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Caries detection using deep learning and convolutional neural networks from radiographic images: A narrative review

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Abstract

Dental caries remains one of the most prevalent chronic diseases worldwide, posing significant public health and economic burdens. Early and accurate diagnosis is critical for effective management and prevention of complications. While traditional diagnostic methods such as clinical examinations and radiographic assessments are widely used, they suffer from limitations including inter-observer variability, low sensitivity in early detection, and subjectivity. The emergence of artificial intelligence (AI), particularly deep learning through convolutional neural networks (CNNs), offers promising advancements in caries detection from dental radiographs.

This narrative review explores the application of CNNs in diagnosing dental caries using various imaging modalities, including bitewing, panoramic, and periapical radiographs. We summarize current evidence from key studies employing architectures such as ResNet, VGGNet, U-Net, and EfficientNet, demonstrating superior diagnostic accuracy, sensitivity, and specificity when compared to conventional approaches. CNN-based models enhance objectivity, reduce diagnostic time, and offer scalable integration into clinical workflows. However, challenges remain regarding dataset standardization, overfitting, model generalizability, and the lack of interpretability of AI decisions.

The review also highlights limitations in image quality, annotation variability, and regulatory constraints hindering clinical deployment. Future prospects include the adoption of explainable AI (XAI), multimodal data integration, and the development of optimized CNN architectures tailored for dental applications. These innovations could lead to more transparent, robust, and widely accepted diagnostic tools in dentistry.

In conclusion, CNN-based caries detection represents a transformative shift in dental diagnostics, enhancing precision, efficiency, and accessibility. Addressing current limitations through technical, ethical, and regulatory advancements is essential to harness the full potential of AI-driven diagnostics and improve global oral health outcomes.

Keywords: Dental Caries Detection; Convolutional Neural Networks; Deep Learning; Dental Radiographs; Artificial Intelligence

1. Introduction

Dental caries are a common oral health concern that, if not managed, may lead to serious issues. Effective care requires an early and precise diagnosis, which is often accomplished by radiographic imaging and clinical testing. However,

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subjectivity and inconsistent interpretation plague traditional radiography techniques. Automated caries detection is one area where artificial intelligence (AI) has recently shown promise, especially in deep learning methods like convolutional neural networks (CNNs). Dental imaging analysis has greatly benefited from the use of CNNs due to their increased efficiency, consistency, and accuracy when compared to more conventional diagnostic methods (1).

In this narrative review, we will look at how convolutional neural networks (CNNs) have been used to identify dental caries in radiographs, and we will examine their strengths, weaknesses, and potential for future work in this area. Current research using CNN designs like ResNet, VGGNet, and U-Net is reviewed, and the basic operation of CNNs is emphasized, as is its incorporation into dental imaging (2). Problems with clinical integration, dataset accessibility, and ethical issues are also looked at.

The results highlight how CNNs considerably lower observer variability and improve diagnostic accuracy. To enable their broad clinical implementation, however, issues like data consistency and model generalizability need to be resolved. Future advancements, such as multimodal AI and explainable AI, are anticipated to further refine the applications of CNN in dentistry (3). All things considered, CNN-based caries diagnosis offers increased accuracy and efficiency, marking a substantial breakthrough in dental diagnostics. To maximize AI-driven solutions for dentists and improve patient care results, further research, multidisciplinary partnerships, and legislative changes are essential (4).

2. Definition and Clinical Implications of Dental Caries

Tooth decay, or dental caries, is a complex illness that has several causes and ultimately demineralizes and destroys the tooth's hard structures. It happens because of the combination of host factors, oral flora, and dietary carbohydrates, which produces acid that gradually erodes dentin and enamel (5). Systemic health problems including diabetes and cardiovascular disease may develop from untreated caries, which cause discomfort, infection, and tooth loss if not addressed. The key to good dental health and general wellness is early and effective diagnosis and treatment.

2.1. Prevalence, Epidemiology, and Public Health Impact of Dental Caries Globally

Dental caries affects people of all ages and is a serious global public health problem. The World Health Organization (WHO) reports that dental caries is still the most common non-communicable illness, affecting over 530 million children with primary tooth caries and approximately 2.3 billion adults with permanent tooth caries. Because they have less access to dental care and preventative measures, low- and middle-income nations are disproportionately affected by illness. Dental caries has a substantial impact on the economy, both in terms of direct treatment expenses and indirect costs like lost productivity and worse quality of life (6).

2.2. Importance of Accurate and Early Detection Methods for Effective Caries Management

If dental caries can be detected early on, the disease may be stopped in its tracks and intrusive procedures can be avoided (7). Conventional techniques like visual-tactile evaluation and standard radiography can cause delayed diagnosis and significant structural damage. Dentists may enhance patient outcomes, use less invasive procedures, and put preventative measures into action with an accurate and fast diagnosis. Artificial intelligence (AI) and imaging technologies provide new ways to improve the precision and effectiveness of diagnosis (8).

2.3. An Overview of Conventional Diagnostic Methods and Their Drawbacks

Clinical examination, ocular inspection, and traditional radiography techniques including bitewing, panoramic, & periapical radiographs are all traditional ways for detecting caries. Despite their continued widespread usage, these techniques have a number of drawbacks:

- Subjectivity and variability: Practitioners may not always agree on diagnoses since they often depend on the experience and interpretation of the clinician.
- Sensitivity problems: Early-stage caries may be difficult to detect with traditional radiography techniques, especially in occlusal and interproximal regions.
- False positives and negatives: Overtreatment or missed diagnosis may result from incorrect interpretation of radiography images. These drawbacks highlight the need for more impartial, trustworthy, and effective diagnostic instruments.

2.4. An Introduction to Dental Digital Radiography

Because digital radiography offers better picture quality, less radiation exposure, and better storage and retrieval mechanisms, it has completely changed dental diagnostics (9). The following are the main categories of digital radiography techniques:

- Bitewing radiographs: These are used to track the development of interproximal caries.
- Panorama radiographs: Offer a thorough perspective of the dental arches and the surrounding architecture.
- Peripheral radiographs: Pay attention to specific teeth and the surrounding bone formations.
- Cone-beam computed tomography (CBCT): This technology helps with difficult diagnosis by providing three-dimensional imaging (10). Even though digital radiography has enhanced diagnostic capabilities, human interpretation, which is still subject to error, is still necessary for its efficacy.

2.5. Brief Overview of AI, Machine Learning, Deep Learning, and CNNs

The use of artificial intelligence (AI) has the potential to revolutionize the dental industry by improving the precision of diagnoses and the efficiency of treatment planning. In artificial intelligence (AI), machine learning (ML) allows computers to gain knowledge from data and enhance their performance without human intervention or code(11). As a branch of machine learning (ML), deep learning (DL) finds patterns in complicated data by using ANNs. Convolutional neural networks (CNNs), one of the DL approaches, have shown exceptional performance in image processing and pattern recognition, which makes them very helpful for deciphering radiography pictures in the context of caries detection. CNNs increase diagnosis accuracy by automatically extracting information from pictures, decreasing the need for human experience.

2.6. Purpose and Significance of Conducting This Narrative Review

The purpose of this narrative review is to investigate how deep learning—in particular, CNNs—can be used to identify dental cavities in radiographic pictures. This study aims to emphasize the benefits, difficulties, and promise of AI-driven caries diagnosis by analyzing the body of current work (12). CNN integration in dental diagnostics might change the field of oral healthcare by improving patient outcomes, reducing diagnostic mistakes, and enhancing early detection.

3. Discussion

3.1. Overview of Convolutional Neural Networks (CNNs) in Dental Imaging

3.1.1. Brief Technical Explanation of CNN Architecture

There is a subcategory of deep learning models known as convolutional neural networks (CNNs), which are specifically intended for the purpose of image analysis and categorization (13). They are made up of many layers, each of which carries out certain tasks to analyze and extract characteristics from input pictures. The following are the main elements of CNN architecture:

- Convolutional Layers: Filters (kernels) are applied to input pictures by these layers to identify patterns, textures, edges, and increasingly complicated structures as the networks depth increases.
- Layers for Pooling: These layers make feature maps with fewer spatial dimensions, which reduces computational complexity without losing any important information. Two popular methods for pooling data are maximum and average pooling.
- Fully linked levels: Following feature extraction, the CNN's last levels are dense, fully linked layers that categorize the picture and interpret the features that were extracted.
- Activation Functions: Rectified Linear Unit (ReLU) and similar functions provide non-linearity to the network, enabling it to understand intricate correlations.
- CNN Workflow Explanation The CNN-based method for identifying dental cavities in radiography pictures adheres to a set of steps:

Picture preprocessing

- To increase picture quality, enhancement methods such noise reduction and histogram equalization are used (14).
- Consistent pixel intensity levels are guaranteed via normalization.
- To improve model generalization, data augmentation techniques like rotation and flipping are used.

Segmentation

- To separate teeth from the background, segmentation techniques such as thresholding and region-growing algorithms are used.
- More sophisticated techniques for accurate tooth & lesion segmentation use U-Net as well as Mask R-CNN architectures.

Feature Extraction

- Hierarchical features, ranging from basic edges in higher layers to intricate anatomical structures in lower levels, are automatically extracted using CNNs.
- Feature maps aid in identifying areas that are healthy and those that are unhealthy.

Classification

- In fully connected layers, the features that have been extracted are used to train a sigmoid or Softmax classifier, which assigns probabilities to various classes (such as "caries present" or "absent").
- To improve accuracy with small datasets, transferred learning with models that have been trained is commonly used, such as ResNet or VGG16.

3.2. Convolutional Neural Networks (CNNs) and Their Role in Dentistry and Other Medical Radiographs

In the field of dental radiography analysis, convolutional neural networks (CNNs) have introduced new ways for automated, precise, and very efficient caries identification (2, 15). The following are some of their significance:

- **Improved Diagnostic Accuracy:** Convolutional Neural Network (CNN) models surpass conventional manual examinations in seeing small radiographic changes that a human eye may miss.
- **Saves Time:** Automated analysis speeds up clinical decision-making by reducing the time needed for picture interpretation.
- **Objectivity and Consistency:** Convolutional neural network (CNN)-based detection is immune to intra- and inter-observer variability, unlike human interpretation.
- **Practical application:** Convolutional neural networks (CNNs) may be included into dental imaging software in order to give real-time diagnostic help (16). We shall examine CNN's uses, difficulties, and comparative performance in caries detection in the sections that follow.

3.3. CNN-Based Caries Detection: Current Applications

3.3.1. Introduction to CNNs in Caries Detection

The use of deep learning, and more specifically CNNs, has completely altered the landscape of medical imaging (17). With the goal of boosting accuracy and decreasing diagnostic subjectivity, convolutional neural networks (CNNs) have found extensive use in the dental field to improve caries identification from radiographic images. Heterogeneity in interpretation is a common result of the heavy reliance on human skill in traditional diagnostic procedures. Contrarily, convolutional neural networks (CNNs) are a priceless asset in caries detection due to their exceptional accuracy in analyzing picture patterns. In this part, we will go over some of the most important CNN research, look at some of the most popular designs, and compare the performance metrics of these with more conventional approaches.

3.3.2. Key Studies on Convolutional Neural Networks for Caries Detection

Researchers have shown that CNNs can effectively identify dental caries utilizing a variety of radiographic imaging modalities, which include as bitewing, periapical, & panoramic radiographs (18). Results and methods of convolutional neural network (CNN) applications in cavities identification are highlighted in the following seminal studies:

3.3.3. Case Study 1: Convolutional Neural Networks for Bitewing Radiographs

With a collection of 5,000 annotated pictures, Lee et al. (2021) used ResNet-50 to bitewing radiographs. The convolutional neural network (CNN) model was 92.5% accurate, 89.3% sensitive, and 94.1% specific (19). This research proved that convolutional neural networks (CNNs) can reliably detect early-stage caries more than general practitioners.

3.3.4. Second Study: Deep Learning and Panoramic Radiographs

Panoramic radiographs help find large carious lesions because they show more of the tooth anatomy. Utilizing VGG-16 and EfficientNet-B0, a dataset consisting of 10,000 panoramic photos was analyzed by Wang et al. (2022). The models outperformed the conventional CAD software image processing methods, achieving an AUC of 0.95. The capacity of CNNs to decrease misdiagnosis in complicated instances was highlighted in the research (20).

3.3.5. Study 3: U-Net Segmentation and Periapical Radiographs

Caries localization has made use of U-Net, a convolutional neural network (CNN) architecture that is well-suited for medical picture segmentation. After using U-Net to 7,000 periapical radiographs, Silva et al. (2023) achieved an F1-score of 0.91. With the model's help, physicians now have a visual tool for accurately segmenting carious lesions (21).

3.3.6. CNN Architectures in Caries Detection

In research involving caries detection, many CNN architectures have been used, each with its own set of benefits:

- ResNet (Residual Networks): Thanks to its deep design, ResNet can identify even the most modest caries lesions and prevents disappearing gradients (22).
- VGGNet: VGGNet has shown great accuracy in medical picture categorization, although it is computationally costly.
  For better performance on smaller datasets, use DenseNet. Its layers are tightly coupled, which improves feature propagation.
- EfficientNet: is a computationally efficient network that reduces the number of parameters while delivering great accuracy.
- U-Net: Rather from focusing just on picture classification, its segmentation architecture makes it an excellent choice for localizing carious lesions (23).

3.3.7. Measures of CNN-Based Cavities Detection Performance

Various measures are used to evaluate CNN models' performance in caries detection:

- Prediction accuracy: is a measure of how well the model fits the data (24).
- Sensitivity (Recall): Assesses the capacity to identify real carious lesions.
- Specificity: Indicates the model's ability to prevent erroneous positives.
- ROC/AUC: which stands for Receiver Operating Characteristic/Area Under Curve, is a measure that evaluates the discriminative capacity of the model.
- F1 Score: Improves overall evaluation by balancing memory and accuracy. When compared to more traditional approaches, CNN models often achieve sensitivity levels over 85%, making them much superior for early-stage caries identification.

3.3.8. Evaluating CNN vs. Conventional Diagnostic Approaches

There are a number of benefits to using CNN models for caries diagnosis, while human observers are still the best:

- Enhanced Accuracy: Research indicates that CNNs are more accurate than general practitioners, especially when it comes to early caries detection (25).
- Consistency: CNNs minimize variability between and between observers by producing repeatable findings, in contrast to human observers.
- Efficiency: Automated analysis speeds up clinical decision-making by cutting down on diagnostic time.

However, there are still obstacles that convolutional neural network (CNN) models must overcome. These include data reliance, the requirement for large training datasets, and the interpretability of judgments.

3.3.9. Convolutional Neural Networks for Caries Detection: Current State and Future Prospects

Among the many benefits of using CNNs for cavity detection are:

- Improved Image Processing: Convolutional neural networks (CNNs) successfully distinguish carious lesions in radiographs from overlapping structures.
- Better Diagnostic Support: Dentists can benefit from AI-assisted tools when dealing with difficult cases.
- Clinical Workflow Integration: Dental imaging software can have AI models embedded for real-time analysis.

In order to achieve more widespread clinical acceptance, future research should center on building hybrid AI models, diversifying datasets, and making models more interpretable (26).

4. Limitations and Challenges

4.1. Technical Limitations

4.1.1. Problems with Radiography Image Quality, Variability, & Standardization

Discontinuities in radiographic picture quality provide a significant obstacle to the widespread use of deep learning and CNNs in caries identification. Image clarity and contrast discrepancies are caused by a variety of factors, including exposure settings, patient placement, operator skill, and various imaging technologies (27). The construction of a uniform CNN model that can function consistently across a variety of datasets is made more difficult by the variation in image capture settings throughout dental clinics. Furthermore, because of the potential impact of capture-related aberrations, noise, and distortions on caries detection model accuracy, sophisticated picture preprocessing methods are required to improve consistency and dependability.

4.1.2. Large-scale, annotated dental datasets are required for reliable CNN training.

Big, high-quality annotated datasets are crucial for CNN training and validation if they are to be successful. Obtaining such datasets is especially difficult in dental radiography because there aren't many publicly available labeled images (28). Carious lesions must be manually marked by skilled radiologists and dentists for annotation, which takes a lot of time and effort. Additionally, inconsistent training data can be introduced by inter-expert annotation variability, which may have an impact on model performance. CNN models may find it difficult to learn reliable and generalizable features in the absence of varied and extensive datasets, which could result in less-than-ideal detection results.

4.1.3. Concerns about CNN Model Overfitting and Generalizability

When models perform extraordinarily well on training data but are unable to generalize to fresh, unknown data, overfitting is a serious problem in CNN-based caries detection. This often happens when CNNs are trained on dataset-specific patterns instead of the fundamental characteristics of carious lesions (29). This issue may be exacerbated by repetitive picture characteristics, unequal class distributions, and a lack of variety in the dataset. It is still very difficult to strike a balance between the complexity of the model and its generalizability, even when using techniques like transfer learning, data augmentation, and dropout layers to reduce the likelihood of overfitting.

4.2. Practical and Clinical Limitations

4.2.1. CNN Technology Integration into Everyday Clinical Workflow

The integration of CNN-based caries diagnosis into ordinary dentistry practice is still difficult, despite the technology's encouraging outcomes in research settings. It is necessary to integrate AI-assisted diagnostic tools seamlessly with current clinical management and dental imaging technologies. Since many dental offices lack the infrastructure required to support AI-driven products, more money must be spent on software, hardware, and dental professional training (30). In addition, CNNs used for real-time radiographic image processing and interpretation need to be both fast and easy to use for them to be useful in hectic clinical settings.

4.2.2. Problems with Dental Professionals' Acceptance and Trust

The acceptability and confidence of dental practitioners are critical to the deployment of AI-based diagnostic technologies in the field. Deep learning models' interpretability worries many physicians, making them reluctant to depend on CNNs(26). CNNs function as "black-box" models, which makes it challenging for users to comprehend how judgments are made, in contrast to conventional diagnostic techniques where practitioners have direct influence over decision-making. Gaining the trust of dental professionals requires openness, explainability, and validation via comprehensive clinical studies. Initiatives for education are also required to acquaint experts with AI-based diagnoses and their possible advantages.

4.3. Regulatory and Ethical Difficulties

4.3.1. Privacy Issues with Patient Data

The privacy and security of patient data are major considerations when using AI for caries detection. Access to many radiography images, many of which include sensitive patient data, is necessary for CNN model training (12). It is essential to make sure that data protection laws like the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) are followed. Strict access restrictions, anonymization methods, and secure data storage must be used to stop patient data from being misused or accessed by unauthorized parties. To preserve patient confidentiality and confidence, ethical issues pertaining to data sharing agreements and informed permission must also be addressed.

4.3.2. Regulatory Acceptance of AI/CNN Tools for Clinical Use

One major obstacle to the practical use of CNN-based caries detection devices is regulatory clearance. To guarantee safety, accuracy, and dependability, AI-driven medical equipment must pass stringent validation, testing, & certification procedures. Prior to its approval, regulatory organizations like the FDA and the EMA conduct thorough validation studies and clinical trials to assess the efficacy of AI applications in dental diagnostics (31). The dynamic nature of AI models, which continuously evolve through retraining, poses additional challenges in regulatory compliance, as ongoing monitoring and updates are necessary to maintain performance standards.

4.3.3. Future Perspectives

Significant strides have been achieved in the identification of caries with the use of DL and CNNs. To guarantee broad clinical acceptance, a number of issues still need to be resolved. This section examines important future prospects, such as how to get over current restrictions, the function of explainable AI (XAI), integrating multimodal AI techniques, and developments in CNN architectures especially suited for dental imaging.

4.3.4. Recommendations for Overcoming Current Limitations

The absence of consistent imaging procedures is one of the biggest obstacles to AI-based caries detection. Variability in imaging equipment, exposure conditions, and radiography procedures results in inconsistent dataset quality, which impacts the generalization of models. Standardized imaging procedures would improve AI models' repeatability and make it easier for various clinical contexts to deploy them (32). The lack of high-quality, freely available annotated datasets is another significant drawback. It is difficult to conduct comparison studies or external validations of deep learning models since they are often trained on private datasets. The robustness and generalizability of AI models may be greatly increased by promoting the development and exchange of large, varied, and annotated datasets via multicenter partnerships. Initiatives like federated learning, which enables artificial intelligence models to be trained on distributed information while maintaining patient privacy, provide potential answers to data-sharing limitations. For more diverse training data, less biased AI models, and therapeutic applicability across populations, multicenter cooperation are particularly crucial. Through these partnerships, we can establish consistent criteria for evaluating AI-based caries detection models and standardize benchmark datasets for this purpose.

Explainable AI's (XAI) Potential in Dentistry Because AI decisions are neither transparent or easily interpretable, they are not yet widely used in clinical dentistry. Without a thorough understanding of the logic behind predictions, clinicians often are hesitant to trust AI-generated diagnoses. By improving the transparency and interpretability of deep learning models, Explainable AI (XAI) seeks to solve this problem (33). Saliency maps, Grad-CAM, and Shapley Additive Explanations are a few techniques that may help visualize CNN choices and identify which parts of a picture are important for a diagnosis. By making it possible to compare AI-generated results with clinical expertise, these tools help increase physician confidence in AI models. To further assist in the transition from automation to expert supervision, human-in-the-loop methods of incorporating AI into healthcare processes allow doctors to examine, alter, and provide comments on AI predictions. While preserving physician control over diagnostic judgment, our iterative learning technique guarantees ongoing model improvement.

Potential for Multimodal AI Approaches Radiography pictures are the main source of caries detection in current CNN models. It is possible to improve diagnosis accuracy by using multimodal AI techniques that integrate radiographic images with other clinical data sources, including intraoral photos, patient histories, and other diagnostic modalities. In order to decrease false positives and negatives, multimodal AI models may make use of complimentary information from several data sources. For example, a more thorough evaluation of caries risk factors may be obtained by merging NLP (natural language processing) methods for patient records with CNN-based radiography analysis. Furthermore, using intraoral photography might enhance the vision of lesions, especially in the early stages of caries identification.

Vision Transformers (ViTs), one of the latest developments in transformer-based AI systems, provide new possibilities for combining and processing multimodal input. These models show promise for enhancing AI-driven dental diagnostics and have shown to be very effective in medical imaging applications (34).

Expected Advancements in Dental Imaging CNN Architectures Dental imaging applications might greatly benefit from the ongoing evolution of deep learning systems. Even if traditional CNN models work well, new architectures made especially for dentistry and medical imaging may be more advantageous (35, 36). Models may learn from unlabeled data using self-supervised learning (SSL) approaches, which can assist overcome the problem of sparsely annotated datasets. Even with little labeled data, SSL may increase feature extraction and model performance by using large-scale unlabeled dental radiographs. Creating small convolutional neural network (CNN) architectures adapted for use in real-time clinical settings is another exciting prospect. Due to their excellent accuracy and low computing needs, models like MobileNet and EfficientNet may be implemented in dental clinics with constrained computational resources. Further improvement in caries detection skills may be achieved by combining volumetric dental imaging with three-dimensional (3D) convolutional neural networks (CNNs), for example, cone-beam computed tomography (CBCT). By better analyzing the spatial correlations between teeth and lesions, these models may improve the accuracy of diagnosis.

5. Conclusion

The substantial progress in caries detection by deep learning, namely with Convolutional Neural Networks (CNNs), is highlighted in this paper. Several studies have shown that convolutional neural networks (CNNs) outperform conventional diagnostic approaches when it comes to sensitivity and specificity while analyzing radiographic pictures. Deep learning provides a strong tool for early and precise caries diagnosis by automating the recognition procedure, which lowers diagnostic variability and improves reliability.

Dental diagnoses might be revolutionized by CNN-based models. Early-stage detection is made possible by their capacity to handle massive datasets and identify complex patterns in radiography pictures, which lowers the possibility of misinterpretation. These models' accuracy and efficiency imply that incorporating them into clinical procedures might improve dental examinations, help clinicians make decisions, and reduce human error. CNNs also make real-time analysis possible, which is very useful for remote diagnostics and tele-dentistry.

Despite its promise, a number of obstacles prevent CNNs from being widely used in clinical settings for caries diagnosis. Significant obstacles still exist in the form of dataset limits, picture quality fluctuation, as well as the need for extensive validation. To increase generalizability, many models need to be extensively trained on a variety of datasets. To guarantee safe and uniform deployment, regulatory clearances and ethical issues pertaining to AI-based diagnostics must also be addressed. Enhancing algorithm interpretability, incorporating multi-modal imaging methods, and boosting CNNs' adaptation to various clinical settings should be the main goals of future research.

Introducing convolutional neural network (CNN) based models created using deep learning to the dentistry field has the potential to provide more accurate, consistent, and time-saving caries diagnosis. Early identification made possible by AI-powered technologies may result in prompt therapies, slowing the course of dental cavities and enhancing patient outcomes. Furthermore, automating diagnostic procedures might maximize workflow effectiveness and free up dentists to concentrate on more intricate clinical judgments. AI-powered diagnostics have the potential to improve oral health standards worldwide in the long run by increasing access to dental treatment, especially in impoverished areas.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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