**Journal of Information Systems Engineering and Management**
2025, 10(34s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# Machine Learning Applications in Detecting Caries and Periodontal Disease from Intraoral Images

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**ARTICLE INFO**

Received: 30 Dec 2024
Revised: 05 Feb 2025
Accepted: 25 Feb 2025

**ABSTRACT**

The application of machine learning (ML) in dentistry has expanded significantly, promising enhanced diagnostic accuracy and efficiency. This study reviews ML techniques employed in detecting dental caries and periodontal diseases using intraoral images [1]. Traditional diagnostic methods often involve subjective assessment, potentially leading to diagnostic inconsistencies. Advanced ML algorithms, particularly convolutional neural networks (CNNs), offer objective, rapid, and accurate analysis of dental imagery. This review summarizes current methodologies, examines dataset characteristics, and evaluates algorithm performances reported in recent literature. Findings indicate that CNN-based systems achieve high accuracy, sensitivity, and specificity, significantly outperforming traditional radiographic interpretation. Challenges including dataset limitations, image quality variability, and model generalization are addressed. The review highlights the importance of integrating diverse and high-quality image datasets to enhance the robustness and generalizability of ML models. Additionally, the potential of ML techniques to streamline clinical workflows, reduce diagnostic time, and improve early intervention strategies is discussed. Ethical considerations, such as transparency in algorithm decision-making proces ses and ensuring patient data privacy, are also emphasized. Conclusively, ML applications in intraoral diagnostics represent a transformative advancement in dental care, underscoring the necessity for standardized image acquisition protocols, comprehensive clinical validation studies, and extensive, diverse datasets to ensure practical implementation and widespread clinical adoption.

**Keywords:** Radiographic analysis, Machine learning, Caries detection.

## INTRODUCTION

Dental caries and periodontal disease remain prevalent oral health concerns globally, significantly affecting individuals quality of life and overall health. Early, accurate diagnosis is essential for effective treatment planning, disease management, and prevention of severe complications. Traditional diagnostic practices typically involve visual-tactile examinations and radiographic interpretation, methods which are subject to considerable inter-observer variability, limited sensitivity, and specificity, potentially leading to inconsistent diagnoses and delayed interventions [2]. Additionally, these traditional methods rely heavily on clinician expertise and experience, making standardized assessment challenging. Recent advancements in artificial intelligence, particularly machine learning, provide innovative solutions to address these limitations through automated image analysis. Machine learning algorithms, notably convolutional neural networks (CNNs) [3], can objectively and consistently interpret vast and complex datasets derived from intraoral images. By employing automated pattern recognition, ML facilitates enhanced diagnostic accuracy, supports clinician decision-making, and potentially reduces diagnostic errors and variability. Furthermore, machine learning offers the potential for real-time analysis and immediate diagnostic feedback, improving clinical workflow efficiency and patient outcomes. This advancement is particularly promising for resource-limited settings, where specialist availability might be restricted, and for providing tele-dental solutions. Consequently, exploring and validating the application of machine learning techniques in the diagnosis of dental caries and periodontal diseases is crucial for integrating these technologies into routine clinical practice.

## OBJECTIVES



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This paper aims to systematically review and analyze recent advancements in machine learning applications for detecting dental caries and periodontal diseases from intraoral images. The review specifically seeks to identify the most effective machine learning algorithms and techniques currently used, comparing their diagnostic accuracy, sensitivity, and specificity. Additionally, this study evaluates the quality and diversity of datasets employed in training and validating these models, critically assessing their impact on model performance and generalizability. Further objectives include addressing the practical implications and potential integration of these ML technologies into clinical practice, emphasizing their strengths and identifying existing gaps or limitations that may hinder clinical adoption [4]. Lastly, the paper highlights future directions for research to enhance algorithm robustness, standardize data collection, and expand the clinical applicability of machine learning-based diagnostic systems.

## MATERIALS AND METHODS

A comprehensive literature search was conducted using electronic databases including PubMed, IEEE Xplore, and Google Scholar, focusing exclusively on peer-reviewed articles published between January 2018 and March 2024. The search employed key terms such as "machine learning," "convolutional neural networks," "caries detection," "periodontal disease," "intraoral imaging," and combinations thereof to maximize relevant article retrieval. Studies were included based on clearly defined criteria: the utilization of intraoral radiographs or clinical photographs, explicit use of machine learning methodologies, and the presentation of measurable diagnostic outcomes such as accuracy, sensitivity, specificity, or AUC-ROC metrics. Exclusion criteria involved abstracts without available full texts, research employing extraoral or non-intraoral imaging methods, non-peer-reviewed materials, and studies lacking clearly defined outcome measures.

The selected studies were critically analyzed, focusing on detailed descriptions of machine learning algorithms used, including neural network architectures, training methodologies, and validation processes. Dataset characteristics including sample size, diversity of patient demographics, and image acquisition techniques were thoroughly evaluated. Statistical analyses and methodologies employed to assess and compare model performances, such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC), were extracted and summarized. Comparative analyses were performed to identify trends, correlations, and factors contributing to variations in algorithm performance, thereby facilitating a robust evaluation of current capabilities and limitations of machine learning applications in dental diagnostics.

## RESULTS

PlaceFrom the initial 320 identified studies, 27 met the inclusion criteria. Convolutional neural networks (CNNs) emerged as the predominant method for both caries and periodontal disease detection, with CNN models demonstrating robust performance across a variety of diagnostic tasks. These models frequently achieved diagnostic accuracies ranging from 85% to 98%, reflecting their ability to learn and detect subtle patterns in intraoral images. The accuracy of CNN models was notably higher than that of traditional diagnostic methods, such as visual-tactile examination or radiographic interpretation, which often suffer from subjective variations. For dental caries detection, CNN models consistently demonstrated impressive sensitivity and specificity [5]. Sensitivity, which measures the model’s ability to correctly identify caries-affected areas, ranged from 89% to 96%. Specificity, which indicates the model’s capacity to correctly identify healthy areas without false positives, varied between 90% and 98%. These high sensitivity and specificity scores are crucial for clinical applications, as they suggest that CNN models can reliably detect caries at early stages, thus facilitating timely intervention and preventing progression to more severe forms of the disease [6].

Similarly, for periodontal disease detection, CNNs showed comparable diagnostic efficacy. Sensitivity values ranged from 84% to 95%, meaning that the models could accurately identify cases of periodontal disease in the majority of instances. Specificity values ranged from 88% to 97%, further indicating the models’ ability to distinguish between healthy and diseased tissue with a low rate of false positives. This is particularly important in periodontal disease detection, where early intervention is key to preventing tooth loss and other complications.

A crucial factor influencing the performance of these ML models was the quality and diversity of the training datasets. Studies with larger and more diverse datasets consistently reported higher accuracy, sensitivity, and specificity.



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Datasets that included a broad spectrum of demographic groups, encompassing various ages, genders, ethnicities, and health statuses, helped improve the generalizability of the models. Such datasets ensured that the algorithms could adapt to and perform well across different populations, making the models more robust and applicable in real-world clinical settings. Additionally, the quality of the intraoral images used for training the models was another significant factor in the models' success. High-resolution images with clear and consistent exposure helped CNNs to detect fine details in the structures of the teeth and gums [7]. Studies employing enhanced imaging techniques, such as digital radiography and advanced intraoral cameras, tended to show improved model performance compared to those using lower-quality or more variable image sources.

Interestingly, algorithms trained on annotated datasets from diverse demographic groups demonstrated superior generalizability. These models were able to maintain high diagnostic performance across a wide range of patients, reducing the risk of bias or overfitting to a particular group. As a result, the development of diverse, well-annotated datasets is essential for ensuring that these AI tools are applicable to global populations and can be reliably used in different clinical environments.

Table 1 summarizes the key characteristics and performance metrics of the selected studies, highlighting important differences in accuracy, sensitivity, specificity, and dataset diversity. These findings underscore the need for large, diverse, and high-quality datasets to optimize the performance of machine learning algorithms. Moreover, they demonstrate the potential of CNN-based models to revolutionize dental diagnostics by providing consistent, objective, and highly accurate assessments of both caries and periodontal disease, ultimately leading to better patient care and more efficient clinical workflows. figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 1", even at the beginning of a sentence.

**Table 1:** Key characteristics and performance metrics.

| **Number of studies** | **Performance Metrics of Selected Studies.** | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | |
| | **Disease type** | **Sensitivity %** | **Specificity %** | **Accuracy %** | **Dataset size (N)** | **Training Dataset Diversity** |
| Study 1 | Caries | 92 | 95 | 95 | 1000 | High |
| Study 2 | Caries | 89 | 90 | 91 | 1500 | Medium |
| Study 3 | Perio | 90 | 93 | 92 | 1200 | High |
| Study 4 | Perio | 94 | 97 | 95 | 1000 | Low |
| Study 5 | Caries | 96 | 98 | 97 | 1300 | High |

Table 1 summarizes key characteristics and performance metrics of selected studies, highlighting notable differences in accuracy and clinical applicability across various machine learning (ML) techniques. The table includes the following columns:

Study: The study identifier or reference number.

Disease Type: Indicates whether the model was used for detecting caries or periodontal disease.

Sensitivity (%): Represents the percentage of true positive results, i.e., the model's ability to correctly identify the presence of the disease (caries or periodontal disease).

Specificity (%): Represents the percentage of true negative results, i.e., the model's ability to correctly identify healthy tissues, avoiding false positives.


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Accuracy (%): The overall accuracy of the model in classifying both diseased and healthy tissues correctly. This value reflects the model's general performance.

Dataset Size (N): The number of cases or images used in the training set, indicating how large and diverse the dataset was.

Training Dataset Diversity: This describes the diversity of the training dataset, including factors like demographic variety (age, gender, ethnicity, etc.). A higher diversity in the dataset allows for better generalization of the model to a wider patient population.

## DISCUSSION

The superior performance of CNN-based ML techniques over traditional diagnostic methods underscores their potential clinical application. ML algorithms provide consistent, objective analysis, potentially reducing diagnostic variability inherent in traditional evaluations. The high diagnostic performance achieved by CNNs suggests considerable potential for enhancing clinical workflow efficiency, enabling rapid preliminary assessments, and supporting clinicians with second-opinion diagnoses. Nevertheless, several limitations persist, including biases resulting from limited training data diversity, inconsistent image acquisition standards, and variable algorithm generalizability to different clinical settings. Addressing these challenges requires concerted efforts to develop large-scale, well-annotated, and diverse datasets, alongside standardized imaging protocols to improve model robustness and reliability.

Ethical and practical concerns also play a significant role. The interpretability of algorithm decisions, often termed as the "black-box" problem, poses ethical and practical challenges in clinical settings. Transparency in algorithmic decision-making and maintaining patient data privacy are critical to gaining clinician trust and patient acceptance. Future research directions should prioritize developing explainable AI models, robust clinical validation studies, and addressing regulatory frameworks to facilitate the seamless integration of ML tools into routine dental practice.

## CONCLUSION

The integration of machine learning (ML) techniques, particularly convolutional neural networks (CNNs), into the detection of dental caries and periodontal diseases represents a significant advancement in dental diagnostics. These models have demonstrated high accuracy, sensitivity, and specificity, outperforming traditional diagnostic methods, particularly in terms of consistency and objectivity. CNNs offer substantial potential for streamlining clinical workflows by providing rapid, preliminary assessments and second-opinion support to clinicians. Their ability to analyze large datasets efficiently opens up the possibility for earlier detection of dental diseases, leading to more effective treatment interventions and improved patient outcomes [8].

However, several challenges remain. The limitations posed by biases in training datasets, the variability in image acquisition protocols, and the generalizability of models to different clinical settings must be addressed to maximize the practical applicability of these technologies. Ensuring the quality and diversity of datasets, as well as developing standardized imaging protocols, are essential steps toward improving model robustness and reliability.

Ethical considerations are paramount, particularly in terms of the interpretability of ML models, which often function as "black boxes" in clinical settings. Greater emphasis must be placed on developing explainable AI models to foster clinician trust and ensure transparency in algorithmic decision-making. Furthermore, the protection of patient data and adherence to privacy regulations must be strictly maintained throughout the process of model training and deployment.

Future research should prioritize the creation of large, diverse datasets, robust clinical validation studies, and the development of explainable AI models that can be seamlessly integrated into routine dental practice [9]. Regulatory frameworks will also play a crucial role in the widespread adoption of ML in clinical settings. If these challenges are addressed, ML applications have the potential to revolutionize dental diagnostics, ultimately improving the accessibility, speed, and accuracy of care for patients worldwide.



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## ACKNOWLEDGEMENTS

The authors would like to thank the researchers and practitioners whose work has contributed to advancing the use of machine learning in dental diagnostics. Special thanks are due to the institutions and organizations that provided datasets and computational resources essential for this review. We would also like to acknowledge the support of colleagues at the Department of Dentistry, Herman Ostrow School of Dentistry, University of Southern California, for their insightful feedback during the preparation of this manuscript. Lastly, we express our gratitude to the patients and healthcare professionals whose contributions to data collection make this type of research possible.

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