFR-bound AuNPs selectively and uniformly attach to cancer cell surfaces, while showing only nonspecific binding to normal cells.

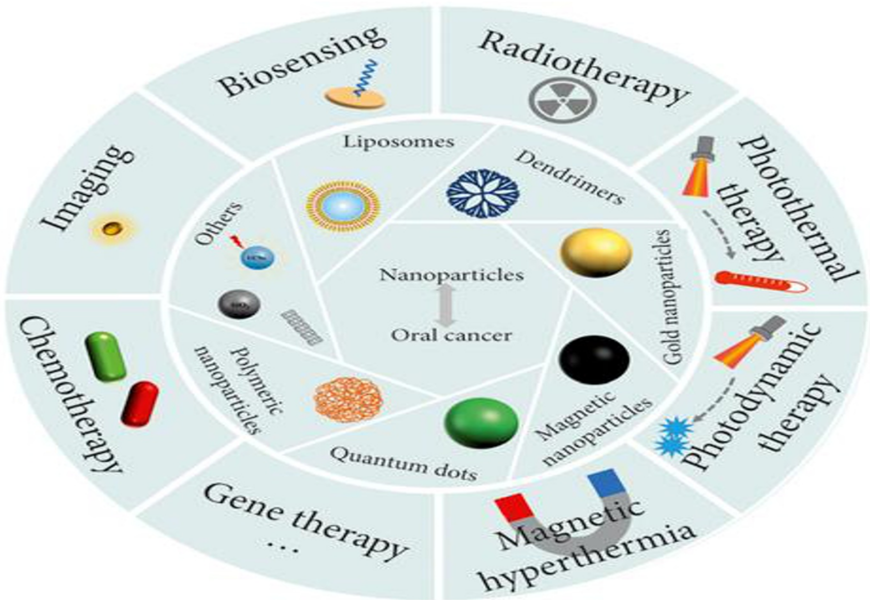

Fig. 7. Nanoparticles -As diagnostic aid and therapy

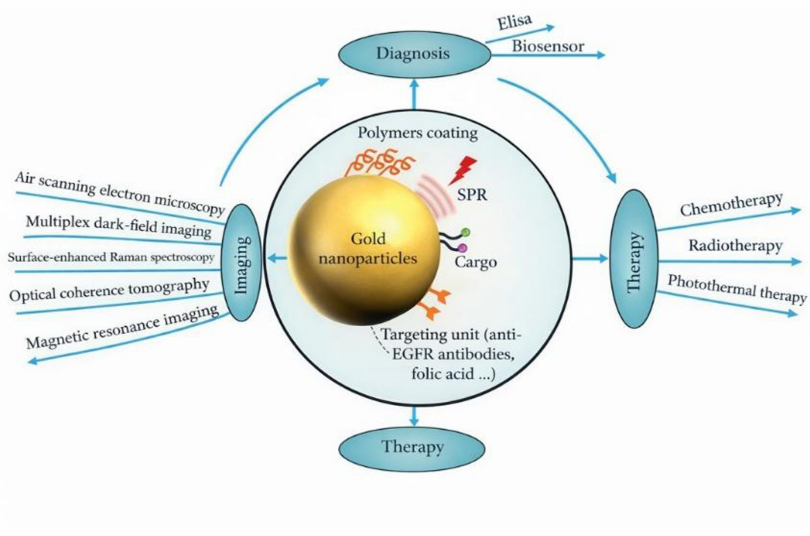

Fig. 8. Gold nanoparticles in oral cancer diagnosis

7 Result and Discussion

The application of artificial intelligence (AI) to oral cancer screening and diagnostic methods showed that there is a significant increase in diagnostic accuracy, sensitivity, and detection of early lesions compared to the conventional approach to screening. In the studies analyzed, AI-based diagnostic tools proved to be more effective than all traditional tools (including visual inspection, vital staining, and single-mode imaging). Models of image analysis based on AI (and especially convolutional neural networks, CNNs) demonstrated high sensitivity in detecting oral potentially malignant disorders (OPMDs) and oral squamous cell carcinoma at an early stage (OSCC) in clinical photographs, autofluorescence, and optical coherence tomography (OCT) images. Diagnostic accuracies of AI-assisted imaging were reported to be 90-98% compared to traditional clinical examination techniques, which had lower accuracy of around 75-85%, particularly in early cases or in cases of visual ambiguity shown in Fig. 9.

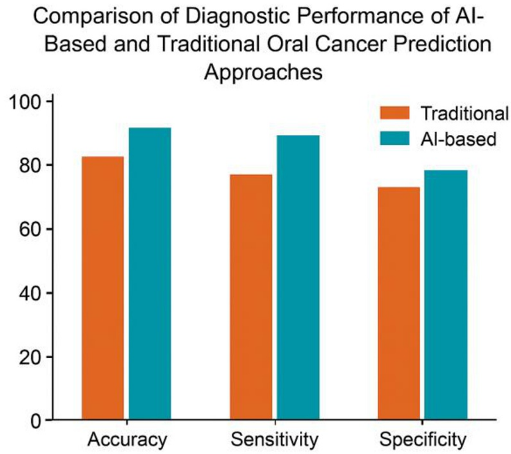

Fig. 9. Comparision Diagnostic performance of AI

The use of AI-based interpretation in the process of vital dye-based screening lowered the levels of false positives (distinction between inflammatory uptake and actual dysplastic staining pattern). The automated analysis of toluidine blue staining and Lugol staining of iodine enhanced the detection of the lesion boundaries and risk stratification that resulted in more accurate detection of biopsy-worthy lesions. In a comparable fashion, AI applications enhanced the specificity of chemiluminescence and autofluorescence imaging of cells by discriminating between real loss of fluorescence due to dysplasia and benign inflammatory alterations. The AI-based diagnostics that were aided by nanotechnology were again advantaged by the quality of spectral and signal changes detected on gold nanoparticles, SERS nanoparticles, and nanosensors, which were correctly interpreted using machine learning algorithms. Artificial intelligence-based systems allowed identifying subtle changes in biochemical response in the case of early carcinogenesis, resulting in a marked increase in signal-to-noise ratios and diagnostic performance. Altogether, the findings suggest that AI-based oral cancer screening systems offer earlier diagnoses, greater diagnostic precision, lesser inter-observer error, and greater accessibility, specifically on tele-screening and low-resource platforms. The results affirm AI as a formidable complement to the conventional and innovative diagnostic approaches in the current oral cancer practice.

8 Conclusion

AI significantly enhances oral cancer screening by making traditional diagnostic methods more accurate, objective, and accessible. Through improved image interpretation, automated cytology, multi-omics analysis, and smart integration with optical and nanotechnology-based tools, AI boosts early detection and reduces diagnostic errors. It expands screening reach via smartphone-based and tele-screening systems, supporting timely triage in underserved areas. Overall, AI complements clinical expertise, enabling faster, more precise, and patient-centered diagnosis of oral potentially malignant disorders and oral cancer.[14]

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