Advances and Challenges in AI-Based Image Processing for Early Oral Cancer Detection: A Narrative Review

N. V. Soma Sekhar Vissamsetti
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad, India
venkatasomu2000@gmail.com

Gandla Shivakanth
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad, India
shvkanth0@gmail.com (corresponding author)

Received: 24 January 2026 | Revised: 26 February 2026 and 11 March 2026 | Accepted: 13 March 2026

DOI: https://doi.org/10.48084/etasr.17740

ABSTRACT

Oral squamous cell carcinoma (OSCC) is a major global health concern, particularly in low- and middle-income countries such as India, where tobacco and areca-nut use are prevalent. Early detection of oral potentially malignant disorders (OPMDs) greatly improves survival, yet conventional diagnostic methods, such as visual inspection and biopsy, are limited by subjectivity, invasiveness, and resource demands. The integration of artificial intelligence (AI) and digital image processing (DIP) has emerged as a promising solution for non-invasive, scalable screening. This narrative review synthesizes recent literature to provide a thematic overview of digital image processing and artificial intelligence approaches for oral cancer detection, rather than conducting a systematic or meta-analytic evaluation. This review analyzes recent research published on DIP techniques such as noise reduction, contrast enhancement, normalization, and segmentation, and their influence on AI-based classification across photographic, histopathological, and optical coherence tomography (OCT) images. Recent studies demonstrate that preprocessing consistency, hybrid feature extraction, and explainable AI improve diagnostic reliability and interpretability. However, most models remain constrained by small datasets, a lack of external validation, and limited feasibility for deployment. This paper identifies the need for standardized, end-to-end frameworks that integrate preprocessing, feature extraction, and classification to advance AI-based oral cancer detection from experimental feasibility to clinical reality.

Keywords-oral squamous cell carcinoma; digital image processing; deep learning; machine learning; feature extraction; optical coherence tomography; explainable AI; early cancer detection; histopathology; clinical imaging

I. INTRODUCTION

OSCC remains a major global health problem and is disproportionately prevalent in low- and middle-income countries, where tobacco, areca nut (betel quid), and alcohol use are prevalent. Global estimates place new cases of lip and oral cavity cancer at roughly 377,700 in 2020, with continued high incidence in several Asian countries from 2022 to 2024 [1, 2]. In India, in particular, the burden is substantial — oral cancers account for a large share of national cancer incidence and remain among the leading cancers among men, reflecting regional risk exposures and late presentation patterns [3, 4]. Early detection is critical: when OSCC is diagnosed at stages I-II, five-year survival exceeds 80–90%, but late-stage diagnoses (III–IV) dramatically reduce survival.

Conventional diagnostic pathways rely on visual inspection followed by biopsy and histopathology. Visual inspection is widely used for community screening because it is low-cost and readily available, but it is subjective, operator-dependent, and vulnerable to missed early lesions under variable illumination and varying examiner expertise. Biopsy/histopathology is the diagnostic gold standard, but it is invasive, carries a risk of sampling error, causes patient morbidity, and is resource-intensive, barriers that are especially important in low-resource settings [5]. These limitations create an urgent need for noninvasive, scalable, and objective triage tools to identify suspicious lesions and enable timely referral.

In recent years, interest in automated, image-based screening has surged. Smartphone photography, intraoral imaging systems, optical coherence tomography (OCT), and autofluorescence have been combined with machine learning (ML) and deep learning (DL) to produce diagnostic aids for OPMDs and OSCC. Early smartphone-based DL pipelines demonstrated feasibility for community screening and symptom triage, while later studies showed improved accuracy with modern CNNs and transformer architectures on clinical photos and histopathology images [6, 7]. OCT and other non-invasive imaging modalities have been successfully paired with DL to identify malignant versus benign tissue patterns without immediate biopsy [8, 9].

Recent peer-reviewed research indicates high performance for many DL-based pipelines, but important translational gaps remain. Large, multi-institutional histopathology and photographic datasets are emerging, enabling more robust model training and external validation, yet many published models still rely on relatively small or single-center datasets that limit generalizability [10]. Explainability methods (Grad-CAM, LIME) are increasingly used to visualize model attention and to increase clinicians' trust, but standardized validation of these explanations within clinical workflows remains lacking [11].

Recent work has emphasized that preprocessing operations such as noise reduction, illumination correction, and segmentation directly influence the downstream performance of AI classifiers, underscoring the need for unified digital image processing workflows. Recent systematic reviews and meta-analyses confirm both the promise and the heterogeneity of the approaches described. Reviews from 2023–2024 summarize that DL yields high diagnostic metrics across photographic, OCT, and histopathology datasets, but they also highlight inconsistent preprocessing reporting, small and imbalanced datasets, lack of external multicenter validation, and limited attention to deployment constraints (model size, inference latency) for point-of-care use [5, 12]. These gaps motivate a focused, up-to-date survey that explicitly links DIP practices to AI model design and evaluation in oral oncology, an integrated bridge that is currently missing in the field.

The present study has been undertaken to address the identified research gap and to establish a stronger theoretical and methodological foundation for future experimental investigations. The specific objectives of this paper are (1) to investigate existing research and techniques for oral cancer detection and (2) to explore the application of digital image processing in the broader context of medical imaging and disease diagnosis. Through these objectives, this review aims to consolidate current knowledge, critically evaluate methodological advances, and highlight the interconnection between image preprocessing and AI-based diagnostic strategies. The insights obtained from this synthesis are expected to contribute to the development of robust, interpretable, and computationally efficient frameworks that enable early, non-invasive, and clinically deployable systems for oral cancer detection. This work adopts a narrative review approach focused on thematic synthesis and the conceptual integration of methodological trends, rather than on statistical comparisons or formal aggregation of quantitative evidence.

II. MATERIALS AND METHODS

This study was conducted as a narrative literature review to synthesize recent methodological advances in digital image processing and artificial intelligence for the detection of oral cancer. A structured yet non-systematic literature exploration was conducted to identify relevant peer-reviewed studies and emerging research themes. No formal Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was followed because the objective was thematic synthesis rather than exhaustive systematic evidence aggregation. A targeted literature search in Scopus and PubMed was conducted to identify peer-reviewed journal articles published between January 2021 and October 2025. Search terms included combinations of oral cancer, oral squamous cell carcinoma, oral potentially malignant disorders, digital image processing, deep learning, optical coherence tomography, autofluorescence, and histopathology. Articles were considered for inclusion if they reported image-based diagnostic approaches, preprocessing workflows, or artificial intelligence techniques relevant to the assessment of oral lesions. Conference proceedings, preprints, and non-peer-reviewed webpages were excluded to preserve scientific rigor. Identified publications were iteratively reviewed to capture representative studies describing preprocessing methods, model architectures, and validation strategies across imaging modalities. Study selection was guided by relevance to the review's thematic objectives rather than by formal eligibility criteria. Consequently, no standardized risk-of-bias assessment, quality scoring, or quantitative data pooling or meta-analysis was performed.

III. OVERVIEW OF ORAL CANCER AND DIAGNOSTIC LANDSCAPE

OSCC, the most common oral malignancy, develops through a multistep progression from normal mucosa to OPMDs, such as leukoplakia, erythroplakia, and oral submucous fibrosis, and, in some cases, to invasive carcinoma. Malignant transformation rates vary by lesion type, patient factors, and geography, ranging from the low single digits to over 10% during follow-up, with higher risk in certain histologic subtypes [13-15]. OPMDs are therefore critical targets for early detection (Figure 1, Table I) [16, 17].

Early diagnosis is essential: stage I–II OSCC has a 5-year survival of 80–90%, whereas advanced stages carry a worse prognosis and greater treatment morbidity. Despite this, population screening often misses subtle lesions, and delays between presentation and diagnosis remain common [13-15]. Current pathways rely on visual inspection for initial screening, with biopsy and histopathology as the gold standard. Visual exams are low-cost but have variable sensitivity, particularly for flat or early lesions. Biopsy provides definitive grading but is invasive, resource-intensive, and prone to sampling error [15, 16] (Figure 2). Adjunct optical techniques enhance detection: autofluorescence and fluorescence imaging reveal metabolic and structural changes, thereby increasing lesion contrast, though with variable specificity [17-19].

OCT provides depth-resolved imaging of mucosal microarchitecture and, when combined with machine learning, improves classification, though it is costly and requires training [5, 20]. Diffuse reflectance spectroscopy and narrow-band imaging also show promise but require further validation [5, 21].

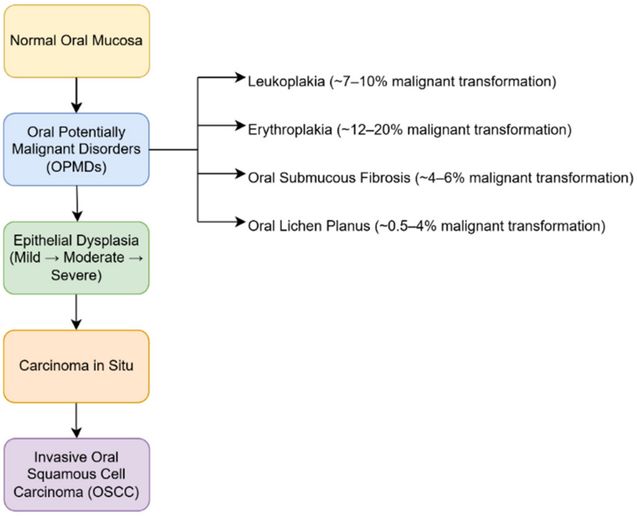

Fig. 1. Disease progression from normal mucosa to oral squamous cell carcinoma [16, 17].

TABLE I. MALIGNANT TRANSFORMATION RATES OF COMMON OPMDS [16, 17]

OPMD Type	Cumulative Transformation Rate (%)	Annual Transformation Rate (%)	Remarks
Leukoplakia	7.2–9.8	~0.6 per year	Higher risk in non-homogeneous and dysplastic lesions.
Erythroplakia	12.7–19.9	~2.7 per year	Often shows severe dysplasia or carcinoma in situ at first presentation.
Oral Submucous Fibrosis (OSMF)	4.2–6.0	—	Chronic areca-nut exposure: strong regional correlation in South Asia.
Oral Lichen Planus (OLP)	0.44–3.8	0.28–0.57 per year	Higher malignant potential in erosive/atrophic subtypes.
Overall (All OPMDs combined)	7.9 (meta-analysis mean)	—	Based on pooled global evidence

Computational approaches that leverage photographs, endoscopic images, OCT images, and histopathology images using CNNs and transformer-based models have demonstrated high accuracy in detection, segmentation, and classification. Transfer learning and lightweight networks enable point-of-care use, but performance often drops in heterogeneous clinical settings without careful preprocessing and external validation [5, 13, 16].

Hybrid AI workflows that combine systematic digital image processing (denoising, illumination correction, color/stain normalization, CLAHE, segmentation) with feature extraction and classification improve generalization more than model tweaks alone. However, preprocessing reporting is inconsistent, and comparative studies linking specific operations to performance remain limited [5, 22]. While AI and adjunct modalities show high sensitivity and specificity in research, their clinical utility depends on screening context, cost, operator skill, and integration with referral pathways. mHealth and community screening indicate that AI-assisted photography can extend reach, while fluorescence and OCT aid specialist assessment but face practical constraints [16, 23].

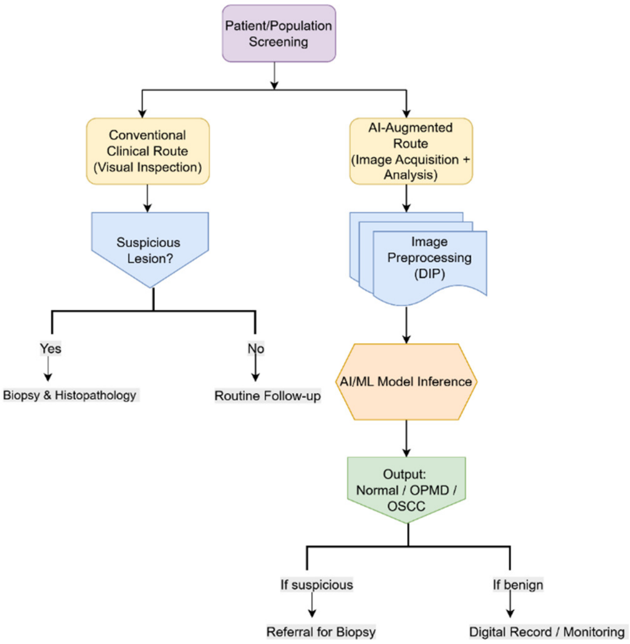

Fig. 2. Diagnostic pathway for oral cancer (conventional and AI-augmented).

Overall, oral cancer diagnostics involve trade-offs: conventional exams are accessible but limited; biopsy is definitive but invasive; optical modalities enhance visualization but require interpretation; and AI can scale and objectify analysis when properly trained and validated. A comparative synthesis of conventional and AI-based strategies highlights opportunities for methodological improvements and translational readiness (Figure 3) [15, 17].

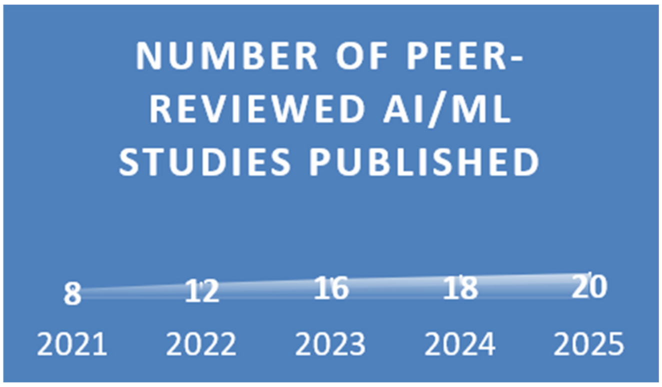

Fig. 3. Approximate number of peer-reviewed AI/ML studies published.

IV. DIGITAL IMAGE PROCESSING IN MEDICAL IMAGING

DIP is a crucial part of AI-based medical imaging pipelines because raw images often contain noise, uneven illumination, and artifacts that can reduce the accuracy of downstream analysis. Key operations such as noise reduction, contrast enhancement, segmentation, and normalization improve image quality, yielding more stable and discriminative features and reducing within-class variability. DIP is essential for the stability, generalization, and interpretability of AI models. Without it, models may focus on noise rather than pathology, and even small differences in illumination or imaging devices can noticeably degrade performance. Studies have shown that carefully designed preprocessing often contributes more to model performance than minor architectural improvements. Integrating DIP with segmentation models has been shown to increase metrics such as Intersection over Union (IoU) and Dice scores compared with using raw images. [24-31].

V. INTEGRATION OF IMAGE PROCESSING AND AI IN ORAL CANCER STUDIES

Recent studies (2020–2025) highlight the synergy between digital image preprocessing and AI in oral lesion classification. Early smartphone-based pipelines demonstrated the feasibility of community screening through simple preprocessing steps, including color normalization and augmentation [6]. Subsequent works scaled datasets and preprocessing rigor: attention-based vision transformers on clinical photographs (n ≈ 1,406) used cropping, resizing, and color correction to address device heterogeneity [7]; OCT studies applied speckle reduction and contrast enhancement before multilevel residual deep learning, improving tissue discrimination [8]; histopathology pipelines leveraged stain normalization and patch extraction with EfficientNet to reduce variability [11]. Hybrid approaches that combine handcrafted features with deep embeddings further improved localization and classification consistency, e.g., by integrating CLAHE, color-space normalization, and morphological segmentation [10], or by jointly optimizing preprocessing parameters with CNN weights to reduce false positives [32]. Despite these advances, generalization across devices and centers remains limited when preprocessing is inconsistent, and explainability tools (e.g., Grad-CAM) are rarely validated clinically. Computational efficiency also constrains the deployment of large models in on-device applications [7, 10, 11].

VI. FEATURE EXTRACTION AND REPRESENTATION TECHNIQUES

Feature extraction transforms enhanced images into discriminative descriptors for classification. Handcrafted methods such as the Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Discrete Wavelet Transform (DWT), Scale-Invariant Feature Transform (SIFT), and Speeded-Up Robust Features (SURF) capture texture and structural patterns, supporting differentiation between benign and malignant cases [33,34]. Deep learning models, including CNNs and transformers, learn hierarchical features that represent local and global dependencies [35, 36].

TABLE II. REPRESENTATIVE STUDIES COMBINING PREPROCESSING AND AI

Study	**Modality**	**Dataset (approx.)**	**Key preprocessing**	**AI model/ approach**	**Noted limitations**
[6]	Smartphone photos	1,200 images	Color normalization, augmentation	CNN (custom)	Retrospective; single-center images
[7]	Clinical photographs	1,406 images	Cropping, resizing, and color correction	Vision Transformer (ViT)	Device heterogeneity; limited external validation
[8]	OCT frames	~1,000 frames	Speckle reduction, contrast enhancement	Multi-Level Deep Residual Network	OCT device dependence; operator skill needed
[11]	Histopathology	1,224–3,000 patches	Stain normalization, patch extraction	EfficientNet	Needs large annotated histology sets
[32]	Photographs + optimization	4,000 images	Preprocessing hyperparameter tuning	CNN + swarm optimization	Complexity of preprocessing tuning

TABLE III. PREPROCESSING TECHNIQUES REPORTED AND THEIR OBSERVED EFFECT

Preprocessing technique	**References**	**Observed effect on model performance/robustness**
Color/stain normalization	[6, 7, 10, 11]	Reduces inter-device/color bias; improves cross-site generalization
CLAHE / local contrast	[10, 32]	Enhances lesion contrast; aids segmentation and localization
Speckle/noise reduction	[8]	Improves delineation of tissue layers; increases classification accuracy
Segmentation (morphological / DL)	[10, 11]	Reduces background confounders; improves feature focus
Preprocessing hyperparameter optimization	[32]	Fine-tuning preprocessing improves false positive rates

Hybrid strategies that combine handcrafted and deep features through fusion or ensemble approaches improve robustness to domain variability and limited datasets while preserving interpretability [33, 37]. Handcrafted features offer efficiency and transparency, whereas deep features provide adaptability at a higher computational cost; integrating them, supported by explainability tools, offers a balanced approach [12, 36].

TABLE IV. REPRESENTATIVE STUDIES AND FEATURE STRATEGY

Study	Modality	Feature strategy (handcrafted / deep / hybrid)	Model family	External validation reported
[35]	Histopathology review	Deep (review of DL methods)	CNNs, transfer learning	Review (multi-study)
[37]	Multiresolution medical images	Hybrid (multiresolution handcrafted + CNN)	Hybrid segmentation / CNN	No / limited
[33]	Brain MRI (method transferable)	Handcrafted + deep fusion (GLCM + LBP + CNN)	Fusion + RF / CNN	External test sets reported
[36]	Radiomics / medical imaging review	Comparative review (handcrafted vs learned)	Radiomics, DL	Review synthesis
[34]	Classification tasks	Hybrid (LBP, GLCM, SIFT + ML)	SVM / RF ensembles	Limited/internal
[12]	Oral imaging (systematic review)	Notes hybrid approaches in the literature	CNNs, transformers	Review (calls for external val.)

VII. COMPARATIVE ANALYSIS OF THE REVIEWED LITERATURE

Recent work on image-based oral cancer detection can be categorized by imaging modality, learning strategy, and clinical applicability. Clinical photographs enable scalable screening but are sensitive to acquisition variability, whereas histopathology provides accurate classification under controlled settings yet requires costly annotation and substantial resources. OCT and related optical techniques offer non-invasive depth information but remain device- and operator-dependent [12, 22]. CNN-based transfer learning predominates, while attention and transformer models capture broader context. Explainability tools such as Grad-CAM are widely used but rarely validated against independent clinical annotations [11, 38, 39]. Preprocessing details, external validation, and deployment considerations remain limited, with many single-center studies and minimal focus on efficiency, latency, or lightweight design [12, 39-41].

VIII. CONCLUSION

Digital image processing plays a pivotal role in advancing AI-based oral cancer detection by enhancing image quality and stabilizing feature extraction. Reviewed studies show that systematic preprocessing improves lesion visibility, while hybrid feature extraction can support interpretability and robustness. However, translation into clinical practice remains constrained by heterogeneous methodologies, inconsistent reporting, limited external and multicenter validation, and insufficient attention to deployment efficiency. Although explainability techniques are increasingly applied, independent clinical validation remains uncommon. As a narrative review, the study selection may be subject to selection bias; no structured quality assessment was performed, and no meta-analytic comparison of model performance was conducted. Future work should prioritize standardized pipelines, collaborative datasets, and efficient, interpretable models for real-world deployment.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

ACKNOWLEDGMENT

Not applicable.

FUNDING SOURCES

This research received no external funding.

DATA AVAILABILITY

No new data were generated or analyzed in this study. All information is available in the cited literature.

AI USE AND DECLARATION OF GENERATIVE AI USE

The authors used generative AI tools for language assistance during manuscript preparation. All content was reviewed and edited by the authors, who take full responsibility for the published work.

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