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The Application of Artificial Intelligence in the Diagnosis of Pulp Diseases and Periapical Periodontitis

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Abstract. Periapical inflammation and pulp diseases are highly prevalent and potentially destructive oral conditions whose early detection remains challenging with conventional modalities such as periapical radiography and CBCT. Recent advances in artificial intelligence (AI), primarily deep convolutional neural networks (CNNs), have enabled image-driven diagnosis and quantitative assessment of periapical and pulpal pathology. Models trained on expert-annotated two-dimensional periapical and panoramic images and 3D CBCT images demonstrate improved sensitivity for subtle bone-density and morphological changes, enabling automated segmentation, volumetric quantification of radiolucent lesions, and delineation of pulp-cavity morphology, occult cracks and early inflammatory signs. Typical 3D pipelines adopt a coarse-to-fine strategy, combining global localization with local 3D-CNN refinement to produce voxel-level outputs suitable for clinical decision support. Progress is nevertheless constrained by the high cost of expert annotation, heterogeneous multi-center data, and a training plateau that yields diminishing returns from simply enlarging datasets. Methodological remedies include semi- and self-supervised pretraining, active learning, synthetic-data augmentation and federated multi-center training, together with uncertainty quantification and explainable outputs to facilitate clinical adoption. This review aims to systematically evaluate recent advances, methodological challenges and translational pathways for AI-enabled imaging diagnosis of periapical inflammation and pulp disease.

Keywords: AI diagnostics, dental pulp, periapical periodontitis

1. Introduction

Apical periodontitis and pulp disease are among the common and most devastating oral diseases. Data from a meta-analysis showed that half of adults worldwide have at least one tooth with apical periodontitis. Over time, if left untreated, it can lead to persistent pain, alveolar bone resorption, and even tooth loss, seriously affecting chewing function and quality of life. However, traditional diagnostic methods such as apical X-rays, probing, electrical activity testing, and cold and heat stimulation tests are often insensitive in the early stages of lesions [1]. Even with cone beam computed tomography (CBCT), the volume threshold, observer experience, and image quality of the lesion still limit accurate judgment. How to detect small lesions, quantify lesion boundaries and

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predict lesion progression early in the course of the disease has become a bottleneck that needs to be broken through in clinical practice.

Deep learning, especially convolutional neural networks (CNNs), presents revolutionary opportunities for quantitative analysis of medical images. Artificial intelligence (AI) has powerful image interpretation capabilities and can analyze both two-dimensional (2D) and three-dimensional (3D) imaging in the dental field. Additionally, AI tools can quickly generate 3D models of dental and maxillofacial structures. AI can also be used in the design of digital guides to help clinicians improve diagnosis and optimize treatment plans. Significantly improved precision and time efficiency in dental practice [2]. Compared with traditional manual feature extraction, CNN can automatically learn texture and morphological features in large-scale training sets, and accurately capture minute bone changes in 2D radiographs and 3D CBCT.

AI has significant advantages in identifying periapical lesions, especially for the analysis of panoramic radiographs. By training AI, subtle changes in bone density and morphology, which are important markers of apical lesions, can be identified, enabling early detection and assisting in the formulation of precise treatment plans. In addition, the AI system can automatically label the morphology of the medullary cavity, identify cryptofiscular and early inflammatory signs, and output quantitative indicators such as lesion volume and the risk of bone plate perforation to provide decision-making support for individualized treatment. This article aims to explore the application of AI in the diagnosis of apical periodontitis and endodontic diseases, focusing on the role of AI in image analysis, automated diagnosis, and clinical decision support [3]. By evaluating the potential of AI technology in improving diagnostic accuracy, optimizing treatment plans, and improving patient treatment outcomes, the application prospects and development trends of AI in the field of stomatology are revealed.

2. Application of AI in the diagnosis of apical periodontitis

2.1. Image analysis and automatic diagnosis

CNN is a deep learning architecture designed for visual data, detecting and learning hierarchical features in images through multi-layer structures. Clinical research usually trains CNNs on 2D and 3D dental structural images such as periodontal disease, oral cancer, caries, and endodontic disease manually annotated by experts. Through the combination of expert supervision and curriculum-based training, experts can continuously control the data input by AI, thereby improving the reliability, efficiency, and accuracy of AI. Gradually increase the complexity of AI tasks during training, helping AI models gain a deeper understanding of images by imitating human learning methods. Experts also need to continuously monitor the output data so that AI can iteratively improve from errors, ensure that the AI model is continuously improved, and ultimately achieve more accurate labeling of lesions and reliable clinical diagnosis and treatment results [4].

Image preprocessing determines the training stability and inference reliability of image-driven algorithms, which is the key link for its successful application. Raw oral images often contain interfering information such as logo text, dental instrument artifacts, or uneven exposure, and other information must be removed from the image to prevent misjudgment of lesion identification caused by such confounding features. During the pre-processing phase, image contrast is often adjusted, such as enhancing differentiation and border clarity between different structures or healthy and diseased tissue. Texture enhancement or histogram equalization is also performed if necessary to highlight the boundary between the lesion and the surrounding healthy tissue [5]. AI deep learning technology has excellent performance in image feature recognition, and the deep learning network

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uses the multi-layer structure of artificial neural networks to independently generate classification results by identifying edge features when analyzing data. Through these preprocessing, the deep network can focus more on the image features associated with the lesion, thereby improving the effectiveness of downstream recognition and segmentation.

In terms of training strategy, AI models usually employ supervised learning, supplemented by transfer learning, self-supervised or semi-supervised pre-training to reduce annotation pressure. Training AI is a step-by-step process. By repeatedly feeding image data and its corresponding labels into the neural network, it is continuously superimposed to improve the recognition accuracy. This field utilizes multi-layer (deep) neural networks to learn hierarchical features in data. The CNN algorithm based on deep learning performed well in the detection of caries on apical radiographs, and was also effective in identifying and classifying impacted supernumerary teeth in patients with fully erupted maxillary permanent incisors on panoramic radiographs [6]. The deep-optimized full-depth mask R-CNN model performed well in the task of automatic tooth segmentation in panoramic images, and the model was also used for the detection of apical lesions on panoramic X-rays.

AI has shown significant advantages in lesion identification. It is excellent in detecting lesions in periapical (PA) radiographs and panoramic radiographs. This technology also has high accuracy in radiographic image-assisted prediction of caries treatment options. In the analysis of apical X-rays, artificial intelligence can effectively identify impacted teeth in the maxillary incisor area and achieve accurate classification. In addition, combined with panoramic tooth sheet data, artificial intelligence can automate the processing of tooth segmentation. CNN has been used for dental arch classification, and multilayer CNN technology has also significantly improved the imaging diagnosis effect of adjacent caries. Machine learning algorithm tools can also effectively detect and classify dental restorations in panoramic images. Artificial neural networks (ANNs) enable accurate working length determination on radiographs [7]. However, it should be noted that most of the results come from retrospective or single-center validation, requiring external validation and blind testing in multicenter, independent cohorts across devices to confirm the clinical applicability of the model.

2.2. Detection of apical lesions by 3D CNN in CBCT images

Detection and quantification of periapical lesions on 3D CBCT images usually adopts a coarse-thinity combination strategy of first coarse localization and then local refinement. First, the initial shallow network is trained using CBCT images, which coarsely locates each landmark point with global anatomical information. Subsequently, around the coarse positioning area, the image blocks are taken from the medium and high-resolution images. Key features (such as density changes in caries, morphology of bone destruction, etc.) are automatically extracted through multi-layer convolutional layers [8]. The 3D convolutional network is used to analyze the fine structure in three-dimensional space, accurately locate the location of the lesion (such as root inflammation, impacted teeth, etc.), and classify the type of lesion (such as caries degree, cyst, etc.) according to the difference in characteristics. It also generates quantitative analysis results to assist doctors in improving diagnostic efficiency and accuracy, especially in the detection of early lesions and complex anatomical areas, which is better than traditional manual radiography.

Although the 3D method has obvious advantages in the characterization of anatomical details and early lesion identification, several key issues restrict its clinical application. The average margin of error for 3D landmark detection is approximately 1.0 mm to 5.8 mm, and the success rate of automatic localization is low for certain complex or highly variable anatomical locations, such as thin bone plates or root bifurcation areas in the vestibular region. In surgical scenarios requiring

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millimeter-level decision support, even a 1mm error can change the treatment strategy, so the accuracy of the algorithm is extremely high. Although AI has achieved a high level of accuracy, its performance has not yet reached the expert level in the field of 3D landmark inspection. Existing studies have also used limited samples for algorithm training and testing in this area.

Although 3D imaging technology can reduce the geometric distortion caused by planar projection to a certain extent, the precise segmentation method of CBCT has not yet formed a unified standard in semi-automatic workflow. Even a 2 mm error can have a significant impact when dealing with smaller patients or specific anatomical landmarks. Therefore, the highest precision must be pursued in these cases to ensure the best treatment results. Among the various landmarks annotated by 3D images, vestibular angle landmarks are always one of the most difficult areas to automatically locate, and their detection success rate is also the lowest. This is mainly because the landmark is a construction point on a two-dimensional head map, formed by an imperfect superposition of male bilateral pubic structures. Points located in the buccal thin bone area or at sharp changes in curvature are heavily affected by bone thickness, artifacts, local noise, and voxel resolution, resulting in a low success rate for automatic detection. In addition, three-dimensional errors can arise from differences in volume segmentation or bending structures and vertical positions. Therefore, these constraints must be fully considered when training the model.

Experimental data show that the model performance improves steadily with the increase of training cycle. However, when a certain tipping point is reached, about 50% of the images cannot be significantly improved by existing image sources and classification methods, indicating that data saturation does exist, and that even better results can be achieved by simply increasing the number of exponentially increasing images. For tasks such as apical periodontitis, which require voxel-by-voxel segmentation to quantify the volume, boundaries, and bone destruction of the translucent zone, further improving accuracy relies more on sample diversity, high-quality 3D annotation (voxel-wise annotation), and the introduction of multicentric heterogeneous data rather than just amplifying the amount of data. At the same time, this technique must be operated by a professionally trained and qualified dentist under the guidance of a senior expert. To break through this bottleneck, it is recommended to improve data diversity (cross-device, multicenter), use semi-supervised or self-supervised pre-training, active learning to prioritize labeling high-information samples, and use synthetic data or weakly supervised methods to complete rare lesion samples, so as to maximize the clinical value of apical periodontitis detection and quantification models at a controllable annotation cost.

3. Application of AI in the diagnosis of endodontic diseases

Recent studies have shown that ANN can not only assist radiographic images in locating the apical leading edge and working length like a second opinion, but also significantly improve the accuracy and consistency of working length in radiological detection. In a wider range of endodontic disease scenarios, deep learning-based models can automatically extract multi-scale morphological and grayscale features from 2D apical profiles, panoramas, and 3D CBCT to identify pulpitis, pulp necrosis, and related periapical complications. Typical applications include the dichotomy of reversible versus irreversible pulpitis, voxel-level segmentation of apical translucent areas, and automated annotation of complex anatomy of root canals (e.g., canal curvature, branching). By fusing imaging features with clinical parameters (such as pain scores and electroactivity test results), machine learning models can also improve the ability to discriminate between disease stage and prognostic risk, thereby providing quantitative basis for individualized treatment decisions.

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Achieving these capabilities still faces several technical and practical challenges. Obtaining diverse high-quality training datasets is difficult, mainly due to the inherent limitations of imaging techniques, such as overlapping anatomy in 2D imaging that masks subtle changes in the medullary cavity or apex, while CBCT is susceptible to high-density restoration artifacts and patient movement [9]. Secondly, the supervised learning process is highly dependent on the professional ability of operators. The professional capabilities of operators behind AI-supervised learning and the limited universality of AI models have hindered the development of artificial intelligence in the field of dental diagnosis and treatment [10]. To overcome these bottlenecks, future research should focus on building cross-device and multi-center labeling protocols and benchmark datasets, using semi-supervised or self-supervised pre-training and domain adaptation methods to improve model robustness to heterogeneous data, and integrating image interpretability and uncertainty estimation into clinical workflows to enhance auditability and improve clinicians' trust in AI systems.

4. Conclusion

AI shows clear potential to enhance image-based diagnosis and management of periapical inflammation and pulp disease. CNNs applied to two dimensional radiographs and three dimensional CBCT enable automated lesion detection, voxel level segmentation and volumetric quantification, which can improve early detection, reduce inter reader variability and provide objective metrics for treatment planning and follow up. Routine clinical adoption remains constrained by several factors. High costs of expert annotation, especially voxel wise 3D labels, limit dataset scale. Heterogeneity across imaging devices and centers undermines model generalizability. Residual limits in 3D localization accuracy can fall short of the millimetric precision required for some surgical decisions. Many published models have only retrospective or single center validation, which reduces confidence in real world performance. To accelerate translation, priority should be given to assembling multi center, standardized annotation corpora and external benchmarks, and to employing semi supervised, self-supervised and active learning strategies that reduce annotation burden. Federated and other privacy preserving multi-institutional training frameworks can improve robustness. Integration of uncertainty quantification and explainable outputs, combined with human in the loop workflows and prospective multicenter validation, will be essential to build clinician trust and support regulatory readiness. With these developments, AI could become a safe and reliable adjunct in periapical and pulp disease care.

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