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Website: ijcs.stmikindonesia.ac.id | E-mail: ijcs@stmikindonesia.ac.id

Artificial Intelligence for Caries and Tooth Detection in Dental Imaging: A Review

Almonzer Salah Nooraldaim [1,2], Adil Ali Saed[2]
almonzer40@hotmail.com, adilAfr@iua.edu.sd
[1]Department of Computer Science, Faculty of Electronics & Informatics, Xian Jiaotong University, China
[2]Department of Computer Science, International University of Africa, Sudan

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Abstract

This review delves into the application of artificial intelligence (AI) and deep learning, particularly leveraging convolutional neural networks (CNNs), to enhance dental diagnostics and treatment planning. The primary focus is on the detection and classification of caries as well as the identification of teeth in diverse dental images. A thorough exploration was conducted across databases, including PubMed, IEEE Xplore, and arXiv.org, leading to the identification of 29 pertinent studies. These studies employ various neural network models, encompassing different dental image types and employing diverse performance metrics. The review succinctly outlines the key characteristics and outcomes of these studies, underscoring the remarkable accuracy and the promising potential of AI-driven approaches in the realms of caries detection and tooth identification.

Acknowledging the existing limitations within the current body of research, such as small or non-representative datasets, variations in imaging techniques, and a lack of interpretability in deep learning models, the review emphasizes the need for future investigations. It suggests potential research directions aimed at overcoming these challenges, thereby facilitating the seamless integration of AI into routine dental practices.

A. Introduction

Artificial intelligence (AI) is increasingly being adopted in the healthcare industry to enhance patient outcomes[1], streamline clinical workflows, and reduce healthcare costs[2]. In medical imaging[3], AI algorithms have been developed to detect and diagnose various diseases, including cancer and cardiovascular conditions, using data from imaging modalities such as X-ray, MRI, and CT scans. These AI-powered algorithms aid in accurately interpreting medical images, enabling early detection and timely treatment[4].

Clinical decision support systems (CDSS) powered by AI have also been developed to assist healthcare professionals in making informed decisions[5]. By analyzing large volumes of patient data, such as electronic health records, laboratory results[6], and medical imaging scans, these systems provide evidence-based recommendations for diagnosis and treatment planning[7]. Integrating AI into clinical workflows holds tremendous potential for improving healthcare delivery and patient outcomes[8]. Furthermore, AI is revolutionizing the field of drug discovery and development. By analyzing vast molecular structure datasets, AI algorithms can predict compounds' properties and potential applications, expediting drug discovery and leading to more efficient development of new therapeutics[9].

Integrating AI in dentistry holds significant potential for enhancing diagnostic accuracy, treatment planning, and workflow efficiency[10]. By leveraging AI algorithms, dental professionals can make more informed decisions and provide optimal care to patients. However, addressing ethical and regulatory considerations is essential to ensure AI's safe, responsible, and equitable use in dentistry[11]. In dentistry, a promising area known as dental informatics is emerging. Dental informatics leverages computer programs and advanced technologies to enhance treatment and diagnosis, improve workflow efficiency, and reduce the burden on dental professionals[12]. Dental practices generate vast data from sources such as high-resolution dental imaging, continuous biosensor outputs, and electronic dental records[13]. AI-based computer programs can assist dental professionals in making decisions related to prevention, diagnosis, treatment planning, and other aspects of dental care[14].

Convolutional neural networks (CNNs), a type of AI algorithm, have shown promising applications in dentistry[15]. They have been utilized for tasks such as detecting periodontal bone loss[16], identifying caries in bitewing radiographs[17], and classifying various dental conditions in medical images[18]. CNNs detect, classify, and segment dental structures such as teeth and caries[19]. However, to achieve optimal performance, these neural networks need to be trained and optimized using large databases of dental images[20].

Different types of dental images serve specific purposes in dental diagnostics[21]. Periapical images capture complete teeth[22], including anterior and posterior regions and surrounding bone. These images are valuable for detecting caries, assessing periodontal bone loss, and diagnosing periapical diseases. Bitewing images, on the other hand, focus on visualizing the crowns of posterior teeth, offering a more straightforward layout and fewer overlapping structures[17]. They are beneficial for detecting caries in the interproximal regions. Panoramic radiographs are widely used in dentistry to provide an overview of a broader anatomical region with relatively low radiation exposure[23].

This literature review provides a comprehensive overview of the current state of artificial intelligence (AI) applications in dentistry, explicitly focusing on caries detection and tooth identification. It examines the advancements in AI technologies and their potential impact on improving dental diagnostics and treatment planning. By leveraging AI algorithms and machine learning techniques, dental professionals can benefit from automated and accurate caries detection systems, enabling early intervention and preventive measures. Additionally, AI-based approaches can assist in tooth detection tasks, streamlining treatment planning processes and enhancing overall dental care outcomes. The review highlights the integration of AI algorithms with dental imaging technologies. It emphasizes the need for ethical considerations and robust validation studies to ensure AI's safe and responsible implementation in dentistry. Overall, this literature review provides valuable insights into the current progress and future directions of AI applications in caries detection and tooth identification, contributing to the advancement of dental practice.

B. Research Method

On May 16, 2023, an extensive exploration was conducted utilizing electronic databases, namely MEDLINE/PubMed, Institute of Electrical and Electronics Engineers (IEEE) Xplore, and arXiv.org. MEDLINE/PubMed served as the primary repository for medical journal manuscripts, while IEEE Xplore was focused on publications in computer science, electrical engineering, and electronics. Additionally, arXiv.org, an electronic archive, contained pertinent scientific manuscripts in physics, computer science, and mathematics. The search methodology outlined in Table 1 was applied to identify studies relevant to this review. Inclusion criteria encompassed full manuscripts and conference proceedings that specifically reported the utilization of neural networks for teeth and caries detection, without any language or publication date constraints. Exclusion criteria involved reviews, studies unrelated to dental applications, and those lacking neural networks in their methodology.

Table 1. Search strategy.

Database	**Search Strategy**	**Search Data**
MEDLINE/PubMed/ IEEE Xplore	(Deep learning OR artificial intelligence OR neural network *) AND (dentistry OR dental carries or dental tooth) OR “Full Text Only”: artificial intelligence) OR “Full Text Only”: neural network)	May 16, 2023

C. Relevant Data of Included Studies:

The selected manuscripts included in this review were published from 2013 to 2022. Table 2 and Table 3 provide an overview of the critical characteristics of these studies of carries and detection of teeth. As shown in Table 1 and Table 2, the number of published studies increased yearly. The selected studies were conducted in twelve countries, with the highest studies conducted in China (n =6) and the United States (n = 4).

D. Caries Detection

In the research conducted by Casalengo and colleagues, a deep learning model was applied to detect dental lesions in near-infrared transillumination images of molars and premolars. Their study, based on 217 images, achieved an area under the curve (AUC) of 85.6% for proximal lesions and 83.6% for occlusal lesions [24]. Similarly, Zanella-Calzada et al. utilized an Artificial Neural Network (ANN) to analyze caries in relation to socioeconomic and dietary factors, achieving an accuracy of approximately 0.69 and an AUC of 0.75 with their model [25]. Srivasta and colleagues employed a deep, fully convolutional neural network to detect dental caries in 3000 bitewing images, achieving a recall of 0.805, a precision of 0.615, and an F1-score of 0.7 [26].

Prajapati et al. utilized a convolutional neural network for caries detection in 251 radiovisiography images, reaching an accuracy of 0.875 [27]. Geetha et al. used a back-propagation neural network on 105 intra-oral images, achieving an accuracy of 0.971 and a high precision-recall curve area of 0.987 [28]. In another study, a fully convolutional neural network was employed for proximal caries detection and compared against traditional dentist evaluation methods. The study involving 22 dentists revealed significantly higher mean area under the Receiver-Operating Characteristics curve (0.89; 95% CI: 0.87–0.90) for dentists using AI compared to traditional methods [29].

A diagnostic study involving 2,417 photographs utilized convolutional neural networks (CNNs) for caries detection and categorization. The CNN approach demonstrated a high accuracy of 92.5% in detecting caries, showcasing its comparable performance to expert standards [30]. Additionally, a U-shaped deep convolutional neural network (CNN) model was developed for early dental caries detection in bitewing radiographs. This model achieved a precision of 63.29%, recall of 65.02%, and an F1-score of 64.14%, indicating its potential in assisting clinicians with caries detection [31].

Furthermore, deep learning techniques were employed to detect and classify caries lesions on panoramic radiographs. The results showed an intersection over union (IoU) value of 0.785 and an accuracy and recall rate of 0.986 and 0.821, respectively [32]

In a novel approach, researchers combined image processing techniques with Convolutional Neural Networks (CNNs) to identify and classify proximal dental caries in bitewing radiographic images. This groundbreaking method achieved an impressive accuracy rate of 73.3%, showcasing its potential to enhance the detection and categorization of dental caries, thus supporting early diagnosis and treatment planning [33]. Furthermore, another study[34] introduced an innovative classification and segmentation model specifically designed for endoscope images obtained from patients at the Department of Stomatology, People's Liberation Army General Hospital. Employing deep convolutional neural networks, the researchers trained the model using 194 non-caries images and 1,059 images depicting permanent molar and premolar caries. The model's evaluation demonstrated a mean area under the curve (AUC) of 0.9897, with a 90% confidence interval ranging from 0.9821 to 0.9956. This outcome underscores the high accuracy of the model in classifying and segmenting caries in endoscope images, showcasing the significant potential of deep learning techniques in advancing the analysis and diagnosis of dental conditions through endoscopic imaging.

In one study conducted by[35] , the focus was on detecting proximal caries at varying severity levels in periapical radiographs through the use of Convolutional Neural Networks (CNNs). Their dataset, consisting of around 800 randomly selected periapical radiographs, underwent different training approaches, including image recognition (IR), edge extraction (EE), and image segmentation (IS). The evaluation metrics, specifically the area under the curve (AUC), yielded values of 0.805, 0.860, and 0.549 for IR, EE, and IS, respectively. These outcomes underscore the efficacy of CNNs in proximal caries detection while highlighting the influence of different training strategies on model performance. In a separate study by , 844 periapical radiographs were employed for analysis. Among these, 717 radiographs (85%) were used for training, and the remaining 127 (15%) were allocated for testing three distinct convolutional neural networks (CNNs) – VGG19, Inception V3, and ResNet18. The results demonstrated the superiority of the ResNet18 CNN over VGG19 and Inception V3, as well as over comparator dentists. The ResNet18 CNN exhibited an accuracy of 0.82 and an AUC of 0.89, confirming its effectiveness in precise radiographic image classification, further emphasizing the reliability of this model in analyzing periapical radiographs. In the study conducted [36] , a dataset comprising 3000 periapical radiographic images was utilized. This dataset was partitioned into a training and validation set (2400 images, 80%) and a test set (600 images, 20%). Leveraging the pre-trained Google Net Inception v3 CNN network for preprocessing and transfer learning, the developed models demonstrated robust diagnostic accuracy for premolar, molar, and combined premolar and molar cases. Specifically, the premolar model achieved an accuracy of 89.0% (CI: 80.4-93.3) and an AUC of 0.917 (CI: 0.860-0.975), while the molar model achieved an accuracy of 88.0% (CI: 79.2-93.1) and an AUC of 0.890 (CI: 0.819-0.961). The combined premolar and molar model displayed an accuracy of 82.0% (CI: 75.5-87.1) and an AUC of 0.845 (CI: 0.790-0.901). These findings underscore the efficacy of deep CNN algorithms in accurately classifying periapical radiographic images and evaluating diverse dental conditions.

In a recent study by [37] , a deep convolutional neural network (CNN) was developed to diagnose interproximal caries lesions in digital bitewing radiographs. Using a dataset of 1,000 radiographs and advanced data augmentation techniques, the CNN model demonstrated remarkable accuracy. Specifically, the model achieved an overall accuracy of 94.59%, with specific accuracies of 94.19% for premolars and 94.97% for molars. Furthermore, the model exhibited an impressive overall area under the curve (AUC) of 87.19%, underscoring its effectiveness in accurately identifying interproximal caries lesions in digital bitewing radiographs.

In [38] , a web-based AI program achieved an AUC of 0.777 in accurately detecting interproximal caries in 300 bitewing radiographs. Similarly, Schwendicke et al. (2020) employed Resnet18 and Restext50 CNNs to predict caries on extracted human teeth using NILT images, obtaining an AUC of 0.74.

These findings demonstrate the promising accuracy of AI-based approaches in caries detection, highlighting their potential in dental diagnostics.

Table 2. Carries Detection Main Characteristics.

AUTHORS	JOURNAL	COUNTRY, YEAR	IMAGE	TOTAL IMAGE	NEURAL NETWORK	OUTCOME
Sarah Mertens	Journal of Dentistry	Germany,2021	bitewings	140	CNN	AUC
Zanella-Calzada	Bioengineering	Switzerland, 2018		9812	ANN	ACCURACY/AUC
J. Kühnisch	Journal of Dental Research	Germany,2021	photographs	2,417	CNN	ROI/AUC
Prajapati et al.	5th International Symposium on Computational and Business Intelligence	United Arab Emirates, 2017	Radiovisiography image	251	CNN	ACCURACY
Shinae Lee	Scientific Report	Korea,2021	bitewing	304	CNN	ACCURACY/PRECISION RECALL
Geetha et al.	Health Information Science and Systems	Switzerland, 2020	Intraoral radiographs	105	BACK-PROPAGATION NEURAL NETWORK	ACCURACY/ PRECISION RECALL
Xiaoyi	Annals of Translational Medicine	China,2022		1,059	CNN	ACCURACY/AUC
Casalengo et al.	Journal of Dental Research	USA, 2019	Near-infrared transillumination	217	CNNS FOR SEMANTIC SEGMENTATION	AUC
Luya Lian	MDPI stays neutral	China,2021	panoramic	1160	CNN	ACCURACY
Srivastava et al.	NIPS 2017 workshop on Machine Learning for Health (NIPS 2017 ML4H)	USA, 2017	Bitewing	3000	DEEP, FULLY CONVOLUTIONAL NEURAL NETWORK	RECALL/PRECISION/F1-SCORE
Xiujiao Lin	MDPI stays neutral	China,2022	periapical	800	CNN	AUC
Schwendicke et al.	Journal of Dentistry	England, 2019	Near-infrared light transillumination	226	RESNET18 RESNEXT50	AUC/SENSITIVITY/SPECIFICITY
Maira Moran	MDPI stays neutral	Brazil,2022	bitewing	112	CNN	ACCURACY
Liwen Zheng	Annals of Translational Medicine	China 2021	periapical	844	CNN	ACCURACY /AUC

Jae-Hong Lee	Elsevier	Korea 2018	periapical	3000	CNN	ACCURACY /AUC
Yusuf Bayraktar	Springer	Turkey2021	Bitewing	1,000	CNN (THE YOLO ALGORITHM IS USED)	ACCURACY /AUC
García Ángel	Karger	Spain 2022	bitewing	300	CNN	ACCURACY /AUC

E. Tooth Detection

Utilized a deep convolutional neural network (DCNN) based on AlexNet architecture for tooth type classification in dental cone-beam computed tomography (CT) images. Their study, using 42 training images and 10 testing images, achieved an accuracy exceeding 80%[39]. Zhang et al, focused on periapical images, employing faster-RCNN and region-based fully convolutional networks (R-FCN) with 700 training images, 200 testing images, and 100 validation images. Their method demonstrated high precision (approximately 95.8%) and a recall of 0.961.[40]. compared radial basis function neural network (RBFNN) and GAME neural network efficiencies in predicting the age of the Czech population (3-17 years) from panoramic X-rays of 1393 individuals, using standard deviation for evaluation. [41]. Muramatsu et al. employed a four-fold cross-validation approach with 100 dental panoramic radiographs, achieving a tooth detection sensitivity of 96.4% and 93.2% accuracy[42]. Oktay employed an AlexNet-based architecture on 100 panoramic radiographs, achieving over 0.92 accuracy in tooth detection, varying based on tooth type.[43].This study[44] utilized Artificial Neural Networks (ANNs) to classify dental tooth cusps, integrating this technology into dental workflows. Analyzing 3D images from 69 patients, their ANN model exhibited impressive accuracy, achieving classification accuracy rates of 93.3% and 93.5% for tooth cusps identification.

Guo et al.[45] proposed a novel methodology for crack detection in images, utilizing a deep CNN classifier and a sliding window algorithm. Their CNN model, inspired by ResNet50 architecture, was optimized with modified input layer dimensions and a fully connected layer of 2 units. With a dataset of 20,000 images at 1920 × 1080 pixels resolution, the model achieved an impressive accuracy of 90.39%. This study highlights the effectiveness of deep CNNs in precise and efficient crack detection, promising advancements in image analysis applications. In a study by [46] a pioneering approach for dental radiograph analysis was introduced using convolutional neural networks (CNNs). Their model, enhanced with VGG-16 CNN architecture, was trained on a dataset comprising 1352 panoramic radiographs of adult patients. The results demonstrated exceptional performance, with a sensitivity of 0.9941 and precision of 0.9945. This research underscores the potential of CNNs in dental radiograph analysis, offering valuable insights for the progression of clinical applications in the field.

In a study by[47] , a deep neural network approach was developed to automatically detect natural teeth and dental treatment patterns in dental panoramic radiographs. Analyzing 1638 images spanning from January 2000 to November 2020, the method achieved remarkable results with an average precision of 99.1% for natural teeth, 80.6% for prostheses, 81.2% for treated root canals, and 96.8% for implants. Corresponding recall values were equally high, indicating the effectiveness of this approach in accurately identifying dental structures and treatment patterns in panoramic radiographs. Chen et al.[22] focused on developing an auxiliary diagnostic system for dental periapical radiographs using deep convolutional neural networks. Their study incorporated various training strategies with a dataset comprising 2900 digital dental periapical radiographs. The precision and recall values for different disease categories ranged between 0.5 and 0.6, showcasing the potential of this deep convolutional neural network-based system as a supportive tool for diagnosing dental conditions based on periapical radiographs. In another approach, Prados-Privado et al[48] proposed an automated method utilizing convolutional neural networks (CNNs) to analyze panoramic radiographs. Their study involved a dataset of 8000 panoramic images, employing ResNet101 in the classification layer of the CNN. The approach achieved an impressive accuracy rate of 99.24%, indicating the potential of the proposed CNN-based method for accurate analysis and interpretation of panoramic radiographs. Jader et al. [49]. employed a Mask R-CNN in their study to extract tool profiles from 1500 panoramic X-ray radiographs. Their method exhibited high performance metrics, including accuracy (0.98), F1-score (0.88), precision (0.94), recall (0.84), and specificity (0.99). These results highlight the accuracy and effectiveness of their approach in the precise detection of tool profiles in panoramic radiographs.

Table 3. Tooth Detection Main Characteristics.

AUTHORS	JOURNAL	COUNTRY, YEAR	IMAGE	TOTAL IMAGE	NEURAL NETWORK	OUTCOME
Oktay, A	IEEE	Turkey, 2017	Panoramic	100	AlexNet	Accuracy
Muramatsu et al.	Oral Radiology	Japan, 2020	Panoramic	100	Object detection network using fourfold cross-validation method	Sensitivity/Accuracy
Velemínská et al	Anthropologischer Anzeige	Germany, 2013	Panoramic	1393	RBFNN GAME	Accuracy
Miki et al	Computers in Biology and Medicine	USA, 2017	Cone-beam computed tomography	52	AlexNet	Accuracy
Jader et al.	IEEE	Brazil, 2018	Panoramic	1500	Mask R-CNN	Accuracy
Zhang et al	Computerized Medical Imaging and Graphics	USA, 2018	Periapical	700	Faster-RCNN/ region-based fully convolutional networks (R-FCN	Precision
Stefan Raith et al.	Elsevier(Computers in Biology and Medicine)	Germany 2016	3D images	69	ANNs	Accuracy

Juncheng	Applied Bionics and Biomechanics	China 2022		20,000	CNN	Accuracy
Dmitry	Dentomaxillofacial Radiology	Russia 2019	panoramic	1352	CNN	Accuracy
Hye-Ran	Forensic sciences research	Korea 2022	panoramic	1638	CNN	precision /recall
Hu Chen	International Journal of Computer-Assisted Radiology and Surgery	China 2021	periapical	2900	Deep convolutional neural networks	precision /recall
María	BioMed Research International	Spain 2021	panoramic	8000	CNN	Accuracy

F. Discussion

Caries detection is a critical aspect of dental diagnosis and treatment planning. Traditional caries detection methods rely heavily on dentists' visual inspection and radiographic examination, which can be subjective and time-consuming. In recent years, the application of artificial intelligence (AI) and deep learning techniques, particularly convolutional neural networks (CNN), has shown great promise in enhancing the accuracy and efficiency of caries detection. Several studies have utilized deep learning models, specifically convolutional neural networks (CNNs), to detect and classify dental caries in various imaging modalities, such as near infrared transillumination, radiographs, and endoscope images. The performance of these models has been compared to traditional methods and expert dentists' evaluations to assess their diagnostic accuracy and potential for enhancing dental diagnostic practices.

Casalengo et al.[7]employed a deep-learning model to detect dental lesions in near-infrared transillumination images. Their model achieved an area under the curve (AUC) of 85.6% for proximal lesions and 83.6% for occlusal lesions. This indicates a good performance in identifying and localizing caries in these images. Zanella-Calzada et al. [8] analyzed caries concerning socioeconomic and dietary factors using an artificial neural network (ANN). Their ANN model achieved an accuracy of approximately 0.69 and an AUC of 0.75. While the accuracy is moderate, the AUC suggests a reasonable ability to discriminate between caries and non-caries cases. Srivasta et al. [9] developed a fully convolutional neural network to detect dental caries in bitewing images. Their model achieved a recall of 0.805, precision of 0.615, and F1-score of 0.7. These metrics indicate relatively good performance in identifying caries cases while considering sensitivity and precision. Prajapati et al. [10] used a convolutional neural network to detect caries in radiovisiography images. Their model achieved an accuracy of 0.875, indicating a high level of correct classification. However, additional metrics such as sensitivity and specificity were not reported. Geetha et al. [11] employed a back-propagation neural network to detect caries in intra-oral images, achieving an accuracy of 0.971 and a high precision-recall curve (PRC) area of 0.987. These results demonstrate high accuracy and precision in caries detection using this neural network approach.

In a cluster-randomized cross-over controlled trial, a fully convolutional neural network was compared to traditional methods of dentist evaluation for detecting proximal caries in bitewing images[12]. Dentists using AI achieved a significantly higher mean AUC (0.89) than conventional methods. This highlights the potential of AI-based approaches in enhancing caries detection accuracy and improving dental diagnostic practices. Another study [13]compared a CNN approach with expert standards in detecting and categorizing caries using a dataset of 2,417 photographs. The CNN approach achieved a high accuracy of 92.5% in detecting caries across all test images. When considering caries-related cavitation, 93.3% of tooth surfaces were accurately classified. These results demonstrate the promising potential of CNN-based approaches and their comparable performance to expert standards. A U-shaped deep CNN model was developed for the early detection of dental caries in bitewing radiographs[14]. The model achieved a precision of 63.29%, recall of 65.02%, and F1-score of 64.14%, indicating its potential to assist clinicians with caries detection and improving overall diagnostic accuracy. Deep learning techniques were employed for detecting and classifying caries lesions on panoramic radiographs[15]. The convolutional neural network achieved an IoU value of 0.785 and a Dice coefficient value of 0.663 for caries lesion segmentation. Miki et al. [24]used a DCNN with an AlexNet architecture to classify tooth types in dental cone-beam computed tomography (CT) images. They achieved a high accuracy above 80% in tooth classification, indicating the effectiveness of their model. Zhang et al. [25]focused on periapical images and employed faster-RCNN and region-based fully convolutional networks (R-FCN). Their proposed method achieved a high precision of approximately 95.8% and a recall of 0.961, demonstrating the potential of these models' inaccurate classification. Velemínská et al. [26]compared the efficiencies of a radial basis function neural network (RBFNN) and a GAME neural network in predicting the age of individuals using panoramic X-rays. The performance of the neural networks was evaluated using the standard deviation. This study highlights the application of neural networks in age prediction using dental imaging. Muramatsu et al. [27]utilized a four-fold cross-validation method and dental panoramic radiographs to detect teeth. They achieved a high tooth detection sensitivity of 96.4% and an accuracy of 93.2%, indicating the effectiveness of their approach.

Oktay [28]employed an AlexNet architecture to detect teeth in panoramic radiographs with an accuracy of over 0.92. The accuracy varied depending on the type of tooth (molar, incisor, and premolars), demonstrating the potential of deep learning models in tooth detection. This study [29]used artificial neural networks (ANNs) to classify dental tooth cusps based on 3D images. The developed ANN model achieved a classification accuracy of 93.3% and 93.5%, demonstrating its effectiveness in accurately identifying tooth cusps. This study emphasizes the integration of ANNs into dental workflows. This article [30] proposed a methodology for image crack detection using a deep CNN classifier. The CNN model exhibited a remarkable accuracy of 90.39% in crack detection, indicating its potential for enhancing image analysis applications. Another study [31]focused on dental radiograph analysis using

CNNs. The model achieved remarkable performance metrics by integrating the VGG-16 CNN architecture, including a sensitivity of 0.9941 and a precision of 0.9945. This study demonstrates the potential of CNNs in dental radiograph analysis. The study [32] presented a deep neural network approach for automatically detecting natural teeth and dental treatment patterns in panoramic radiographs. The proposed method achieved impressive precision and recall values, highlighting its efficacy in accurately identifying dental structures and treatment patterns. A deep convolutional neural network-based system was developed for analyzing dental periapical radiographs in this study[33]. The system showed potential in identifying different disease categories and severity levels based on periapical radiographs. Lastly, a study [34]proposed an automated approach using CNNs for analyzing panoramic radiographs. The CNN model with ResNet101 achieved an impressive accuracy rate of 99.24%, indicating its potential for accurate analysis and interpretation of panoramic radiographs. One of the primary limitations could be using a limited dataset. The effectiveness of deep learning models heavily relies on the quantity and diversity of the dataset used for training. If the study has a small or unrepresentative dataset in terms of demographics, imaging modalities, or severity levels of caries, the generalizability of the results may be compromised. Another limitation to consider is the variability in imaging techniques. Different imaging modalities, such as periapical, bitewings, or panoramic radiographs, may exhibit image quality, resolution, and positioning variations. These variations can significantly impact the performance of deep learning models. If the study does not account for or validate the models across different imaging techniques, the applicability of the results may be limited to specific imaging modalities. In the future, addressing the limitations of deep learning models in caries studies could involve expanding and diversifying the dataset, standardizing imaging techniques, optimizing the model, and validating it in a real-world clinical setting. This would enhance the model's performance and applicability, ensuring it is effective across various demographics, imaging modalities, and caries severity levels. The continual evolution of the deep learning field opens up exciting possibilities for advancements in caries research.

G. Conclusions

The study on caries detection and tooth detection using deep learning models shows promising results for their application in dental diagnostics. The models exhibited high accuracy in identifying caries and locating teeth, offering valuable assistance to dentists in clinical settings. However, the study's limitations, such as the small sample size and limited dataset diversity, should be acknowledged, and future research should address these shortcomings. Additionally, further investigations are needed to enhance the interpretability of the deep learning models and develop explainable algorithms. Nevertheless, this study lays a foundation for future dental imaging and diagnostics advancements, potentially leading to more accurate diagnoses, improved treatment planning, and streamlined dental care

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I. References

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