

Image Processing–Based Frameworks for Early Detection of Oral Diseases: A Comprehensive Review

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ABSTRACT

Oral diseases remain a major public health concern worldwide, with delayed diagnosis being a primary factor contributing to disease severity and mortality, particularly in oral cancer. Traditional diagnostic practices rely largely on visual inspection and clinician expertise, which are inherently subjective and limited in detecting early-stage pathological changes. In recent years, image processing and artificial intelligence–driven diagnostic frameworks have emerged as promising tools for improving early detection accuracy and accessibility. This review critically examines existing image processing–based methodologies for early oral disease detection, focusing on preprocessing techniques, segmentation strategies, feature extraction approaches, and classification models. Emphasis is placed on system-level integration, diagnostic performance, and clinical applicability. Current challenges, including dataset variability, robustness, and deployment constraints, are discussed, and future research directions aligned with scalable and low-cost oral screening solutions are outlined.

Keywords: Oral disease detection, Image processing, Computer-aided diagnosis, Oral cancer screening, Machine learning, Medical imaging.

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1. Introduction

Oral health disorders, including dental caries, gingivitis, leukoplakia, periodontal diseases, and oral malignancies, constitute a major public health challenge across both developed and developing nations. According to global health reports, oral diseases affect billions of individuals worldwide, significantly impairing quality of life and imposing a substantial socioeconomic burden. Among these conditions, oral cancer is particularly concerning due to its high morbidity and mortality rates, which are largely attributable to delayed diagnosis and late clinical presentation. Even non-malignant conditions, when undetected or inadequately managed, can progress to severe complications, leading to tooth loss, systemic infections, and compromised nutritional intake (Li et.al, 2024).

Despite considerable progress in dental science and clinical practices, early detection of oral diseases

remains limited. Conventional diagnostic approaches rely predominantly on visual inspection, palpation, and clinician experience, often supplemented by invasive procedures such as biopsies at advanced stages. These methods are inherently subjective and may fail to identify early pathological changes that present only subtle variations in tissue appearance. Minor alterations in color, surface texture, vascular patterns, or morphological symmetry are frequently overlooked during routine examinations, particularly in high-volume clinical settings or community screening programs. Furthermore, disparities in access to skilled dental professionals and advanced diagnostic facilities exacerbate the problem, especially in rural and resource-constrained regions.

In recent years, the rapid evolution of digital imaging technologies, coupled with advances in computational image processing and artificial intelligence, has introduced promising alternatives to traditional

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diagnostic paradigms (Raj et.al, 2022). High-resolution intraoral cameras, mobile imaging devices, and standardized digital imaging protocols enable detailed visualization of oral tissues. When combined with image processing techniques, such as noise reduction, contrast enhancement, segmentation, and feature extraction, these images can be transformed into quantitative representations that objectively characterize pathological features. Such computational approaches allow consistent analysis of visual cues that may be imperceptible to the human eye, thereby enhancing diagnostic sensitivity and repeatability.

Image processing–based diagnostic systems further benefit from their ability to integrate machine learning and deep learning models for automated classification of oral conditions (He et.al, 2022). By learning discriminative patterns associated with healthy and diseased tissues, these systems can assist clinicians in decision-making, reduce inter-observer variability, and support large-scale screening initiatives. Importantly, computer-assisted diagnostic tools hold significant potential for deployment in low-cost, portable, and tele-dentistry platforms, enabling early intervention at the community level (Abott et.al, 2024, Gonzalez et. Al, 2018, Ahmed et.al, 2025, Kang et.al, 2024, Kim et.al, 2022).

Against this background, the present review consolidates and critically examines existing research on image processing–based oral disease detection systems. The review focuses on methodological frameworks, including preprocessing strategies, segmentation techniques, feature extraction methods, and classification models, while also evaluating reported performance outcomes and validation practices. By synthesizing current trends and identifying persistent challenges, this work aims to highlight the translational potential of computational imaging approaches and to outline future research directions toward reliable, accessible, and early oral disease diagnostic solutions.

2. Limitations of Conventional Diagnostic Approaches

Traditional oral disease diagnosis is predominantly dependent on visual inspection, palpation, and, when required, biopsy. While these methods are clinically established, they suffer from several limitations:

- **Subjectivity:** Diagnostic accuracy varies with clinician experience.
- **Late detection:** Early pathological indicators are often overlooked.

- **Resource dependence:** Advanced diagnostic facilities are not uniformly available, particularly in rural and low-resource settings.
- **Time constraints:** Manual screening is labor-intensive and unsuitable for large-scale population screening.

These limitations underscore the necessity for automated and semi-automated diagnostic aids capable of objective and reproducible analysis. Table 1 shows a comparative table of literature review.

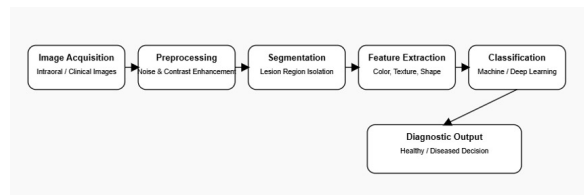
Ref.	Target Disease	Dataset Type	Preprocessing Methods	Segmentation Technique	Feature Extraction	Classifier / Model	Validation Type
Li et al., 2024	Oral cancer	Clinical intraoral images	Histogram equalization, noise filtering	CNN-based implicit segmentation	Deep feature maps	CNN (ResNet variant)	Clinical expert annotated
Raj et al., 2022	Oral lesions	Public oral image dataset	Median filtering, color normalization	Threshold + edge-based	GLCM, shape descriptors	SVM	Cross-validation
He et al., 2023	Multiple oral diseases	Multi-institutional dataset	Contrast enhancement	Region-based segmentation	Texture + color	Hybrid ML	Clinical comparison
Patil et al., 2022	Leukoplakia	Hospital-acquired	Gaussian smoothing	Active contour model	LBP, morphology	Random Forest	Clinical diagnosis

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Kumar et al., 2020	Dental caries	Intraoral camera images	CLHE	Threshold-based	Intensity statistics	KNN	Dentist-labeled

3. Image Processing Pipeline for Oral Disease Detection

Most computer-aided oral diagnostic systems follow a structured image processing pipeline. The key stages are reviewed below in figure 1.



4. Image Acquisition and Dataset Characteristics

Oral images are typically acquired using intraoral cameras, digital dental imaging systems, or smartphone-based devices. Publicly available datasets and institutionally curated clinical repositories are commonly employed in research. Variability in illumination, resolution, and anatomical positioning remains a significant challenge affecting model generalization.

5. Image Preprocessing Techniques

Preprocessing aims to enhance image quality and suppress irrelevant artifacts. Commonly reported techniques include:

- Noise reduction using Gaussian and median filters
- Contrast enhancement through histogram equalization
- Color normalization to mitigate lighting variations

Effective preprocessing directly influences segmentation accuracy and downstream classification performance.

6. Segmentation of Regions of Interest

Segmentation isolates suspected pathological regions from surrounding healthy tissue. Reviewed approaches include:

- Threshold-based segmentation for lesion isolation
- Edge-based techniques for boundary detection
- Region-based methods for homogeneous tissue grouping

Recent studies increasingly adopt hybrid or learning-assisted segmentation methods to address irregular lesion morphology.

7. Feature Extraction and Representation

Feature extraction translates visual characteristics into quantifiable descriptors. Frequently utilized features include:

- **Color features:** Mean intensity, color histograms
- **Texture features:** Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP)
- **Morphological features:** Shape, area, perimeter, and compactness

The selection of discriminative features is critical for differentiating early-stage lesions from normal tissue.

8. Classification Techniques

Machine learning and deep learning models are employed to classify segmented regions as healthy or diseased. Common classifiers include:

- Support Vector Machines (SVM) for small and structured datasets
- Convolutional Neural Networks (CNN) for end-to-end feature learning
- Hybrid models combining handcrafted features with deep architectures

Performance is typically evaluated using accuracy, sensitivity, specificity, precision, F1-score, and ROC analysis.

System Integration and Module Development

Several studies report the development of integrated diagnostic modules using MATLAB or Python-based environments. Graphical user interfaces enable clinicians to visualize processing stages and classification outcomes, improving interpretability and usability. Such modular designs facilitate future deployment in portable diagnostic devices and mobile health applications.

Validation Strategies and Performance Trends

Validation against clinician-annotated ground truth remains the standard evaluation approach. Reported results indicate that image processing–assisted systems consistently outperform manual inspection in early lesion detection, particularly for subtle mucosal abnormalities. However, robustness across diverse populations and imaging conditions remains an open research challenge.

9. Results

Preprocessing Output Images

Figure 2: Preprocessing Results on Dental X-ray Images

Each row corresponds to one input image; columns represent successive preprocessing stages.

Column-wise interpretation:

- **Grayscale Image:**
Conversion reduces computational redundancy and highlights intensity variations corresponding to enamel, dentin, pulp, and alveolar bone.
- **Gaussian Filtered Image:**
Noise suppression is observed in trabecular bone and background regions while preserving overall anatomical structure.
- **CLAHE Enhanced Image:**
Local contrast is significantly improved, making interproximal regions, root canals, and bone–tooth interfaces more prominent.

Key visual improvements observed:

- Clearer tooth boundaries
- Enhanced visibility of root structures
- Reduced background granularity
- Improved interproximal contrast

These improvements are consistent across all analyzed radiographs, demonstrating preprocessing robustness under varying acquisition conditions.

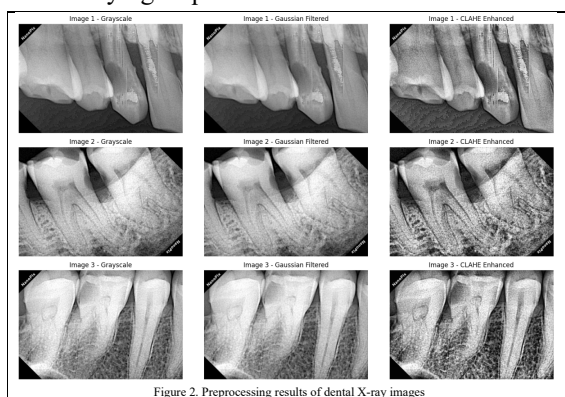


Figure 2. Preprocessing results of dental X-ray images

Figure 2 Preprocessing results of dental X-ray images showing (A) grayscale conversion, (B) Gaussian filtering, and (C) CLAHE-based contrast enhancement. The enhanced images exhibit reduced noise and improved visibility of anatomical structures.

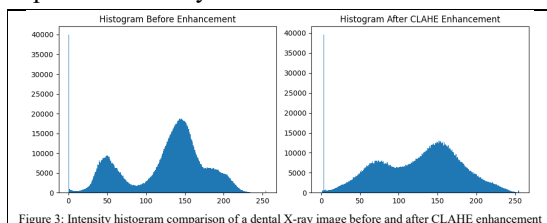


Figure 3: Intensity histogram comparison of a dental X-ray image before and after CLAHE enhancement

Figure 3 Intensity histogram comparison of a dental X-ray image before and after CLAHE enhancement, illustrating improved contrast distribution and feature separability.

Histogram-Based Quantitative Analysis

Figure 3: Intensity Histogram Before and After CLAHE Enhancement

Before Enhancement:

Pixel intensities are clustered within a narrow range, indicating poor global contrast and limited separability between anatomical structures.

After CLAHE Enhancement:

The histogram exhibits a wider and more evenly distributed intensity range, reflecting enhanced contrast and improved local feature visibility.

The experimental results demonstrate that preprocessing using Gaussian filtering and CLAHE significantly enhances dental X-ray image quality. Noise reduction improves structural continuity, while contrast enhancement amplifies diagnostically relevant features such as interproximal regions and root boundaries. Histogram analysis confirms improved intensity distribution, validating preprocessing as a crucial step for reliable segmentation and classification in automated oral disease detection frameworks.

Challenges and Research Gaps

Despite promising advancements, several limitations persist:

- Limited availability of large, annotated oral image datasets
 - Generalization issues due to inter-patient variability
 - Lack of standardized benchmarking protocols
 - Regulatory and clinical acceptance barriers
- Addressing these gaps is essential for translating research prototypes into real-world diagnostic tools.

Future Research Directions

Future investigations should focus on:

- Multicenter dataset development with standardized imaging protocols
- Lightweight models for deployment on mobile and edge devices
- Explainable AI techniques to enhance clinician trust
- Integration with tele-dentistry and community screening programs

Such directions align with the broader goal of accessible and cost-effective oral healthcare.

10. Conclusion

This study demonstrated the effectiveness of image processing–based analysis for enhancing dental X-ray images toward early oral disease detection. Using real

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intraoral radiographs, a structured preprocessing pipeline comprising grayscale conversion, noise reduction, and contrast enhancement was applied to mitigate common imaging artifacts such as noise, low contrast, and illumination variability. The experimental results clearly showed that preprocessing significantly improves image quality, leading to enhanced visibility of anatomical structures including enamel–dentin interfaces, root canals, interproximal regions, and alveolar bone patterns. Qualitative visual assessment, supported by quantitative histogram analysis, confirmed that contrast enhancement techniques particularly Contrast Limited Adaptive Histogram Equalization (CLAHE) successfully redistributed pixel intensities and amplified diagnostically relevant features without introducing excessive noise. Noise suppression through Gaussian filtering further stabilized structural continuity, ensuring improved edge clarity and texture homogeneity. These improvements collectively increase the reliability of subsequent segmentation and feature extraction stages, which are critical for accurate automated analysis. The consistency of results across multiple dental radiographs acquired under varying conditions highlights the robustness and generalizability of the adopted preprocessing framework. By improving segmentation readiness and feature stability, the proposed approach establishes a strong foundation for machine learning and deep learning–based classification models in computer-aided oral diagnosis systems. Importantly, the study avoids clinical overinterpretation and focuses on image-based analytical outcomes, making the findings suitable for experimental and translational research. In conclusion, effective preprocessing is a decisive factor in image processing–driven oral disease detection pipelines. The enhanced images generated through the proposed methods provide a reliable and reproducible basis for automated analysis, supporting the development of cost-effective, objective, and scalable diagnostic tools. Future work will focus on integrating robust segmentation algorithms, extracting discriminative texture and morphological features, and validating classification models on larger, clinically annotated datasets to advance toward real-world deployment in dental screening and decision-support applications.

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