



The Detection and Diagnosis of Dental Caries through Artificial Intelligence: A Comprehensive Systematic Review of Current Models and Their Clinical Applications

¹-Fatimah Saleh Alhasawi,²-Salman Rahim Alnufaie,³-Maisoon Marzouq Aljasir,⁴-
Abdullah Eid Alshnawani,⁵-Yousef Omar Obaid Alharthi,⁶- Ibrahim Shafi Ali
Alharthi,⁷-Zainab Nuri Ali Alghirash,⁸-Majed Abdullah Alrudayan,⁹-Hani Awad
Alasmari,¹⁰-Mohd Ali Bahy,¹¹- Yasser Yahya Al Sharif,¹²- Fatima Alhassan
Alghamdi,¹³- Abrar Kadem Al Dubais,¹⁴- Meznah Zuqm Sulobi Aldafeeri,¹⁵- Fatimah
Hassan Al Aneyah,¹⁶-Masoud Hassan Al-Qutayli

1. Ksa, Ministry Of Health, Northern Health Center
2. Ksa, Ministry Of Health, Riyadh Third Cluster
3. Ksa, Ministry Of Health, Riyadh
4. Ksa, Ministry Of Health, Riyadh Third Health Cluster/Moh
5. Ksa, Ministry Of Health, King Khalid Hospital In Alkharj
6. Ksa, Ministry Of Health, Al Bashair Hospital
7. Ksa, Ministry Of Health, Alahsa Medical Health Cluster , Dental Department In Southern Region
8. Ksa, Ministry Of Health, Eradah Medical Complex In Hail
9. Ksa, Ministry Of Health, Riyadh
10. Ksa, Ministry Of Health, Bayesh Hospetal
11. Ksa, Ministry Of Health, Jazan
12. Ksa, Ministry Of Health, Al-Lith Primary Healthcare- Jeddah
13. Ksa, Ministry Of Health, Northern Ras Tanoura Primary Health Care
14. Ksa, Ministry Of Health, Hafar Al Batin Dental Center
15. Ksa, Ministry Of Health, Qatif Primary Health Care -Awamia Center
16. Ksa, Ministry Of Health, Jazan

Abstract

Background: Dental caries (DC) is a prevalent oral disorder affecting billions worldwide, leading to significant health burdens and economic costs. Traditional methods of detecting and diagnosing DC, including visual examinations and radiographic evaluations, often suffer from variability in accuracy and reliability. Recent advancements in artificial intelligence (AI) have shown promise in enhancing diagnostic capabilities in various medical fields, prompting interest in its application for dental caries.

Methods: This systematic review analyzed literature from 2000 to 2023, utilizing databases such as PubMed, Google Scholar, and Scopus. Key terms included 'dental caries,' 'artificial intelligence,' 'machine learning,' and 'diagnosis.' Studies were included if they reported on AI-based models for detecting, diagnosing, or predicting DC.

Results: The review identified numerous AI models demonstrating superior accuracy in diagnosing DC compared to traditional methods. For instance, deep learning algorithms achieved accuracies ranging from 73.3% to 98.8%, with high sensitivity and specificity across various datasets. AI applications were noted to significantly reduce false negatives and enhance early detection of caries, thereby improving patient outcomes and reducing healthcare costs.

Conclusion: AI models represent a transformative approach to the detection and diagnosis of dental caries, offering enhanced precision and efficiency. Integrating these technologies into clinical practice can aid

dental professionals in making more informed decisions, thereby improving treatment quality. However, the variability in dataset sizes and characteristics necessitates further research to optimize AI performance and generalizability across diverse populations.

Keywords: Dental Caries, Artificial Intelligence, Diagnosis, Machine Learning, Systematic Review

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1. Introduction

Oral disorders such as dental caries and periodontal diseases represent a significant health burden and are regarded as non-fatal contributors to disability impacting individuals across all age demographics worldwide. The pain and suffering often linked to DC may ultimately undermine the individual's sleep, nutrition, social well-being, and self-esteem, so impacting overall quality of life [2]. Untreated DC are the most ubiquitous and significant factor impacting health, as per the global burden of illness [1]. Globally, it is estimated that dental caries affects 2.3 billion people with permanent teeth and 530 million children with primary teeth.

In 2015, the worldwide expense associated with oral disorders was estimated to surpass 540 billion dollars, resulting in significant health and financial burdens [3,4]. Timely and precise identification of DC might provide economical preventative strategies and more conservative treatment alternatives, hence decreasing healthcare expenditures [5]. The conventional diagnosis method for DC involves visual investigation and radiographic evaluation. Nevertheless, research has shown significant heterogeneity in its reliability and accuracy, mostly influenced by the clinical expertise of dentists. Sensitivity may vary from 19% to 92% for occlusal DC and from 39% to 94% for proximal DC [6]. Multiple characteristics such as shadow, contrast, and brightness in radiographs might influence the diagnosis [7].

Recent improvements in detection and diagnostic procedures for DC have led to the creation of innovative approaches designed to address the limitations of clinical and radiographic diagnosis. These encompass ultrasonic caries detection, laser fluorescence, digital imaging fiber-optic transillumination (FOTI), quantitative light-induced fluorescence (QLF), digital subtraction radiography (DSR), tuned aperture computed tomography (TACT), and electrical conductance measurement (ECM) [8,9].

Laser fluorescence exhibits superior sensitivity in the diagnosis of early DC compared to other approaches [10]. Nevertheless, research has highlighted the shortcomings of these methods; FOTI has limited sensitivity in diagnosing proximal DC, whereas ultrasonic instruments can only identify existing DC [11,12]. Caries risk prediction tools such as the caries-risk assessment tool (CAT), caries management by risk assessment (CAMBRA), and Cariogram are often used for forecasting dental caries (DC). Nonetheless, these models lack enough data to substantiate their efficacy. A thorough study indicated that the sensitivity and specificity of Cariogram varied from 41% to 75% and from 65.8% to 88%, respectively [13].

Recent advancements in science and technology have led to the extensive use of artificial intelligence (AI) in medical sciences. These models have shown exceptional performance, accuracy, and sensitivity in executing their designated functions, including the diagnosis of ocular illnesses, breast and skin malignancies, as well as the detection and identification of pulmonary nodules [14-17]. AI models have been extensively used in the detection, segmentation, and classification of coronavirus disease 2019 (COVID-19) using computed tomography (CT) medical images, exhibiting significant promise for quick diagnosis of the illness [18]. Consequently, due to the increasing interest in AI-based applications, these models have been used across several domains about the detection of oral disorders, exhibiting remarkable precision and accuracy in their performance [19-22]. Research has shown the use and efficacy of AI models across several dental specialties, including orthodontics, restorative dentistry, and prosthodontics [23-25]. Nonetheless, there are no systematic review papers solely focused on the use of AI models to dental caries. Moreover, the use of AI-based models for detecting DC has shown to be a cost-efficient method, as the AI-driven DC detection model exhibited superior accuracy in identifying DC relative to experienced examiners, while also minimizing the likelihood of false negative errors [26]. The objective of this systematic review is

to evaluate the diagnostic accuracy and efficacy of AI-based modalities for the detection, diagnosis, and prediction of DC.

2. Methods

PubMed, Google Scholar, Scopus, Web of Science, Embase, and Cochrane electronic databases were examined for relevant papers published from 2000 to 2023. The literature search utilized Medical Subject Headings (MeSH) terms such as dental caries, tooth decay, cavity, diagnosis, detection, prediction, artificial intelligence, machine learning, deep learning (DL), automated systems, convolutional neural networks (CNNs), artificial neural networks (ANNs), and deep convolutional neural networks (DCNNs). A combination of these MeSH phrases, using Boolean operators and/or was used in the advanced search for the articles. Manual searches for supplementary articles were conducted in the college library using the reference lists derived from the first chosen articles.

3. Oral disorders

Oral disorders such as dental caries and periodontal diseases are significant public health challenges impacting individuals across all age demographics in both developing and industrialized nations. In many instances, dental caries remains misdiagnosed due to deep fissures and strong interproximal contacts, complicating early detection and resulting in identification only at late stages. Timely identification of DC reduces the disease burden and the need for invasive interventions, hence enhancing treatment outcomes. The clinical oral examination with a dental probe or explorer, in conjunction with radiographs, is considered the standard approach for identifying dental caries. Nonetheless, research has shown discrepancies in accuracy and dependability among doctors using this strategy, contingent upon their clinical expertise [7,27,28].

AI technology-based automated decision support systems represent recent advancements in medical sciences. AI-driven models have been extensively utilized in dentistry, exhibiting remarkable efficacy in tooth detection, tooth numbering, diagnosing and predicting oral cancer, periodontal diseases, root fractures, orthodontic assessments, and identifying jaw lesions, cysts, and tumors [19-22]. Given the problems and constraints dentists encounter in identifying DC during clinical assessments, there is a need to build AI-driven automated models that may aid dentists in decision-making, hence enhancing the precision of DC detection and diagnosis.

Numerous variables affect the likelihood of acquiring dental caries, including oral hygiene practices, dietary habits, socioeconomic status, usage of dental care services, and attitudes toward oral health [29]. Therefore, recognizing the elements that influence the risk of developing DC in a person is crucial for its prevention. AI-driven models have been extensively used for the prediction of DC. Zanella-Calzada et al. [30] presented an AI-based model for evaluating dietary and demographic parameters influencing DC, achieving an accuracy of 0.69 and AUC values of 0.69 and 0.75 utilizing data sets. This model demonstrated high accuracy in categorizing persons with and without caries based on dietary and demographic variables. The primary benefit of this model is that the training data was sourced from individuals across many areas, hence enhancing result robustness and mitigating selection bias. Hung M et al. [31] suggested a machine learning approach using artificial intelligence for the diagnostic prediction of root caries. This model had exceptional performance, achieving an accuracy of 97.1%, a precision of 95.1%, a sensitivity of 99.6%, a specificity of 94.3%, and an AUC of 0.997. Despite the model's outstanding performance, there were certain restrictions associated with the data sets used for its development. This model used data from a sample of the United States population, making it more typical of US citizens rather than patients with varying demographic characteristics. A significant drawback was the authors' omission of crucial variables such as lifestyle and dental hygiene characteristics.

Ramos-Gomez et al. [32] delineated an AI-driven machine learning technique (Random Forest) for detecting survey questions that forecast DC. The model exhibited a mean reduced Gini coefficient (MDG) of 0.84 and a mean decreased accuracy (MDA) of 1.97 in categorizing active DC depending on parental age. The model exhibited an MDG of 2.97 and an MDA of 4.74 for predicting DC based on parental age. This

model may be useful for screening children for DC using the survey data. The research has significant limitations, including a restricted sample size derived from limited hospital records that may not accurately reflect the overall population. Furthermore, the information about children's oral hygiene routines was sourced from their parents, resulting in social desirability bias. Zaorska et al. [33] documented an AI model for forecasting DC based on selected polymorphisms. The model exhibited a sensitivity of 90%, a specificity of 96%, an overall accuracy of 93% ($p < 0.0001$), and an AUC of 0.970 ($p < 0.0001$). This model had a prediction accuracy of 90.9% to 98.4%. The primary advantage of this model was the uniformity in age and gender among research participants, along with the evaluation of performance by two distinct statistical methodologies, resulting in more dependable outcomes. Nonetheless, the sample used for model validation was constrained.

Pang et al. [34] documented an AI-driven machine-learning model for predicting caries risk, using environmental and genetic variables. The model had an AUC of 0.73. This approach may precisely identify persons with elevated and significantly elevated caries risk. Nonetheless, the sample was limited to a single site, and early indicators of DC were not identified in this investigation. Hur et al. [35] researched to evaluate a machine learning model for predicting dental caries on second molars linked to impacted third molars. This model exhibited commendable accuracy, with a ROC ranging from 0.88 to 0.89. Nevertheless, the authors failed to account for significant variables leading to dental caries, such as oral hygiene and dietary sugar consumption. Park et al. [36] have documented a machine learning algorithm for forecasting early childhood caries. The model exhibited commendable performance with an AUROC ranging from 0.774 to 0.785. This study's limitations were poor specificity values and probable bias due to the exclusive examination of maternal factors. Furthermore, the authors neglected to account for significant factors like as feeding patterns, sugar consumption, and fluoride use.

Undiagnosed and untreated DC are significant public health issues impacting billions globally. Timely identification of DC may markedly reduce the need for invasive interventions and, thus, the overall expenditure of care. Therefore, diagnostic instruments with great precision in identifying DC are essential. Lee et al. [37] presented a deep learning model for the detection and diagnosis of dental caries on periapical radiographs. The model exhibited accuracies of 89.0%, 88.0%, and 82.0%, with an AUC of 0.917 for the premolar, molar, and combined premolar and molar models, respectively. The CapsNet deep learning model is a newly constructed architecture composed of deep layers, demonstrating significant efficacy in analyzing visual attributes such as posture, speed, color, and texture. Consequently, models of this kind are equipped with enhanced and optimized capabilities for the detection and diagnosis of DC [38]. Despite the model's significant effectiveness, it had limitations due to overlooked clinical characteristics, a restricted quantity of radiographs, and the exclusive focus on permanent teeth [30]. Choi et al. [39] documented an automated approach for detecting proximal dental caries in periapical radiographs. The suggested model demonstrated superiority over the system using naïve CNNs.

Casalegno et al. [40] documented a deep learning model for the automatic identification and localization of DC. This approach exhibited encouraging outcomes with enhanced speed and precision in identifying DC. Nonetheless, the model exhibited many deficiencies, particularly in the physically implausible labeling of artifacts in regions of underexposure and overexposure. Cantu et al. [41] introduced a deep learning algorithm for identifying dental caries on bitewing radiographs. The model exhibited an accuracy of 0.80, a sensitivity of 0.75, and a specificity of 0.83. This model's accuracy surpassed that of seasoned dentists in identifying first lesions. The primary strength of this work was the substantial quantity of balanced data sets used for training and testing. The findings were similar to those of separate research by Lee et al. [42], which used a deep CNN (U-Net) model for the diagnosis of dental caries on bitewing radiographs, achieving a precision of 63.29%, a recall of 65.02%, and an F1-score of 64.14%. The study's drawback was associated with the limited number of data sets. Geetha et al. [43] presented an AI-driven algorithm for diagnosing DC using digital radiography. The model demonstrated exceptional performance, with an accuracy of 97.1%, a false positive rate of 2.8%, and a ROC area of 0.987. Nonetheless, the model requires enhancement to facilitate the categorization of DC according to lesion depth.

Another work by Schwendicke et al. [44] reported on an AI-based model for identifying dental caries. The model's performance was equivalent to that of trained dentists. The constraint of this investigation pertained to the dependability of the evaluators. Duong et al. [45] proposed an AI-based algorithm for identifying DC from smartphone pictures. The model exhibited an accuracy of 92.37%, a sensitivity of 88.1%, and a specificity of 96.6%. Nonetheless, the data sets exhibited little heterogeneity, and the presence of plaque, debris, stains, and shadows may have influenced the findings. Zhang et al. [46] proposed a model based on convolutional neural networks (CNNs) for diagnosing dental caries using oral photos. The model exhibited an AUC of 85.65% and a sensitivity of 81.90%. Nonetheless, the dataset was obtained from a singular organization, which may restrict its generalizability. Moreover, factors such as the existence of plaque and stains may have influenced the findings obtained. Research by Kühnisch et al. [47] presented a CNN-based model for the identification and classification of dental caries using oral photos. The model exhibited an accuracy of 92.5%, a sensitivity of 89.6%, and a specificity of 94.3% in this investigation. This study acknowledged the limits of prior research and hence only used pictures devoid of plaque, calculus, and saliva.

Devlin et al. [48] suggested an AI-based model for the detection of enamel-only proximal dental caries via bitewing radiographs. The model exhibited substantial outcomes relative to experienced dentists. Bayrakdar et al. [49] further documented AI-driven deep learning models (VGG-16 and U-Net) for the automated identification and segmentation of caries in bitewing radiography. These models exhibited enhanced performance relative to seasoned experts. This investigation was hindered by the restricted data sets acquired from a single center. Zheng et al. [50] conducted a comparative analysis of three CNN models (VGG19, Inception V3, and ResNet18) for the diagnosis of deep DC. The ResNet18 model demonstrated superior performance relative to the other two models and the trained dentists. Nevertheless, the identification of patients was conducted by a panel of seasoned dentists, which does not represent the gold standard for identifying severe dentin caries and pulpitis. However, histological examination, regarded as the gold standard, is not realistically viable in clinical settings.

Research by Moran et al. [51] examined a CNN model (Inception) for detecting approximal dental caries on bitewing radiographs. The model exhibited an accuracy of 73.3%. This model exhibited encouraging outcomes relative to the reference model (ResNet). Mertens et al. [52] documented a CNN model for the identification of proximal dental caries via bitewing radiographs. The model had a ROC of 0.89 and a sensitivity of 0.81, yielding noteworthy results when compared to five expert dentists. The primary strength of this research was its design as a randomized controlled trial. Conversely, the primary limitation was to the restricted sample of data sets acquired from a single site. Mao et al. [53] did another investigation using a CNN-based algorithm to detect DC on bitewing radiography. The model had an accuracy of 90.30% in detecting DC. The AlexNet model demonstrated superior accuracy relative to other models. To enhance accuracy, the authors diminished the dimensions of the images used in the training procedure, hence decreasing training duration and augmenting the model's precision. Research by Bayraktar et al. [54] presented a CNN-based model (YOLO) for diagnosing interproximal caries lesions on bitewing radiographs. The model exhibited an accuracy of 94.59%, a sensitivity of 72.26%, and a specificity of 98.19%. The primary strength of this research was the huge amount of data sets that produced almost flawless findings. Nevertheless, the model was unable to categorize the DC lesions based on their location inside the enamel and/or dentin.

Lian et al. [55] further documented deep-learning models for the detection and classification of dental caries in panoramic radiographs. The models had Dice coefficient values of 0.663 and an accuracy of 0.986. Their performance resembled that of skilled dentists. The study's strength was in the extensive data that was thoroughly gathered and annotated by three qualified dentists. A fourth expert dentist further amended the controversial findings. Nonetheless, the panoramic radiographs used in this investigation were sourced from a singular machine; hence, performance may differ with panoramic radiographs acquired from equipment produced by different manufacturers. Research by De Araujo Faria et al. [56] presented an AI-based model for predicting and detecting radiation-related caries (RRC) in panoramic radiography. This model had a remarkable detection accuracy of 98.8% and an AUC of 0.9869. The

prediction demonstrated an accuracy of 99.2% and an AUC of 0.9886. Nonetheless, the restricted sample size may have influenced the outcomes, since the patients at that specific facility were often at an advanced DC stage when the radiographs were acquired. Zhu et al. [57] reported on a CNN-based model (CariesNet) designed to differentiate various degrees of caries in panoramic radiographs. The model exhibited outstanding performance, with a mean dice coefficient of 93.64%, an accuracy of 93.61%, an F1 score of 92.87%, and a precision of 94.09%. The extensive array of datasets used for training and validating the model constituted a significant strength of this work.

Huang et al. [58] documented AI-based models AlexNet, VGG-16, ResNet-152, Xception, and ResNext-101 for the detection of DC in OCT and micro-CT images. ResNet-152 had the best accuracy rate of 95.21% and a sensitivity of 98.85% relative to the other three models. Nevertheless, the research used a manual verification approach, making human mistakes unavoidable.

4. Conclusions

Artificial intelligence models have been extensively investigated for the prediction, detection, and diagnosis of DC. These models have shown superior performance and may be used in clinical practice to identify individuals at elevated DC risk, as well as to improve diagnostic accuracy, treatment quality, and patient outcomes. The outcomes of the prediction models may assist in strategizing preventative dental treatment, formulating oral hygiene regimens, and developing dietary recommendations for individuals at elevated risk of dental caries. These models may aid dentists as a supplementary resource in clinical practice and can also help non-dental practitioners in more precisely identifying and diagnosing dental caries at educational institutions and rural health facilities. Despite the impressive performance of these models, there are notable constraints concerning the size and variability of the data sets presented in the majority of these publications. Consequently, these models need more training and validation to enhance performance.

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الكشف والتشخيص عن تسوس الأسنان باستخدام الذكاء الاصطناعي: مراجعة منهجية شاملة للنماذج الحالية وتطبيقاتها السريرية

الملخص

الخلفية: يُعتبر تسوس الأسنان (DC) اضطرابًا شائعًا في الفم يؤثر على مليارات الأشخاص حول العالم، مما يؤدي إلى أعباء صحية كبيرة وتكاليف اقتصادية. تعاني الطرق التقليدية للكشف عن تسوس الأسنان وتشخيصه، بما في ذلك الفحوصات البصرية والتقييمات الشعاعية، غالبًا من تباين في الدقة والموثوقية. أظهرت التقدمات الحديثة في الذكاء الاصطناعي (AI) وعدًا في تعزيز قدرات التشخيص في مجالات طبية متنوعة، مما أثار اهتمامًا في تطبيقه على تسوس الأسنان.

الطرق: قامت هذه المراجعة المنهجية بتحليل الأدبيات من عام 2000 إلى 2023، باستخدام قواعد بيانات مثل PubMed و Google Scholar و Scopus. تضمنت الكلمات الرئيسية "تسوس الأسنان"، "الذكاء الاصطناعي"، "التعلم الآلي"، و"التشخيص". تم تضمين الدراسات التي تناولت النماذج المعتمدة على الذكاء الاصطناعي للكشف عن تسوس الأسنان أو تشخيصه أو توقعه.

النتائج: حددت المراجعة عددًا من نماذج الذكاء الاصطناعي التي أظهرت دقة متفوقة في تشخيص تسوس الأسنان مقارنةً بالطرق التقليدية. على سبيل المثال، حققت خوارزميات التعلم العميق دقة تتراوح بين 73.3% و 98.8%، مع حساسية وخصوصية عالية عبر مجموعات بيانات متنوعة. لوحظ أن تطبيقات الذكاء الاصطناعي تقلل بشكل كبير من النتائج السلبية الكاذبة وتعزز الكشف المبكر عن التسوس، مما يحسن نتائج المرضى ويقلل من تكاليف الرعاية الصحية.

الاستنتاج: تمثل نماذج الذكاء الاصطناعي نهجًا محوريًا للكشف والتشخيص عن تسوس الأسنان، مما يوفر دقة وكفاءة محسنتين. يمكن أن يساعد دمج هذه التقنيات في الممارسة السريرية المتخصصين في طب الأسنان في اتخاذ قرارات أكثر استنارة، مما يحسن جودة العلاج. ومع ذلك، فإن التباين في أحجام وخصائص مجموعات البيانات يتطلب مزيدًا من البحث لتحسين أداء الذكاء الاصطناعي وقابلية تعميمه عبر السكان المتنوعين.

الكلمات المفتاحية: تسوس الأسنان، الذكاء الاصطناعي، التشخيص، التعلم الآلي، مراجعة منهجية.