Chapter

Revolutionizing Dental Caries Diagnosis through Artificial Intelligence

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Abstract

The diagnosis and management of dental caries, a prevalent global oral health issue, have traditionally depended on clinical examination and the interpretation of radiographic images. However, with the rapid advancements in technology, the landscape of dental diagnostics is transforming. This chapter delves into the revolutionary impact of artificial intelligence (AI) on detecting and managing dental caries. Dental professionals can now achieve enhanced diagnostic accuracy by harnessing the power of machine learning algorithms and image recognition technologies, even identifying early-stage caries that conventional methods might overlook. The integration of AI into dentistry not only promises improved patient outcomes by facilitating timely interventions and streamlining clinical workflows, potentially redefining the future of oral healthcare. While the prospects are promising, it is imperative to concurrently address the challenges and ethical considerations accompanying AI-driven diagnostics to ensure that the technology augments, rather than supplants, the expertise of dental professionals. The chapter serves as a comprehensive overview of the current state of AI in dental caries diagnosis, its potential benefits, and the road ahead.

Keywords: dental caries, artificial intelligence, machine learning, early diagnosis, clinical decision-making, diagnostic imaging, image interpretation

1. Introduction

Dental caries is a pervasive global oral health issue, impacting individuals across all age demographics. Recognized by the World Health Organization as a significant public health challenge, it carries a substantial health burden due to its ubiquity and potential for severe complications [1]. This chronic condition is marked by the gradual degradation of dental hard tissues, primarily due to the metabolic activities of oral bacteria [2]. Such deterioration stems from the demineralization of tooth enamel and dentine, a result of acids produced by bacteria in plaque-a sticky film that continually forms on teeth. The etiological factors underpinning dental caries are diverse, encompassing microbial presence, dietary habits, host reactions, and temporal elements [2]. While initial manifestations might be subtle lesions on the enamel, unchecked progression can lead to pronounced cavitations, threatening the tooth's structural integrity and paving the way for more grave dental issues, including pain, infection, tooth loss, and even broader systemic health complications [3].

Technology has been a driving force in improving oral healthcare, especially in recent decades. Artificial Intelligence (AI) stands out among the technologies making a transformative impact. At its core, AI is a branch of computer science that aims to create machines that mimic human intelligence [4]. This includes learning from experience, understanding language, recognizing patterns, solving problems, and making decisions. AI has many applications, from autonomous vehicles and voice assistants to healthcare diagnostics and treatment planning. AI has shown promising potential in healthcare, enhancing precision, improving patient outcomes, and streamlining processes. It has been applied in various areas, such as radiology, cardiology, oncology, and, more recently, dentistry. In the context of dental care, AI can offer several advantages. For instance, it can automate routine tasks, assist in the interpretation of radiographs, aid in diagnosing oral conditions, and even predict the risk of future oral health problems. This has profound implications for managing dental caries, where early and accurate detection is paramount. The use of AI in dentistry is an evolving field, with advancements in Machine Learning (ML), a subset of AI that uses statistical methods to enable machines to improve with experience, and image recognition playing a significant role [5]. These technologies have enabled the development of systems that can analyze dental radiographs or intraoral images, detect signs of dental caries, and alert the dentist to potential areas of concern.

However, as with any technological innovation, challenges and ethical considerations must be considered. Integrating AI into clinical practice requires understanding these aspects and strategies to manage them [6]. Despite these challenges, the potential of AI to revolutionize dental care is considerable. The promise of AI for the future of dental caries management is exciting. It can enhance accuracy in diagnosis, optimize treatment planning, improve patient outcomes, and advance dental care delivery. This chapter aims to provide a comprehensive understanding of the role of AI in dental caries, highlighting its potential, exploring its applications, discussing challenges and ethical considerations, and speculating about future directions.

2. Methods for diagnosing dental caries

Dental caries is one of the most widespread chronic diseases globally, affecting individuals across the lifespan. Effective management of dental caries hinges on early detection and accurate diagnosis [7]. Over time, several diagnostic methods have been developed and employed in dental practice, each with merits and limitations. The main techniques for diagnosing dental caries are visual-tactile examination, radiographic evaluation, and advanced imaging technologies [8].

2.1 Visual-tactile examination

The visual-tactile examination is the most basic and commonly used method for caries diagnosis. It involves thoroughly examining the teeth using a dental explorer and mirror, accompanied by sufficient lighting. The dentist assesses the teeth' color, texture, and transparency, looking for signs of decay such as discolorations, cavitations, or changes in enamel reflection. While this method is simple and cost-effective, it has limitations [8]. Early dental caries may not cause noticeable changes in the tooth's appearance, making visual-tactile examinations less effective for detecting caries in their initial stages.

2.2 Photographs

Intraoral photographs serve as valuable aids in diagnosing dental caries. High-quality digital images allow for visualizing teeth in detail, which can help identify early signs of caries. Photographs also enable longitudinal assessment of a patient's oral health, allowing for comparison over time to detect changes or progressions in dental caries [9]. However, while photographs can provide detailed surface images, they cannot provide insights into subsurface structures or the extent of internal decay.

2.3 Radiographic examination

Radiographic examinations, particularly dental bitewing X-rays, are widely used to diagnose dental caries [10]. They offer the ability to visualize both the surface and subsurface structures of teeth, enabling the detection of caries that might be hidden from the naked eye or in areas like interproximal spaces, which are hard to inspect visually. There are two primary types of dental X-rays: bitewings and periapical. Bitewing X-rays are beneficial for detecting caries in the crowns of teeth, especially between the teeth. In contrast, periapical X-rays can show the entire tooth, including the roots, and help detect abscesses and cysts [11]. However, radiation exposure, albeit minimal, and the potential for overdiagnosis are considerations with radiographic examinations.

2.4 Advanced imaging techniques

In recent years, advanced imaging techniques have emerged that aim to overcome the limitations of traditional methods. These include optical coherence tomography (OCT), laser fluorescence devices (DIAGNOdent), and near-infrared light transillumination [12]. For example, OCT can provide detailed, cross-sectional images of dental tissues, allowing for the early detection of caries. Laser fluorescence devices measure changes in tooth fluorescence to identify carious lesions. Near-infrared light transillumination exploits the different light-scattering properties of healthy and carious dental tissues to detect decay. While promising, these techniques have yet to be widely used in routine dental practice, primarily due to their cost and the need for specialized equipment and training.

Diagnosing dental caries involves a combination of methods, from the traditional visual-tactile examination to advanced imaging techniques. Each method has strengths and limitations, and the choice often depends on the clinical scenario, the dentist's expertise, and available resources [13]. As research progresses and technology advances, we can anticipate more precise and effective tools for caries detection, leading to improved patient outcomes.

3. The role of AI in dental caries diagnosis

The integration of Artificial Intelligence in healthcare has opened new avenues for enhancing patient care, and dentistry is no exception. The use of AI in dentistry has been a transformative step, promising more accurate diagnoses, more efficient practices, and better patient outcomes. The use of AI in dentistry is only partially a recent development [14]. The journey began in the late 20th century with expert systems that attempted to replicate the decision-making abilities of dental experts. For instance, the DENTSYS system developed in the 1980s used AI to generate dental treatment plans. However, in the last decade, AI's application in dentistry has gained significant momentum, spurred by advancements in machine learning algorithms and increased computing power. Researchers and tech companies developed AI tools to analyze dental images and detect oral conditions, including dental caries [15].

AI's importance in managing dental caries cannot be overstated. Dental caries is a prevalent condition, often requiring time-intensive analysis of dental images for diagnosis. AI systems, particularly those using machine learning, can quickly analyze these images and detect signs of caries. They save time and can improve the accuracy of diagnosis by catching early-stage caries that the human eye may miss [16]. AI can also be used to predict the risk of dental caries. By analyzing patient data and identifying risk factors, AI systems can predict a patient's likelihood of developing caries in the future. This allows for early intervention and preventive care, which is more cost-effective and beneficial for the patient's oral health [17].

The pressing need for early detection and intervention is evident. With the advent of digital dentistry, the incorporation of Artificial Intelligence (AI) heralds a transformative approach in the detection, management, and prophylaxis of dental caries, highlighting the significance of this condition both clinically and in the broader public health context. Artificial Intelligence (AI), an area that seeks to emulate human cognitive functions through machines, has witnessed rapid advancements over the past decades and has infiltrated various domains of healthcare, revolutionizing diagnostic and therapeutic processes [18]. Its integration within dentistry, particularly in dental caries detection and management, has shown promising potential. This chapter delves into AI's role in dental caries, offering insights into its applications, benefits, challenges, and prospects. But before we proceed to understand AI's role, it is pivotal to have a foundational understanding of dental caries. This condition remains one of the most prevalent oral diseases globally.

4. AI methods used for diagnosis of dental caries from photographs and X-rays

4.1 Reinforcement learning

This type of machine learning, where an agent learns by taking actions in an environment to optimize a reward, has seen less prominence in medical imaging than in supervised or unsupervised methods. Nevertheless, it holds substantial promise for specific applications. In dental imaging, reinforcement learning can serve vital roles, such as guiding image segmentation or pinpointing optimal imaging parameters. Ren et al. (2021) highlighted that this approach's potential in dental diagnostics is considerable [19].

4.2 Generative adversarial networks (GANs)

Generative Adversarial Networks, commonly known as GANs, are at the forefront of unsupervised machine learning algorithms, characterized by their unique structure of two contesting neural networks. These networks, working in tandem, have historically been deployed to craft synthetic images that closely replicate real ones. However, their application is not confined to this realm alone. Increasingly, GANs are finding utility in augmenting data sets, creating additional synthetic training examples, and, crucially, anomaly detection. In dentistry, for instance, they can effectively identify teeth conditions that deviate from the expected, such as dental caries [20].

4.3 Support vector machines (SVMs)

SVMs, are specialized supervised learning models tailored for classification and regression tasks. In dental imaging, SVMs play an instrumental role in classifying images, particularly in determining the presence or absence of caries [21]. The distinctive feature of SVMs lies in their ability to generate a boundary, a demarcation that effectively separates various image classes. This separation is not arbitrary; the algorithm constructs it to ensure the maximal margin between the differing image categories [22].

4.4 Random forests

Random Forests are ensemble machine-learning algorithms that build upon multiple decision trees. The output is derived from the class mode of the results produced by these individual trees. As an ensemble learning method, it amalgamates the predictions from various machine learning models to yield a more precise prediction [23]. As corroborated by Breiman, when applied to dental health, Random Forests are particularly adept at classifying dental images and even forecasting the progression of diseases such as dental caries [24].

4.5 Semantic segmentation

Semantic Segmentation is a pivotal technique in computer vision that classifies individual pixels within an image into distinct categories. Applied to dental radiographs, this method can deftly categorize pixels into labels such as 'healthy tissue,' 'caries,' or 'other.' Such granular, pixel-level analysis furnishes a comprehensive assessment of dental images, facilitating the pinpointing of the exact location and extent of dental caries, thus aiding in accurate diagnostics [25].

4.6 Self-supervised learning

Self-Supervised Learning is a nuanced approach in machine learning, distinguished by its reliance on data's inherent structure for guidance. Abandoning the conventional dependence on explicit labels, these sophisticated algorithms derive pseudo-labels from the data to discern representations. Within the realm of dental caries detection, this methodology emerges as particularly advantageous [26]. By harnessing the power of extensive unlabeled dental image datasets, self-supervised learning can amplify a model's adeptness at extracting salient features. These enhanced models, equipped to predict sequences or deduce image orientations, set the stage for monumental advancements in diagnostic precision [27].

4.7 Capsule networks

Capsule Networks, often called CapsNets, represent a pioneering stride in artificial neural networks. Their unique strength lies in capturing hierarchical relationships intrinsic to data. Traditional neural networks might overlook specific details in their processing, but CapsNets stand apart by meticulously preserving nuanced data aspects, encompassing spatial relationships and other intricate properties [28]. This retention of detail augments their potential, making them particularly favorable for specialized tasks such as dental caries detection. In such applications, understanding the spatial interplay between distinct tooth components becomes pivotal for accurate diagnosis, underscoring the significance of CapsNets [29].

4.8 Federated learning

Federated Learning represents a novel paradigm in machine learning that focuses on harnessing vast, decentralized data sprawled across numerous devices or servers to train models [30]. The essence of this approach is its inherent safeguard for privacy; AI models can be developed and fine-tuned without requiring raw data transfer. This becomes indispensable in sectors that handle sensitive information. For instance, in dental caries detection, federated learning stands out as an effective method. This technique can build models using data from dental clinics and hospitals [31]. This is especially remarkable because patient confidentiality remains unassailable even with such extensive data amalgamation, highlighting the immense potential of federated learning in privacy-centric scenarios.

4.9 Multimodal learning

Multimodal Learning is a sophisticated approach in machine learning that thrives on fusing data from diverse modalities, such as text, images, and sound, to refine predictions. This method showcases its strength in dental caries detection by potentially intertwining various strands of information. A typical multimodal learning model can deftly merge dental images with patient medical histories and other pertinent data, paving the way for more precise diagnostic outcomes and better forecasts of disease progression. By harnessing this multifaceted data, practitioners can achieve an enriched understanding, thereby enhancing the overall effectiveness of the diagnostic process [32].

The realm of AI in dental caries detection is poised for transformative progress. While each method has inherent strengths and drawbacks, the selection invariably hinges on the task, the data available, and the unique demands of the challenge. Often, amalgamating various methods can offer the most optimal outcomes. The convergence of burgeoning AI and machine learning innovations with the surge in dental imaging data indicates a trajectory towards highly precise, streamlined, and tailor-made diagnostic techniques. Beyond mere diagnostics, these state-of-the-art tools profoundly elevate the quality of patient care, ushering in a new era for dental health and treatment.

5. Machine learning and image recognition in dental caries

This "data-driven learning" approach has found significant application across the healthcare spectrum, notably in dentistry [33]. Historically, the management of dental caries, particularly its early detection and treatment, has been anchored in clinical evaluations and the interpretation of radiographic images. This method, though adequate to an extent, has its limitations. Subjectivity in interpretations and the potential oversight of nascent caries are notable drawbacks. Enter machine learning and the narrative changes. When exposed to a vast collection of dental images, machine learning algorithms can discern even the subtlest signs of dental caries in their infancy. The efficiency of these models in analyzing and understanding a multitude of images within a short timeframe surpasses human capability, signifying a potential surge in the productivity of dental practices [34].

Supplementing this prowess of machine learning is image recognition. This facet of AI equips machines with a quasi-visual understanding, enabling them to dissect and infer data from images. When it comes to dental caries, this technology becomes invaluable. AI systems harness image recognition to meticulously scan dental radiographs or intraoral photographs, highlighting potential decay sites. The precision of this technology lies in its capability to differentiate between a healthy tooth structure and areas affected by caries, thus streamlining further clinical examinations. Integrating machine learning and image recognition crafts a formidable method for detecting dental caries. The fusion of these technologies ushers in an era of advanced diagnostic instruments characterized by remarkable accuracy and efficiency. It is pivotal to understand that the efficacy of such AI systems is directly proportional to the quality and variety of the training data. A machine learning model exposed to diverse dental images representing various caries stages and a broad patient demographic will likely be the gold standard in reliability.

However, the journey of integrating machine learning and image recognition into dental caries management is full of hurdles. The technological quandary of securing pristine input data and the enigmatic nature of some AI-driven decisions pose challenges. Add to this the ethical conundrums of patient consent and data privacy, and the complexity magnifies. Yet, with adequate safeguards and relentless research, these obstacles are surmountable. The alliance of machine learning and image recognition redefines how dental caries are detected and managed. This transformation promises enhanced diagnostic precision and paves the way for timely and efficacious interventions. As these technologies continue to evolve, it becomes imperative to periodically assess and hone them, ensuring they serve as invaluable adjuncts to the expertise of dental professionals, fostering superior oral healthcare.

5.1 Image processing and analysis techniques for identifying caries lesions

With the rise of digital imaging in dentistry, there has been a growing interest in leveraging image processing and analysis techniques to aid in the early detection and management of dental caries. Early identification of caries lesions can lead to timely intervention, potentially saving the patient from more extensive treatments in the future (**Figure 1**).

5.1.1 Image acquisition

The first step involves acquiring a high-quality image of the tooth or teeth. This could be done using various modalities such as intraoral cameras, digital radiographs, or optical coherence tomography. The quality of the image acquired significantly influences the subsequent analysis; thus, ensuring a clear, high-resolution image is imperative. The process begins with selecting an appropriate imaging modality [35]. Traditional dental radiographs, such as bitewings, periapical, and panoramic images, remain popular due to their comprehensive visualization capabilities. However, intraoral cameras have gained traction for offering a live, high-resolution glimpse into the oral cavity, highlighting potential early-stage caries or enamel anomalies. More recently, Optical Coherence Tomography (OCT) has emerged as a non-invasive technique that captures detailed cross-sectional views of dental structures, thereby aiding in the early identification of caries [36].

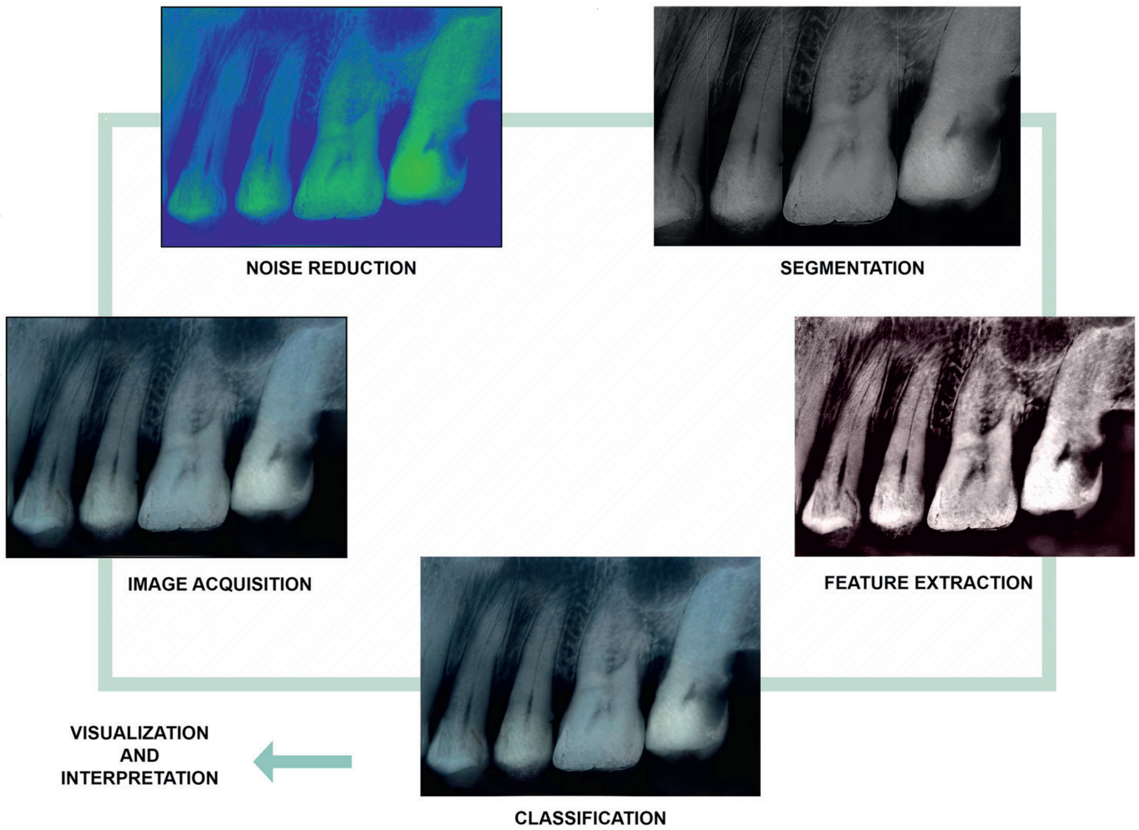

Figure 1.
Dental radiograph analysis and dental caries detection through artificial intelligence.

Quality, especially resolution, is indispensable. While higher resolutions offer detailed insights, revealing even minute structural changes indicative of caries onset, they also pose storage and processing challenges due to larger file sizes. Consistency further accentuates image acquisition, especially when monitoring caries progression or conducting research. Factors like angle, lighting, and imaging settings must remain uniform. Image acquisition in dental caries detection transcends mere picture capturing. It is a meticulous procedure that, when executed with precision, promises an accurate and efficient diagnostic trajectory in the stages that follow.

5.1.2 Pre-processing in dental caries image analysis

The pre-processing stage holds pivotal significance in the dental caries image analysis continuum. It primarily bridges raw image acquisition and intricate analysis, ensuring the input images are refined and optimized for subsequent stages. Dental images, even when captured meticulously, often contain noise, artifacts, or variances in illumination, which can influence the accuracy of caries detection. Pre-processing techniques are designed to mitigate these imperfections and enhance the image's quality [37]. Common methodologies include:

Noise Reduction: Dental images, especially radiographs, can be subjected to random noise due to equipment, transmission errors, or external interferences. Techniques like Gaussian blurring, median filtering, and wavelet denoising are employed to smooth out the image, preserving the essential features while removing extraneous details.

Contrast Enhancement: The image's contrast can be amplified to better visualize dental structures and potential caries lesions. Histogram equalization and adaptive histogram equalization are standard techniques to adjust image contrast, emphasizing subtle differences between healthy and carious dental tissues.

Normalization: Inconsistencies in lighting or image acquisition settings across multiple images can be counteracted by normalizing the intensity levels. This ensures a consistent brightness and contrast range, facilitating comparability across various images.

Segmentation: Only some parts of an image are often relevant for caries detection. Pre-processing may involve segmenting the image, isolating the region of interest (e.g., a specific tooth or quadrant) from the background or adjacent structures. This streamlines the subsequent analysis, focusing only on pertinent areas.

Resolution Scaling: To manage computational efficiency, images may be rescaled to a standardized resolution, especially in AI or machine learning models. This harmonizes the input size for subsequent processing, although care must be taken to ensure that vital diagnostic details are not lost in the rescaling process.

Artifact Removal: Dental images can sometimes contain artifacts - extraneous features or distortions, often arising from equipment malfunctions, patient movement, or external objects (like metal restorations). These artifacts can interfere with accurate caries detection. Pre-processing aims to identify and mitigate these disturbances, ensuring the integrity of the diagnostic image.

The overarching objective of pre-processing is to curate an image that is void of distractions and optimized for clarity. It accentuates the relevant features, equips the image for efficient analysis, and sets the stage for accurate caries detection. As dental imaging evolves with technology's strides, the pre-processing phase will undoubtedly adapt, integrating more sophisticated techniques to ensure that the foundational image quality is preserved and enhanced for crucial diagnostic tasks.

5.1.3 Feature extraction in dental caries image analysis

Feature extraction is a crucial step in the image analysis process, especially in the context of dental caries detection. This phase involves isolating and quantifying pertinent attributes from the pre-processed image, instrumental in characterizing and distinguishing between healthy and carious dental tissues. These attributes or "features" become the foundation upon which classification models make decisions, especially in machine learning or AI-based systems.

5.1.3.1 Texture analysis

Dental caries often manifest changes in the texture of dental tissues. Techniques like gray-level co-occurrence matrix (GLCM), local binary patterns (LBP), and wavelet transforms are employed to extract texture-related features. These methods quantify variations in the image, capturing nuances that can signal the presence of early or advanced carious lesions [38].

5.1.3.2 Shape and morphological features

The contours and morphologies of carious lesions can be distinct from the regular dental anatomy. Edge detection algorithms, such as the Canny or Sobel operators, can help identify the boundaries of lesions. Once the edges are identified, shape descriptors, like compactness, elongation, or roundness, can be calculated to provide insights into the lesion's characteristics.

5.1.3.3 Intensity and statistical features

The pixel intensity distribution within an image or a segmented region can offer valuable information. Mean, variance, skewness, and kurtosis of the pixel intensities can be computed. Carious regions might present with different intensity distributions compared to healthy tissues, making these features valuable for differentiation.

5.1.3.4 Frequency domain features

Transforming the image from the spatial domain to the frequency domain using methods like the Fourier Transform or Wavelet Transform allows the extraction of features that might not be discernible in the standard spatial domain. These frequency-based features can be susceptible to subtle changes caused by caries.

5.1.3.5 Color-based features

While more relevant for intraoral photographs than radiographs, the color attributes of an area can be informative. RGB (Red, Green, Blue) values, Hue-Saturation-Value (HSV) descriptors, or other color spaces can be analyzed to extract features differentiating healthy and carious enamel or dentin.

5.1.3.6 Spatial relationships

In some instances, the relative positioning of features within the dental anatomy can be insightful. For example, the proximity of a potential lesion to known anatomical landmarks, like the enamel-dentin junction, can provide context for the extracted features.

5.1.3.7 Deep learning features

With the advent of deep learning techniques, particularly convolutional neural networks (CNNs), feature extraction can also be automated. In these models, the initial layers often act as feature extractors, identifying and emphasizing attributes of the image that are crucial for caries detection.

Feature extraction transforms an image's rich, intricate details into a structured, quantitative format. These distilled features capture the essence of the image, allowing diagnostic models to efficiently and accurately differentiate between healthy and carious tissues. As image analysis technologies advance, the feature extraction phase will continue to evolve, incorporating more nuanced and sophisticated techniques that elevate the precision and reliability of dental caries detection.

5.1.4 Classification in dental caries image analysis

In dental caries image analysis, classification is the stage where the extracted features from the images are used to categorize or label the data, determining whether a particular region of interest in a dental image is healthy or carious. Given the complexity and variability of oral images, an effective classification system is pivotal for accurate diagnostics [39].

5.1.4.1 Machine learning algorithms

Traditional machine learning techniques have been widely employed for classification tasks in dental imaging. Algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN) can be trained on labeled datasets to recognize patterns in extracted features and classify new, unseen images. Each algorithm offers a distinct approach. For example, SVM works by finding a hyperplane that best separates the classes, while Random Forests employ multiple decision trees to vote on the classification [40].

5.1.4.2 Deep learning and neural networks

In recent years, deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in dental image classification. CNNs are a subset of neural networks designed to learn spatial hierarchies of features automatically and adaptively from images. They can be trained end-to-end, meaning raw images can be input, and the network handles feature extraction and classification. Due to their depth and complexity, CNNs can capture intricate patterns in images, often outperforming traditional methods, especially when vast amounts of data are available.

5.1.4.3 Ensemble methods

These methods combine multiple classifiers to produce a final decision, typically yielding better performance than individual classifiers. Techniques like bagging, boosting, or stacking can be employed, pooling insights from different models for more robust classification.

5.1.4.4 Evaluation metrics

Once classification models are trained, their performance must be assessed. Metrics such as accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) are used. These metrics give insights into the model's actual positive rate, false positive rate, false negatives, and more, facilitating the choice of the most effective classifier for a particular application.

5.1.4.5 Regularization and overfitting

One challenge in classification is overfitting, where the model performs exceptionally well on training data but needs to generalize on unseen data. Techniques such as dropout, L1 or L2 regularization, and early stopping are implemented to ensure robust models generalize well to new data.

5.1.4.6 Transfer learning

Given the challenges in obtaining vast amounts of labeled dental images, transfer learning has emerged as a beneficial approach. Pre-trained models trained on large datasets like ImageNet are fine-tuned on smaller, domain-specific datasets, leveraging the knowledge acquired during the initial training phase to enhance performance in dental caries classification.

5.1.4.7 Continuous learning and model updates

Given the evolving nature of dental imaging and the continuous accrual of new data, classification models should be designed for periodic updates. This ensures they remain current and maintain high-performance levels as new patterns or variations in dental caries emerge.

The classification step in dental caries image analysis is the culmination of all preceding stages. It determines the final diagnostic output, labeling regions as carious or healthy. With the rapid advancements in machine learning and deep learning, classification algorithms are becoming increasingly sophisticated, paving the way for more accurate, efficient, and reliable dental diagnostics.

5.1.4.8 Post-processing

Once the potential caries lesions are identified, post-processing techniques can be used to refine the results. This might involve removing any small, isolated regions identified as caries (which might be false positives) or filling in small gaps in detected caries regions.

5.1.5 Visualization and interpretation

The final processed image is then visualized, highlighting areas detected as caries lesions. Dental professionals can interpret these highlighted areas with clinical knowledge, ensuring the results align with clinical observations and radiographic findings [41]. Image processing and analysis techniques provide a systematic and efficient approach to identifying caries lesions. When combined with the expertise of dental professionals, these techniques can significantly enhance the accuracy of caries detection, leading to better patient outcomes. As technology and algorithms evolve, integrating such techniques in everyday dental practice is set to become more prevalent, revolutionizing the early detection and management of dental caries.

6. Various AI based methods used in the detection of dental caries

6.1 Deep learning for proximal caries detection in bitewings

Proximal dental caries lesions are intricate cavities that develop on the surfaces where teeth come into contact. Their concealed location often makes early detection challenging, leading to a reliance on bitewing radiographs. These radiographs have historically been essential, delivering an in-depth view of the hidden proximal surfaces, including both the maxillary (upper) and mandibular (lower) teeth crown sections. Despite the significant reliance on these radiographs, traditional methods, characterized by visual evaluations and manual image analysis, are susceptible to human subjectivity and potential oversights. The advent of artificial intelligence (AI) and its integration into the healthcare sector heralded a seismic shift in the diagnostic approach to these dental challenges [42]. Deep learning, a sophisticated subset of machine learning, employs multi-layered artificial neural networks to interpret intricate patterns within extensive datasets. These neural networks emulate the complexity and interconnections observed in human neural circuits. In dentistry, deep learning algorithms, especially Convolutional Neural Networks (CNNs), are adept at scrutinizing bitewing radiographs with unmatched precision. The primary aim is to detect proximal caries [43] accurately.

The efficacy of these algorithms is contingent upon rigorous training. An extensive, annotated collection of bitewing images, meticulously marked by seasoned dental experts to indicate caries' presence or absence, serves as the foundational dataset. These models can adeptly analyze new, unlabeled radiographs upon exhaustive training, identifying potential carious patterns based on their learned knowledge [44]. Integrating deep learning offers dual advantages: swift image analysis and mitigating interpretative discrepancies or errors from human fatigue or inherent subjectivity. Contemporary research underscores the unparalleled proficiency of deep learning models, emphasizing their exceptional sensitivity and specificity in detecting proximal caries on bitewing radiographs. In numerous instances, these models rival or surpass the diagnostic acumen of experienced dental professionals [43]. Incorporating deep learning techniques marks a transformative epoch in dental radiographic analysis. By harnessing these avant-garde algorithms, dental practitioners can significantly enhance the precision and efficiency of their diagnoses, culminating in improved patient outcomes and streamlined clinical workflows.

6.2 Deep learning for ICDAS™ classification in bitewing radiographs

The ICDAS™ system, an internationally recognized standard, has ushered in a new era of caries detection and assessment [45]. But with the surge of technological advances, particularly the integration of artificial intelligence, we are on the brink of a revolution in dental diagnostics. Deep learning, characterized by its use of intricate artificial neural networks, can delve deep into extensive datasets, analyzing multiple hidden layers and recognizing nuanced patterns that may elude the human eye. The potency of this technology becomes palpable when applied to bitewing radiographs, the cornerstone of dental imaging. Here, the aim is not just detection but the precise classification of dental caries according to the rigorous benchmarks set by the ICDAS™ system. This level of granularity in diagnostics is pivotal, as it facilitates more personalized treatment plans and proactive interventions.

Central to this endeavor are Convolutional Neural Networks (CNNs). Their architecture makes CNNs uniquely equipped to process visual data, making them the model of choice for imaging-based diagnostics. However, the true efficacy of a CNN is contingent on the quality and comprehensiveness of its training data. An annotated with ICDAS™ scores by expert dental practitioners, a meticulously curated dataset lays the foundation. The rigorous training regimen involves the CNN making predictive inferences on caries classifications, juxtaposed with actual ICDAS™ scores. Discrepancies between predicted and actual scores serve as a feedback mechanism, activating backpropagation algorithms [22]. These algorithms adjust the CNN's parameters, fine-tuning its predictive prowess in a relentless pursuit of diagnostic perfection. Upon satisfactory training, CNN's capabilities are put to the test. Presented with the novel, unlabeled bitewing radiographs, it undertakes the task of discerning and classifying dental caries, assigning them ICDAS™ scores [22]. This marriage of deep learning technology with the ICDAS™ system is emblematic of the future of dental diagnostics — one where precision, consistency, and technology converge to optimize patient outcomes.

6.3 Dental radiographic segmentation with neutrosophic logic

Segmentation of dental radiographic images is pivotal for effective dental caries diagnosis. Traditional methods often grapple with noise and image uncertainties. However, neutrosophic logic presents an innovative solution [46]. Conceived by Florentin Smarandache, this logic comprehends imprecision typical of human cognition and tangible scenarios, surpassing the binary logic's confines of strict truth and falsehood by introducing indeterminacy. When applied to image processing, neutrosophic logic capably navigates radiographic ambiguities. The initial step entails transforming the image to the neutrosophic domain. Pixels are defined by three sets: truth (T), falsehood (F), and indeterminacy (I). These sets reflect the pixel's affiliation to the object (like tooth structure), non-affiliation, and uncertain status [47].

After this transformation, neutrosophic-centric image enhancement methods amplify contrast and minimize noise, heightening structure visibility. Segmentation then employs neutrosophic-designed techniques, utilizing membership degrees within the T, F, and I sets for pixel classification. This neutrosophic segmentation strategy touts several merits, notably its capacity to adeptly manage dental radiographic image uncertainties adeptly, resulting in consistent, precise segmentations, thus refining subsequent analytical procedures [48]. However, it demands significant computational resources, as each pixel requires a three-set analysis. Additionally, selecting optimal parameters for image amplification and segmentation can be intricate, potentially necessitating expert insight. Nevertheless, neutrosophic logic in dental radiographic image segmentation offers a groundbreaking, dependable methodology, propelling advancements in dental ailment detection and diagnostics.

6.4 YOLOv3 and ICCMS™ in bitewing radiographs

YOLO, standing for "You Only Look Once," represents the forefront of object detection in computer vision. Its third version, YOLOv3, offers unmatched speed and accuracy, opening new doors across various detection scenarios. One field ripe for innovation is dentistry, where YOLOv3's capability for accurately detecting and classifying dental caries is now being explored. YOLOv3's adaptation is based on the comprehensive ICCMS™ (International Caries Classification and Management System) radiographic scoring system [49].

YOLOv3, a deep-learning gem, is designed for rapid and sharp object detection. Its efficiency stems from its regressive method, marking objects and predicting class probabilities straight from an image in one step. To align YOLOv3 with dental caries detection, it is trained on a vast bitewing radiographic dataset annotated with caries details and matching ICCMS™ scores. As YOLOv3 trains, it recognizes the visual markers linked to different stages of caries as classified by ICCMS™. In practice, the trained model identifies and matches caries with ICCMS™ scores, annotating a radiograph with accurate caries borders and classifications [50]. YOLOv3's effectiveness in this application is gauged using metrics like precision, recall, F1-score, and mAP, which collectively shed light on its skill in identifying and categorizing dental caries. However, the pathway to embed YOLOv3 in dental diagnostics is challenging. Collecting an extensive, diverse, and well-annotated training dataset is a significant hurdle. YOLOv3's inherent "black box" nature, typical of many deep learning models, can raise questions about its decision-making transparency. This method emphasizes YOLOv3's transformative capability in dental caries detection, particularly its alignment with the ICCMS™ system. While obstacles remain, the convergence of YOLOv3 and ICCMS™ paints a bright picture for the future of dental diagnostics [51].

6.5 Blob detection in dental caries diagnostics

The dawn of blob detection in dental diagnostics represents a paradigm shift in how dental caries are identified and diagnosed. This technique, rooted in image processing, recognizes and distinguishes regions termed 'blobs' based on their unique brightness attributes. In dental radiographs, these blobs are often discerned as shadowy indicators of dental caries, contrasting vividly against the healthier parts of tooth structures [52]. The merits of blob detection in dentistry are multifaceted. Firstly, its precision is noteworthy. The technique's ability to pinpoint even the most nascent lesions facilitates prompt interventions, potentially halting further tooth damage. Then comes the aspect of efficiency. Traditionally, dental professionals might invest significant time in meticulously examining radiographs. With blob detection, this analysis is streamlined, allowing dentists to channel more of their time and focus on direct patient care. Another pivotal advantage is the promise of consistency. By shifting diagnosis to an algorithm-driven approach, the interpretation process sidesteps individual professionals' personal biases and nuances, ensuring a standardized evaluation.

The procedure of blob detection in dental diagnostics unfolds systematically. Initially, radiographs are subjected to pre-processing, where they undergo optimization for contrast and noise reduction. This stage is foundational, priming the images for the rigorous blob identification that follows. The actual process of blob detection sees specialized algorithms deployed to scan the radiograph meticulously. The objective is to highlight areas exhibiting pronounced brightness disparities. As these darker regions come into focus, they are typically flagged as indicators of decay [53]. The concluding phase, post-processing, plays a critical role. Here, the detected blobs are assessed for validity. Determinations are drawn regarding whether they genuinely represent caries, gauging their severity and even predicting potential progression trajectories based on the characteristics of these blobs.

A fascinating frontier in this domain is the burgeoning synergy between blob detection and machine learning. Merging the pinpoint accuracy of blob detection with the dynamic adaptability of machine learning paints a promising picture for dental diagnostics. The combined prowess promises speed and heightened accuracy, and uniformity in diagnosis. And while integrating these technologies is not without its challenges, their combined potential to redefine the landscape of dental care is undeniably vast. As a relatively recent entrant in dental diagnostics, blob detection is rapidly becoming an invaluable tool [54]. With its continued integration with technologies like machine learning, the future of dental diagnostics and care seems poised for significant innovation and patient-centric advancements.

6.6 Dental caries detection with meta-heuristic-based ResNeXt-RNN

The innovative fusion of the ResNeXt-RNN model emerges as a trailblazer in dental caries detection. Building on the foundational prowess of deep learning, the ResNeXt architecture distinguishes itself in managing high-dimensional data sets, especially intricate images. A breakthrough conceptualized by Ramana Kumari, Nagaraja Rao, and Ramana Reddy [55], ResNeXt introduces "cardinality" as an added dimension, augmenting the conventional depth and width dimensions that define neural architectures. But the genius does not stop here. The Recurrent Neural Network (RNN) component is integrated into this image processing. Historically recognized for its aptitude in managing sequences and retaining memory states, RNN offers the ability to analyze temporal dynamics, a particularly crucial facet for assessing the progression of dental conditions over time.

The synergy of ResNeXt and RNN culminates in a model that excels on dual fronts. While the ResNeXt component meticulously captures spatial intricacies, the RNN counterpart evaluates the temporal evolution of dental caries. Elevating this amalgamation further is the integration of meta-heuristic algorithms. These advanced computational blueprints enhance and guide models' learning trajectories, amplifying their overall performance. The methodology unfolds systematically [56]. Dental images are first channeled into the ResNeXt component, which performs the initial feature extraction phase, identifying critical markers that might indicate the presence of caries. These features, once isolated, are directed to the RNN module, which assesses their temporal dynamics – invaluable insights, particularly for studies tracking the longitudinal progression of caries. Simultaneously, the inherent meta-heuristic algorithm plays its part in fine-tuning and optimizing the model's learning parameters.

While the merits of this integrated approach are manifold, promising a panoramic and dynamic view of dental caries detection, it is full of challenges. The complexity inherent in the model might raise interpretability issues. Validating its decisions could become an intricate task. Additionally, sourcing a rich repository of high-quality dental images for training is not only a logistical challenge but also broaches concerns related to patient privacy. Yet, optimism and anticipation are the overarching sentiments surrounding the meta-heuristic-based ResNeXt-RNN model. Its unparalleled capabilities in dental image analysis herald a potential paradigm shift, particularly for early-stage caries detection. As the confluence between AI and dentistry deepens, it is becoming evident that models like these will profoundly shape the future contours of oral health diagnostics.

6.7 PaXNet: Ensemble and capsule classifier for panoramic X-ray caries detection

The application of artificial intelligence (AI) in dentistry has been transformative. One standout model demonstrating its prowess in this domain is PaXNet. This innovative technique leverages Ensemble Transfer Learning and the Capsule Classifier to optimize dental caries detection in panoramic X-rays. PaXNet is a custom-built AI model to identify dental caries using panoramic X-rays [57]. Its two-fold system magnifies the advantages of Ensemble Transfer Learning and Capsule Networks. The former, Ensemble Transfer Learning, amalgamates insights from various pre-trained deep learning models, re-purposing them for dental caries detection. Such integration ensures that the model extracts the most salient features across multiple datasets, augmenting its predictive prowess and adaptability. Conversely, Capsule Networks (CapsNets) introduce a revolutionary neural network structure. They retain nuanced information about the spatial hierarchies and relationships within the features of an image. A Capsule Classifier, built atop the CapsNets, classifies images based on the calculated probabilities of specific feature presence [58].

Within PaXNet, Ensemble Transfer Learning takes the lead, teasing out relevant features from panoramic X-ray captures. Subsequently, these features undergo evaluation by the Capsule Classifier, determining the presence or absence of dental caries. A notable advantage of PaXNet is its capability to identify intricate feature interrelationships within panoramic X-ray images—details that often elude conventional convolutional neural networks. This intrinsic strength translates to enhanced accuracy and precision in caries detection. Empirical evidence supports PaXNet's prowess. Comparative studies have underscored its superior sensitivity, specificity, and accuracy vis-à-vis other machine learning paradigms. Given its formidable performance metrics, PaXNet is preferred for dental healthcare setups. It offers a swift and dependable adjunct opinion on dental caries, streamlining diagnostic processes. PaXNet's synergistic utilization of Ensemble Transfer Learning and Capsule Classifier signifies a watershed moment in dental caries detection from panoramic X-rays [27]. Embracing its potential and mitigating its challenges, we can anticipate PaXNet to redefine dental diagnostic protocols, fostering enhanced patient care trajectories.

6.8 Pervasive deep gradient-based LeNet

The transformative "Pervasive Deep Gradient-Based LeNet Classifier" stands as a beacon in the evolving landscape of dental caries detection, signaling a departure from traditional diagnostic methods. Initially designed by Yann LeCun for character recognition, the LeNet structure, with its specialized convolutional layers, has proven invaluable in processing dental imagery and capturing intricate spatial data hierarchies. Transitioning seamlessly through its layers, from convolutional and pooling stages to a SoftMax classifier, LeNet provides a comprehensive image analysis.

In dental diagnostics, this specific iteration of LeNet has been meticulously tailored. Equipped with an uncanny ability to parse nuanced patterns within data, it scrutinizes dental images precisely, distinguishing pivotal features and subsequently classifying them based on the presence or absence of caries [59]. The model's integration of the "pervasive deep gradient-based" methodology is particularly noteworthy. This technique employs gradient descent, a cornerstone of machine learning optimization, to iteratively refine the model's parameters, ensuring its diagnostic accuracy improves with each training cycle. Among its salient strengths, the model boasts an unparalleled prowess in data management. It can deftly navigate extensive dental image datasets, rendering manual feature extraction a relic of the past. Its operational speed and diagnostic precision allow for swift and accurate disease identification, paving the way for timely and effective treatments. Furthermore, its heightened sensitivity ensures the detection of even the most subtle structural tooth changes, often identifying caries in their initial stages when they are most amenable to treatment. The introduction of the "Pervasive Deep Gradient-Based LeNet Classifier" into the field of dental diagnostics heralds a new era, one in which carries detection becomes increasingly efficient, predictive oral health measures are refined, and overall patient care standards soar to new heights [60].

6.9 AssistDent®: aI-assisted dental diagnostics

AssistDent® is a cutting-edge AI software tailored for precise dental caries detection. Utilizing deep learning algorithms, particularly Convolutional Neural Networks (CNNs), it excels in analyzing dental images, ensuring dental professionals can make informed decisions quickly and accurately. The strength of AssistDent® stems from its ability to scrutinize dental radiographs with unparalleled precision. These capabilities arise from extensive training on numerous dental radiographs annotated by seasoned professionals. As a result, the early stages of dental caries are quickly identified, making early intervention feasible. The software's intuitive interface seamlessly integrates into a dental clinic's workflow, offering real-time feedback that revolutionizes the diagnostic process, giving practitioners more time with their patients. Rigorous tests confirm AssistDent®'s exemplary sensitivity and specificity in caries detection, further establishing its role as an indispensable tool for dental diagnostics [61, 62].

However, like most AI tools, AssistDent® has its challenges. Its efficacy is largely contingent upon the quality of its training data, emphasizing the need for ongoing updates and training with diverse datasets. Efforts to enhance its transparency and interpretability in decision-making are continuous. Looking to the future, the potential for AssistDent® extends beyond merely caries detection. As AI evolves and datasets grow, it is poised to become a holistic diagnostic powerhouse for a spectrum of oral conditions. In essence, AssistDent® embodies the next giant leap in AI-enhanced dental care, pointing towards a future where diagnostics are more refined, swift, and universally accessible.

6.10 Bitewing radiographs: deep learning caries classification with ICDAS™

Deep learning algorithms have seen a rising application in identifying and classifying dental caries in bitewing radiographs, mainly using the globally acknowledged ICDAS™ (International Caries Detection and Assessment System) radiographic scoring. This system standardizes caries detection, allowing more streamlined communication among dental professionals. Within the ICDAS™ framework, dental caries is scored on a spectrum from 0 to 6, with 0 denoting sound tooth surfaces and six pointing to pronounced cavities [63]. Deep learning, an advanced branch of machine learning, employs artificial neural networks with numerous hidden layers, enabling intricate pattern recognition from vast datasets. Within dental diagnostics, this technology can be tailored to sift through bitewing radiographs and categorize dental caries based on the ICDAS™ criteria. Convolutional neural networks (CNNs), a type of deep learning model, play a pivotal role due to their aptitude for visual data analysis, making them ideal for image-centric tasks.

The initial step to developing such a model demands a comprehensive dataset of annotated bitewing radiographs. Expert dental professionals must meticulously label each radiograph with its corresponding ICDAS™ score. During the training phase, the CNN evolves, recognizing radiographic patterns that align with each specific ICDAS™ grade [64]. This learning is facilitated by a mechanism known as backpropagation. Here, the model's predictions are juxtaposed against actual labels, and subsequent adjustments are made to minimize discrepancies. After this rigorous training, the model can autonomously assign ICDAS™ scores to previously unanalyzed bitewing radiographs.

7. Ethical and clinical considerations

A significant cornerstone of any AI system is the vast troves of data it feeds on. This encompasses a wide range of patient-specific data in dentistry: from dental records and radiographic images to detailed medical histories. Acquiring this data mandates an informed consent process, where patients are fully aware of their data's utilization, storage, and potential risks. The subsequent storage of such critical information raises concerns about encryption, unauthorized access, and potential breaches. In today's interconnected digital era, data often traverses various platforms, sometimes extending to third-party vendors. This sharing must stringently align with privacy regulations like GDPR or HIPAA, ensuring uncompromised patient confidentiality. Moreover, anonymizing data for AI model training can further mitigate identification risks.

The potential of AI in revolutionizing dental care pivots on its accuracy and reliability. The backbone of an accurate AI system is the quality of its training data, which must be comprehensive, varied, and genuinely representative of diverse patient demographics to prevent inherent biases and inaccuracies. Rigorous validation processes, where AI outcomes are juxtaposed against traditional diagnostic results, are imperative to vouch for the system's consistency. A challenge often surfaces with AI is its opaque "black box" algorithms, which can hinder a field where traceability and understandability of diagnoses are crucial [65]. Thus, fostering transparency and promoting an environment where AI acts as an assistant to human expertise rather than a replacement can be instrumental. The horizon of AI in dental caries management is undeniably promising. However, its seamless and efficacious integration into the dental sphere demands meticulous navigation of the intertwined ethical and clinical pathways. Addressing these considerations will maximize AI's potential and elevate the dental care standard, blending technology and human expertise in a harmonious symphony.

8. Limitations and challenges

The infiltration of Artificial Intelligence (AI) into the intricate dental caries diagnosis and management domain promises a transformative impact. But like any innovation, AI faces its set of hurdles. These challenges, ranging from technical to human, underscore the need for careful deployment of AI tools while maintaining a balanced perspective on their role in dental care. One predominant challenge is the variability in AI-driven results. AI models, especially when delving into nuanced realms like dental caries detection, may sometimes produce inconsistent or variable outcomes, depending on the algorithm's design or the data it was trained on. These inconsistencies could lead to missed diagnoses or false positives, which can have considerable ramifications in the sensitive patient care environment. Clinicians might find themselves at crossroads, especially when the AI output deviates from their clinical judgment, potentially leading to decision-making dilemmas [16].

At the heart of any effective AI system lies its data – the more robust and diverse, the better. However, AI's dependence on the quality and quantity of data presents a significant challenge. Incomplete, biased, or unrepresentative datasets can skew AI outputs, rendering them less accurate or misleading. In dental caries, where variances can be subtle, training AI models on limited or non-diverse data can gravely compromise their detection capabilities [66]. The quest for substantial, high-quality data is thus not just a technical requisite but a critical determinant of the AI system's clinical utility. But perhaps one of the most profound challenges springs not from technology but from its human stakeholders. The dental community, built on years of rigorous training and honed expertise, might view AI's advent with skepticism or even resistance. The essence of dental care goes beyond mere diagnoses – it encompasses the human touch, experience-based intuition, and a relationship of trust with patients. To many in the dental fraternity, relegating some of these responsibilities to an algorithm might seem disconcerting. Striking a harmonious balance between human expertise and automation is essential. AI should be perceived not as a replacement but as a tool – an adjunct that augments the dentist's capabilities, making their practice more efficient and precise. The promise held by AI in reshaping dental caries management is immense, but it is crucial to approach this frontier with cognizance of its limitations [67]. The true potential of AI in dental care can be realized by addressing these challenges head-on and fostering a collaborative spirit between technology and human expertise.

9. The future of AI in dental caries management

The relentless march of technological progress, coupled with the ever-evolving field of artificial intelligence (AI), heralds an exciting new era for dental care. As AI continues to weave its way into myriad aspects of healthcare, dental caries management stands to benefit enormously. The current landscape of dental caries management has already seen revolutionary changes with the integration of AI, especially in detection. The future, however, is even more promising. Advanced AI algorithms are projected to achieve unparalleled accuracy in spotting early signs of dental caries, reducing the chances of false negatives, and ensuring timely interventions. As AI systems continue to 'learn' from an expanding database of dental images and case studies, their predictive capabilities will be refined further. This implies that, in the future, AI might not just identify existing caries but also predict potential decay based on a combination of the patient's oral history, habits, and genetic predispositions [68].

Moreover, management tools are expected to evolve, integrating real-time feedback mechanisms. Imagine a scenario where, during a dental procedure, an AI-powered tool offers real-time guidance to a dentist, suggesting optimal interventions based on the analysis of thousands of similar cases. Such advancements can drastically reduce procedural errors and improve treatment outcomes. AI's potential is not restricted to stand-alone applications. Its true power might be unleashed when integrated with other emerging dental technologies. Integrating AI with tele-dentistry platforms can democratize dental care, especially in remote regions. AI-powered diagnostic tools can offer preliminary assessments, guiding patients in areas without immediate dental expertise and suggesting when to seek advanced care. The future seems bright as AI matures and finds its footing in dental care. From advanced detection tools to create a comprehensive, patient-centric care model, AI promises to reshape the fabric of dental caries management, steering it towards excellence and holistic well-being.

Conflict of interest

The authors declare no conflict of interest.

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