



# Tooth Detection Technology for Oral Disease Diagnosis

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**Abstract.** With the constant development of digital medical technology, oral disease is gradually shifting from traditional manual examination to automated detection based on image analysis. Tooth detection technology, as an important part of intelligent dental imaging, plays a crucial role in improving early disease detection rates, reducing subjective diagnostic errors and facilitating personalized treatment plans. This paper reviews tooth detection technology for oral disease diagnosis, categorizing and comparing traditional image processing, machine learning with handcrafted features, and deep learning methods. It highlights research progress, applicable imaging types, and performance metrics in tasks like dental caries detection, periodontal lesion identification, and tooth segmentation. The paper also discusses challenges such as data scarcity, high annotation costs, poor model generalization, and low interpretability. Lastly, it explores future trends, including lightweight models, multimodal fusion, and explainable AI in clinical dentistry, offering insights for future development in intelligent dental diagnostics. This comprehensive analysis provides critical insights for researchers and clinical practitioners, bridging the gap between technological innovation and clinical application.

**Keywords:** Dental detection; oral disease diagnosis; image processing; machine learning; deep learning .

## 1 Introduction

Oral health is increasingly recognized as an essential part of overall health and receives high attention in the clinical and public fields. The oral cavity is not only the beginning of the digestive system, but also undertakes multiple functions, such as chewing, pronunciation, and aesthetics, among others. Its health status directly affects nutrition intake, quality of social communication, and is closely related to the occurrence of various systemic diseases. The “Global Status of Oral Health Report” released by the World Health Organization(WHO) in 2022 pointed out that oral diseases are the most common non-communicable diseases in the world and affect nearly 3.5 billion people all over the world, accounting for 45% of the world’s population [1]. In many countries, oral diseases remain a significant health problem that causes pain and reduces the quality of life.

Currently, clinical dental examinations rely heavily on visual observation, probing, and manual measurement. These measures highly rely on operational skills and

experience, and their efficiency is limited. A full-mouth examination takes 15- 20 minutes on average, making it difficult to adapt to the needs of large-scale oral health screening. Furthermore, manual examinations are dramatically subjective, with diagnostic differences between different doctors. Early or latent lesions can be misdiagnosed or missed, impacting the timing of disease prevention and treatment.

With the rapid development of digital dentistry and scientific computer, automated teeth detection technology has emerged, providing new insights into breaking through the bottlenecks of traditional diagnosis. In recent years, computer vision, machine learning and deep learning have achieved remarkable success in medical image analysis, demonstrating high accuracy and efficiency in areas such as lung CT nodule detection and diabetic retinopathy identification in fundus images. In contrast, oral image analysis has developed relatively late due to the complex anatomy of teeth, diverse posture variations, and significant variations in image quality, and related algorithms face greater technical challenges. Currently, tooth detection research primarily focuses on identifying overall dentition or single lesions.

There is significant room for improving individual tooth detection, detailed lesions segmentation, and the combined diagnosis of multiple lesions.

Given this, systematically reviewing the development history and main method categories of tooth detection technology in oral disease diagnosis, and comparing its adaptability and performance across different image types and tasks, will not only help summarize the technological evolution in this field but also provide a reference for subsequent research. This study will summarize and compare three technical levels: traditional image processing methods, machine learning methods, and deep learning methods. The study will analyze the core principles, typical applications, existing limitations, and future development directions of each method, providing a theoretical foundation and supporting ideas for achieving intelligent and precise diagnosis of oral diseases.

## **2 Classification and analysis of dental inspection techniques and methods**

### **2.1 Traditional Image Processing Methods**

Before the generalization of deep learning technology, dental image analysis mainly relied on traditional image processing methods to achieve dental caries detection and tooth diagnosis. These kinds of methods are usually based on pixel intensity, edge intensity, and morphological rules to build the process of image processing.

In the 2010s, the detection technology based on traditional image processing made initial progress in the sphere of tooth detection. This method, which has a simple process, high interpretability, and it doesn't require a large amount of annotated data support, is highly sensitive to image quality and parameter settings, with poor adaptability across devices and populations. These limitations provide visible directions for improvement in subsequent tooth detection methods based on machine learning and deep learning.

## 2.2 Machine Learning Methods

Traditional image processing methods have provided a preliminary exploration foundation for tooth detection. With the improvement of computing power and the advancement of algorithm models, machine learning has gradually become an important research direction in this field. Compared to rule-based image processing workflows, machine learning methods are more data-driven, capable of automatically performing feature extraction and classification tasks by learning the relationship between a large number of features and labels. This method alleviates, to some extent, the problem of traditional methods' strong dependence on image quality and parameters, laying the foundation for subsequent deeper model construction and providing a natural transition for the introduction of deep learning methods.

Typical machine learning methods, such as Support Vector Machines(SVM), Random Forest(RF), and K-Nearest Neighbors(KNN), have shown great performance in tooth image classification and lesion recognition tasks.

A study carried out by Bui's research team proposed a method that integrates multiple traditional classifiers, including KNN, SVM, and Random Forest. The research utilized the tooth regions in panoramic X-ray images and combined deep feature extraction with traditional machine learning classifiers for joint recognition, improving overall robustness through a majority voting mechanism. On a public dataset, the system achieved an accuracy of over 93%, further demonstrating the practical application potential of traditional machine learning methods in medical image-assisted diagnosis [2].

Another study by Singh's research team focused on automatic recognition of tooth types and pathological conditions, constructing a Random Forest ensemble model optimized by a genetic algorithm [3]. The study first preprocessed and enhanced panoramic X-ray images, extracting various structured image features, including geometric shape and texture. Then, an ensemble Random Forest consisting of 10 decision trees was used for classification, and the majority voting mechanism was employed to optimize the prediction results. In the 80/5/15 split dataset, the system achieved an accuracy of 98% in tooth type anomaly recognition tasks, validating the strong performance of traditional machine learning models on small and medium-scale datasets [3].

Machine learning methods have strong controllability in feature engineering, allowing them to achieve good performance with limited data. However, there are still certain limitations in feature selection, generalization ability, and modeling high semantic structures. In a word, researchers start to shift their focus to more expressive deep learning frameworks to further improve detection accuracy and automation levels.

## 2.3 Deep Learning Methods

Based on the traditional image processing and machine learning providing the early exploration and structured modeling, deep learning technologies quickly become a research hotspot in dental imaging analysis, because of their powerful end-to-end expressive ability and self learning capacity for complex data patterns. Compared to

traditional methods that rely on manual feature design and model parameter adjustment, deep neural networks can automatically extract multi-level, semantic image features from large-scale data, dramatically improving detection accuracy and robustness, with stronger adaptability. As a result, deep learning methods are gradually becoming the mainstream approach for tooth detection and diagnosis tasks.

The Alharbi research team further expanded the model structure and proposed a tooth detection system based on a nested U-Net network. They compared the performance of U-Net, U-Net++, and U-Net3++ using a DNS panoramic image dataset annotated by experts (a total of 1500 images). Among them, U-Net3+ showed the best performance in boundary modeling and cavity region segmentation, with the accuracy of up to 95%. The introduction of nested skip connections allowed the model to retain more multi-scale information, significantly improving the continuity and accuracy of segmentation edges [4].

The Beser research team employed YOLOv5 to detect and number primary and permanent teeth in children's mixed dentition. They constructed a large-scale dataset containing 3854 annotated panoramic images and built a tooth detection and instance segmentation system based on YOLOv5. The results showed that the model achieved over 0.98 in metric such as mAP@0.5, precision, recall rate, and F1 score, showing that object detection based on deep networks have great generalization ability and practical value in large-scale, high-complexity dental data [5].

Deep learning methods show significant advantages in tooth detection which not only eliminate the need for complex feature engineering processes but also automatically learn multi-level representations of lesions from raw images, greatly improving detection efficiency and accuracy. However, deep models also face challenges such as strong dependency on training data, high annotation costs and poor interpretability. Therefore, how to integrate the expressive power of deep learning with the structural controllability of traditional methods has become a key direction of current research.

## 2.4 Comparison and Summary

As shown in Table 1, the three methods each have their advantages and suitable application scenarios. Traditional image processing methods are suitable for the early exploratory stage with stable conditions and small datasets; machine learning methods are suited to scenarios with complex data and high requirements for detection accuracy and efficiency,

**Table 1.** Comparison and Summary of Three Categories of Methods.

Method Category	Main Technical Process	Advantages	Limitations	Applicable Scenarios
Traditional Image Processing Methods	Preprocessing (Filtering, Histogram Equalization) → Threshold Segmentation → Morphological Processing/Connected Component Analysis	Clear process, high interpretability; no need for large-scale annotated data	Sensitive to image quality, weak generalization ability, poor cross-device adaptability	Small-scale data, early-stage exploratory research
Machine Learning Methods	Feature Extraction (Texture, Geometric, Grayscale) → Classifier (SVM, RF, KNN) Training and Prediction	Data-driven, relatively high accuracy; good performance even with limited data	Relies on manual feature engineering; difficulty in capturing complex semantic structures, limited generalization	Medium-scale data, tasks with structured features
Deep Learning Methods	End-to-end detection/segmentation models (e.g., CNN, U-Net, YOLOv5)	Automatic feature extraction; end-to-end learning; high precision, strong robustness	Requires large-scale, high-quality data; high annotation costs; poor interpretability	Large-scale complex data, high-precision clinical applications

### **3 Applications of Deep Learning-Driven Techniques in Oral Disease Diagnosis**

#### **3.1 Caries Detection and Grading Diagnosis**

Caries is a highly prevalent oral disease worldwide, and precise detection and grading are core stages in disease prevention and control. Traditional diagnosis relies on visual inspection, probing and conventional radiographs, and is easily affected by clinician experience, equipment precision and timing. It limits diagnostic consistency and accuracy. With the development of digital imaging, digital radiographs and panoramic images with higher resolution have gradually replaced traditional imaging, laying the foundation for automated diagnosis. The International Caries Detection and Assessment System(ICDAS), proposed by Pitts et al, divides caries into grades 0-6 to characterize disease progression and it helps clinicians quantify lesion severity and formulate individualized treatment plans [6].

Deep learning dramatically enhances caries detection by end-to-end feature self-learning: Lee et al. built a model based on deep convolutional neural networks(CNNs), and utilize numbers of periapical radiographs for training to achieve accurate classification of different types of caries. At the mean time it improves robustness to image quality fluctuations[7]. Bui et al. proposed an integrated deep learning framework that combines traditional machine learning models such as Random Forests(RF) and K-Nearest Neighbors(KNN) with a CNN feature extraction module to achieve high accuracy identification and grading caries in panoramic radiographs, maintaining stable performance across lesion types and image quality conditions [5]. Singh et al. developed an automated classification system based on RF that integrates geometric, texture, and shape features; the system achieved 98% accuracy for caries grading, enabling direct clinical assessment of lesion severity [3].

#### **3.2 Periodontal Disease Detection and Bone Loss Assessment**

Periodontal disease mainly includes gingivitis and periodontitis, early manifestations include gingival redness, swelling and bleeding while advanced stage can lead to alveolar bone resorption and even tooth loss. Traditional assessment rely on clinical examination and probing, making it difficult to quantify the extent and scale of the alveolar bone loss [8]. The widespread use of cone-beam computed tomography(CBCT) offers a new path for periodontal diagnosis. Pael et al. points that CBCT can clearly present alveolar bone morphology, periodontal pocket depth and tooth mobility. It can significantly improve bone loss assessment accuracy through high definition 3D images [9].

Deep learning technologies further promotes the automation of periodontal diagnosis. Huang et al developed a CNN-based periodontal disease staging model trained on large-scale periodontal images to automatically predict and output individualized treatment suggestions [10]. The staging and grading standards proposed by Tonetti et al. clarify the key role of bone loss assessment in treatment decisions, and

the integration of artificial intelligence enables multidimensional(eg.,amount of bone resorption, extent of inflammation) automated assessment of periodontal disease [8], especially suitable for rapidly progressing cases such as periodontitis associated with systemic diseases like diabetes.

### **3.3 Apical Lesion and Pulp Disease Auxiliary Diagnosis**

Apical lesions are often triggered by the spread of caries, trauma or infection, typically accompanied by symptoms such as toothache and sensitivity to percussion. Traditional diagnosis relies on X-rays or CBCT to assess apical tissue lesions. It requires comprehensive judgement in combination with clinical symptoms. Katsumata's research shows that computer-aided diagnostic(CAD)systems can effectively assist in the early identification of apical lesions [11]. With the development of deep learning, Ismail et al. expanded the existing computer-aided caries detection system to the field of apical lesions, using X-ray images and CNN to achieve automatic lesion annotation and classification [12].

Lee et al. further developed a CNN-based pulp disease detection system, which automatically identifies early signs of pulp lesions from X-ray images and completes grading. It not only improves diagnosis efficiency and reduces human error but also narrows diagnostic differences among different clinicians, providing technical support for standardized diagnosis of apical lesions and pulp diseases.

## **4 Technical Challenges and Development Trends**

### **4.1 Data Insufficiency and Annotation Cost Issues**

In the automation of oral disease detection and grading, the quality and quantity of data remain one of core factors that limits model performance. Despite the development of digital imaging technology, high quality and accurately annotated datasets are still scarce. This is because the annotation process should relies on experienced dentists who possess solid knowledge of oral medicine and make precise judgement on image details, especially in the early stages of diseases(eg. Mild caries or periodontal disease). This process is time-consuming and requires significant expertise, leading to high annotation costs [6][8]. To address this issue, researchers have proposed various technical paths, including using data augmentation to transform existing images such as rotation, scaling, translation) to expand the data scale and improve model's generalization[9], and employing semi-supervised learning to combine a small amount of labeled data with a large amount of unlabeled data for training, reducing dependence on manual annotation and enhancing the model's adaptability in real clinical scenarios[13]. Meanwhile, with the maturity of synthetic data technologies like Generative Adversarial Networks(GANs), researchers are able to generate virtual samples with realistic image features. This not only alleviates the data shortage issue but also significantly enhances the model's learning ability under small sample

conditions, providing a new development path for the automation of oral disease detection.

## 4.2 Multimodal Image Fusion(2D+3D+Clinical Information)

With the rapid development of oral imaging technology, single-modality images have revealed obvious shortcomings in diagnosing complex diseases. While 2D X-rays are commonly used in early caries detection and routine screening due to their universality and convenience, they are limited in their ability to interpret spatial structure, lesion depth and extent. 3D imaging such as Cone Beam Computed Tomography(CBCT) can more clearly show alveolar bone status, tooth position and the extent of apical lesions, playing a crucial role in diagnosing periodontal diseases, pulp diseases and apical lesions [9]. However, relying solely one modality still cannot fully reflect the entire lesion scope. Therefore, Multimodal image fusion has gradually become an important direction for improving diagnostic accuracy. By combining the universality of 2D images, the spatial resolution of 3D images and clinical information(eg. Symptoms, medical history, age), clinicians can obtain more comprehensive and accurate diagnostic support. It not only improves the diagnosis of single lesions but also enables the joint detection and comprehensive caries assessment, periodontal diseases and pulp diseases [14]. Studies have shown that Bui et al. proposed an integrated deep learning framework that utilizes multi-channel inputs from both panoramic X-ray images and CBCT images, achieving precise detection of caries and periodontal diseases, effectively demonstrating the potential of multimodal learning [5]. Nevertheless, differences in resolution, scale and perspective by modalities still present challenges for image registration and feature alignment. With advances in deep learning and cross-modal alignment algorithms, these issues are expected to be solved in the future.

## 4.3 Enhancing Interpretability and Clinical Usability

While deep learning have shown excellent performance in detection and diagnosis, their “black box” nature limits their adoption in clinical applications. Clinical diagnosis not only requires accuracy but also demands a clear understanding of the rationale behind the model’s conclusions. Therefore, improving interpretability and clinical usability is the key to facilitating their application. To address interpretability, researchers have proposed various technical solutions, such as Grad-CAM-like activation maps that could visually show the model’s focus areas, helping clinicians verify their correspondence with lesions [15]. Additionally, local interpretability algorithms such as LIME and SHAP further reveal the model’s decision logic on different samples, making the prediction results more transparent [10]. In spite of clinical usability, deep neural networks are often dependent on computing resources and achieving real-time, efficient and convenient applications remains a challenge. The rise of lightweight models and model compression techniques has made AI systems capable of running on middle and low performance hardware, dramatically expanding their applicability. Furthermore, the introduction of edge computing technologies effectively reduces

latency and privacy risks, providing new ideas for the fast response and deployability of clinical diagnostics [16].

## 5 Conclusion

This paper provides a comprehensive review of tooth detection technologies in oral disease diagnosis, talking about the applications and developments of traditional image processing methods, machine learning and deep learning methods in this field. By thoroughly reviewing the core technologies, application scenarios and performance metrics of each method, this paper summarizes the advantages and limitations of different technologies in tooth detection tasks and further analyzes the current technical bottlenecks and future development trends.

While Traditional image processing methods lay the solid foundation for tooth detection, they significantly depend on image quality, parameter settings and feature extraction, and struggle to deal with complex lesion structures and large scale data applications. Machine learning methods have demonstrated high performance in feature extraction and classification tasks, especially with smaller sample datasets. However, these methods still face challenges in feature selection, generalization and high-level semantic structure modeling, limiting their application in complex tasks.

Deep learning methods can automatically learn multi-layer features from large-scale data, significantly improved detection accuracy and efficiency. Particularly in tasks like caries detection, periodontal disease grading and apical lesion diagnosis, deep learning has shown advantages over traditional methods and machine learning models. However, deep learning technologies still face some shortcomings, such as strong dependence on training data, high annotation costs and poor model interpretability.

As the advance in research, future tooth detection technologies are expected to further overcome current challenges. The application of multimodal image fusion technologies will enable the integration of 2D X-ray images, 3D CBCT images and clinical information, providing more comprehensive diagnosis support. At the mean time, the development of lightweight models will make deep learning technologies more suitable for real-time diagnosis and large-scale screening in clinical settings. Additionally, the introduction of interpretable AI will increase clinicians' trust in AI-assisted diagnostic results, providing more reliable support for disease prevention and treatment decision-making.

In short, the continuous progress in tooth detection technologies will drive oral disease diagnosis toward a more intelligent and precise direction. With the ongoing maturation of technologies, intelligent dental diagnostic systems is gong to be widely adopted globally, particularly in resource-limited regions. there cloud computing and remote diagnosis will provide timely and accurate oral health management services to more patients.

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