

Deep learning convolutional neural network algorithms for the early detection and diagnosis of dental caries on periapical radiographs: A systematic review

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ABSTRACT

Purpose: The aim of this study was to analyse and review deep learning convolutional neural networks for detecting and diagnosing early-stage dental caries on periapical radiographs.

Materials and Methods: In order to conduct this review, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed. Studies published from 2015 to 2021 under the keywords (deep convolutional neural network) AND (caries), (deep learning caries) AND (convolutional neural network) AND (caries) were systematically reviewed.

Results: When dental caries is improperly diagnosed, the lesion may eventually invade the enamel, dentin, and pulp tissue, leading to loss of tooth function. Rapid and precise detection and diagnosis are vital for implementing appropriate prevention and treatment of dental caries. Radiography and intraoral images are considered to play a vital role in detecting dental caries; nevertheless, studies have shown that 20% of suspicious areas are mistakenly diagnosed as dental caries using this technique; hence, diagnosis via radiography alone without an objective assessment is inaccurate. Identifying caries with a deep convolutional neural network-based detector enables the operator to distinguish changes in the location and morphological features of dental caries lesions. Deep learning algorithms have broader and more profound layers and are continually being developed, remarkably enhancing their precision in detecting and segmenting objects.

Conclusion: Clinical applications of deep learning convolutional neural networks in the dental field have shown significant accuracy in detecting and diagnosing dental caries, and these models hold promise in supporting dental practitioners to improve patient outcomes. (*Imaging Sci Dent 2021; 51: 237-42*)

KEY WORDS: Deep Learning; Neural Network Models; Dental Caries; Radiography, Dental

Introduction

The Fourth Industrial Revolution is expected to lead to widespread, sophisticated improvements in quality of life compared to previous industrial revolutions. Specifically,

the medical and life sciences are expected to be a vital part of this revolution. Dental caries is well-known as the most prevalent chronic infection, occurring in about 90% of the global population and therefore affecting the lives of many people throughout the world.^{1,2}

A vast majority of studies have shown that people from disadvantaged and socially marginalized population groups have a greater risk of dental caries.¹ This trend poses a critical problem; according to the World Health Organization, oral diseases are the fourth most expensive condition to treat in industrialized countries.^{2,3} Moreover, many studies

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have documented that tooth loss originating from oral disease, including dental caries, is related to detrimental changes in the diet and is a risk indicator for cognitive impairment and cardiovascular disease.¹ Zanella-Calzada et al.² stated that according to the *Organización Panamericana de la Salud* (OPS), the development of dental caries is associated with carbohydrate consumption frequency, food characteristics, time of exposure, plaque removal, and host susceptibility.

Rapid and precise detection and diagnosis are vital for implementing appropriate prevention and treatment of dental caries. If dental caries is improperly diagnosed, the lesion may eventually invade the enamel, dentin, and pulp tissue, causing immense pain.¹ The standard method for caries detection is carried out with the help of a dental probe and relies heavily on observation using the naked eye. Hence, it is considered to be effective only for the detection of extensive, visible caries.³ Radiographs have been used to visualize caries, periodontal bone loss, and periapical diseases, but enamel caries can only be detected using this method when more than half of the enamel width has been affected. Moreover, radiography settings, including brightness, shadow, and contrast, can make it difficult to identify dental caries without an objective assessment.¹

Numerous methods for detecting and diagnosing dental caries are being developed to overcome limitations in the clinical and radiographic diagnosis, such as fibre-optic trans-illumination (FOTI) and ultrasonic caries detectors. Proximal caries can be easily spotted using bitewing radiographs and FOTI. However, bitewing radiographs have a low diagnostic yield for early dental carious lesions, and FOTI similarly shows low diagnostic sensitivity.¹ Ultrasound devices are known to be highly responsive to proximal caries, but can only detect caries after a certain extent of destruction in the enamel and dentin structures has occurred.^{1,4}

Periapical radiography is a commonly used intraoral

imaging technique that can capture several teeth. The entire crown and root of the teeth can be observed, which provides vital information to aid the diagnosis of most dental diseases.⁵ Unusual dark regions in tooth crowns are usually classified as dental caries since dental bacteria destroy solid healthy tissues. Nevertheless, dark areas in images are present even in healthy parts of the teeth as a result of uneven X-ray exposure, varying sensitivity of the receiver sensor, and natural variability in the density or thickness of the tooth; hence, over 20% of non-carious lesions are incorrectly diagnosed as caries.^{1,6}

Convolutional neural networks (CNNs) are a type of deep learning algorithm that has shown a remarkable potential to assist doctors in many fields, such as dermatology, ophthalmology, and radiology.^{7,8} In radiology and intraoral imaging, CNNs take an input image to detect structures and pathologies (e.g., caries lesions on teeth), assign importance to various aspects/objects in the image (e.g., identifying the exact shape of the tooth or pathology in an image), and differentiate one tooth from the other (e.g., separating each tooth in the dentition, distinguishing acquired enamel and developmental enamel white spot lesions from each other).^{7,9-12} The diagnostic accuracy of CNNs in the dental field comes close to human competence levels.^{2,5} These abilities have facilitated the integration of computer-assisted diagnosis into the workflow of medical practitioners.^{2,9}

Materials and Methods

This review was done following the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) guidelines, which help authors conduct a literature search and write a systematic review from the wording of the title to the conclusion.

PubMed MEDLINE, SpringerLink, and Google Scholar were explored using the keywords [(deep convolutional

Table 1. Eligibility criteria

Category	Inclusion criteria	Exclusion criteria
Participant characteristics	Permanent teeth, deciduous teeth	Studies that discuss dental diseases other than caries
Intervention	A deep learning CNN using intraoral images	Other artificial intelligence besides deep learning CNN, Caries evaluation using panoramic, bitewing, and occlusal radiographs
Comparison	Radiograph interpretation by an expert clinician	
Outcome	Evaluation of a deep learning CNN in caries detection	
Study design	Clinical trials, journal articles	Reviews, systematic reviews

CNN: convolutional neural network

neural network) AND (caries)], [(deep learning caries) AND (convolutional neural network) AND (caries)]. Only studies published in English from 2015 to 2021 were reviewed.

Qualified studies were chosen according to inclusion/exclusion criteria that were predetermined following the participant-intervention-comparison-outcome-study design (PICOS) schema, as presented in Table 1. The PICOS schema is commonly used for studies of evidence-based medicine to improve the critical appraisal of the selected literature. The authors included only clinical trials and excluded reviews in order to avoid attrition bias.

Results

The search yielded 248 articles, of which 243 remained after removing duplicates and checking the titles and abstracts. Five articles met the pre-established criteria. The flow diagram of the systematic review is presented in Figure 1.

Overall, the studies included 4,725 periapical radiographs and 4,020 intraoral images. The clinical studies are presented in Table 2 below.

In 2018, Lee et al.¹ investigated 3,000 periapical radiographs consisting of 778 maxillary premolars, 769 maxillary molars, 722 mandibular premolars, and 731 mandibular molars. In the study, 719 (26.1%) premolars and 728 (24.3%) molars were determined not to have dental caries, and 781 (23.9%) premolars and 771 (25.7%) molars were classified as having dental caries. Diagnostic precision, sensitivity, specificity, the positive predictive value, and the negative predictive value were evaluated. *P*-values < 0.05 were considered to indicate statistical significance, and 95% confidence intervals (CIs) were calculated. The results of the study are listed in Table 3.¹⁰

Ali et al.,¹³ in a study published in 2016, identified tooth photographs with deep neural networks using the stacked sparse auto-encoders framework. This method used multiple hidden layers, which were able to overcome classification issues with complex data. Each layer was able to read characteristics at various levels of abstraction. There were two possible marks for each photograph: decayed or normal. The qualitative results of the deep CNN showed excellent performance, with an accuracy as high as 97%, as seen in Table 4.

Choi et al.⁶ in 2016 investigated 475 periapical images using a combination of CNN and crown extraction. Their procedure involved horizontal alignment of the pictured

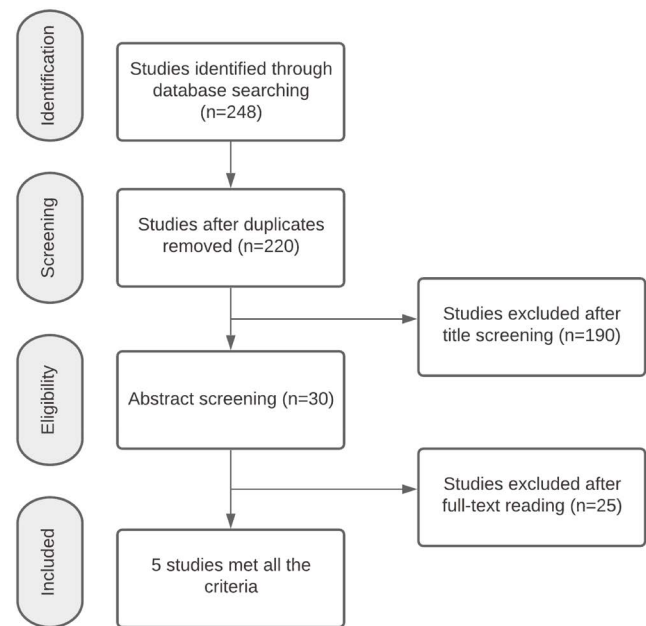


Fig. 1. Conceptual framework of study selection.

Table 2. Characteristics of each study

Author (year of publication)	Architecture	Number of training data	Advantage (+)/Limitation (-)
Ali et al. ¹³ (2016)	Stacked sparse auto-encoders	1,250	(+) comparison of annotated images with CNN and 3 dentists
Choi et al. ⁶ (2018)	Combination of CNN and crown extraction	475	(+) comparison of annotated images with the radiologist (-) downscaled images, small datasets
Lee et al. ¹⁰ (2018)	GoogLeNet Inception v3	3,000	(+) conventional approach (-) cropped and downscales images
Moutselos et al. ⁴ (2019)	Mask R-CNN	88	(+) this approach was able to detect and classify dental caries across the 7 ICDAS classes, (-) small dataset
Zhang et al. ¹⁴ (in press)	ConvNet	3,932	(+) the model was able to classify and localize the accuracy for locations of predicted dental caries, (-) limited dataset

CNN: convolutional neural network, ICDAS: International Caries Detection and Assessment System

Table 3. Accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) for the detection of dental caries in premolars and molars by Lee et al.¹⁰

Tooth	Accuracy (%, 95% CI)	Sensitivity (%, 95% CI)	Specificity (%, 95% CI)	PPV (%, 95% CI)	NPV (%, 95% CI)
Premolar	89.0 (80.4-93.3)	84.9 (75.4-88.3)	94.0 (85.4-98.3)	93.3 (83.8-98.1)	85.5 (77.7-89.4)
Molar	88.0 (79.2-93.1)	92.3 (83.2-97.1)	84.0 (75.2-89.1)	85.2 (77.0-89.9)	91.3 (81.7-98.8)
Premolar and molar	82.0 (75.5-87.1)	81.0 (74.5-86.1)	83.0 (76.5-88.1)	82.7 (76.1-87.9)	81.4 (75.0-86.4)

Table 4. Qualitative results of the deep convolutional neural network developed by Ali et al.¹³

Accuracy 97%		Target class		
		Tooth decay	Normal tooth	Class precision
Output class	Tooth decay	48%	1%	98%
	Normal tooth	2%	49%	96.1%
	Class recall	96%	98%	

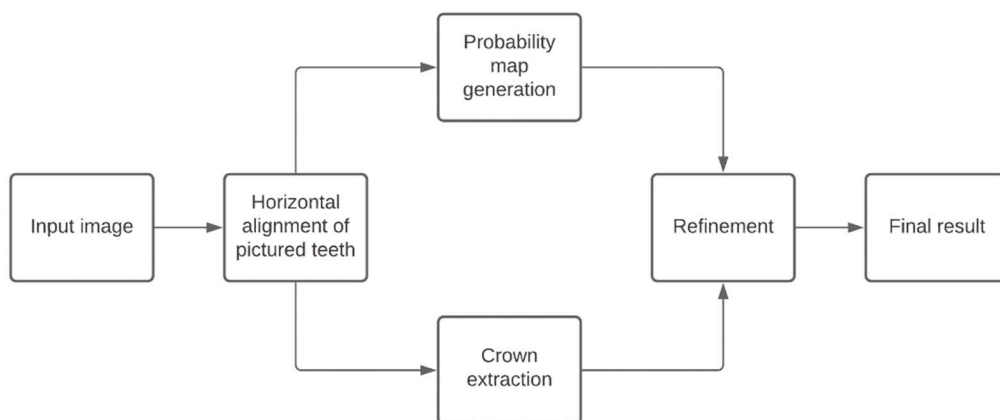


Fig. 2. Block diagram of the proposed methods.⁶

tooth, probability map generation, crown extraction, and refinement. The workflow is shown in Figure 2. The results of the proposed method showed a significant difference between naive CNN alone and the above-mentioned combination of methods.

Seventy-nine dental images for a training dataset and 9 images for validation were tested by Moutselos et al.⁴ in 2019. Images were segmented and classified into homogeneous segments before training using superpixels to reduce computational complexity and make it easier to compare annotations among expert clinicians. Their model was able to detect lesion types in the tested intraoral images. This

model could predict occlusal caries as precisely as interpretation of the images.

Zhang et al.¹⁴ in 2020 developed a ConvNet model for dental caries images taken from phone and manual cameras. In total, 2,507 images were used for the training dataset, and 1,125 others were used for the testing dataset. The sensitivity and specificity were measured. Hard negative mining (M3) was also developed to increase box model sensitivity. The image-wise sensitivity was 81.90% and the box-wise sensitivity was 63.60%. The results showed that M3 had a better capacity for detecting caries and was also effective for improving model performance.

Discussion

Artificial intelligence (AI) is a fast-growing field in medicine. Within the broader category of machine learning, deep learning involves the use of networks with computational layers, as seen in Figure 4.⁷ The emergence of deep learning algorithms, such as CNNs, has offered fascinating results in medical and dental imaging analysis. The term deep learning convolutional neural network or deep neural network (DNN) refers to the application of an artificial neural network (ANN) with multiple layers to analyse visual imagery, assign importance (learnable weights and biases) to various aspects of the image, and distinguish one characteristic from another.^{1,8,15,16} A DNN can perform pattern recognition of images without human intervention. Once the program is established, raw data is processed via non-linear activation functions from shallow to deeper layers; as the layers get deeper, the raw data is translated into characteristics matching the representation of raw data.^{4,7} DNN performs well with large datasets; hence, as much data as possible should be collected and categorized into input data and teaching data. Training using small sample sizes results in a high risk of overfitting.^{7,11} An overview of the deep learning process is presented in Figure 3.

The authors reviewed 5 clinical trials that met the inclusion and exclusion criteria. The studies used relatively small datasets (fewer than 1,000 units per group); however, the reviewed studies' accuracy ranged from 75.5-97%. Deep learning requires a large amount of data because it

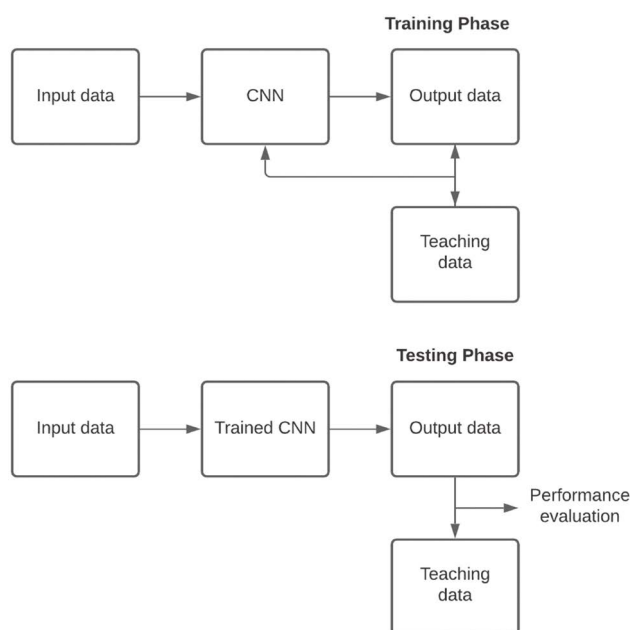


Fig. 3. Overview of a typical deep learning process.⁶

learns features directly from the data via an end-to-end process.³ For this reason, it is important to construct a large-scale dental public dataset to enhance the clinical applications of deep learning.^{10,17,18}

Various architectures were used in this review, such as GoogLeNet Inception v3, stacked sparse auto-encoder, CNN with crown extraction, Mask R-CNN, and ConvNet. Lee et al. showed that the GoogLeNet Inception v3 architecture detected dental caries with high accuracy and efficiency, as shown in Table 3. Despite the small dataset, that study used a high-quality training dataset with dental caries diagnosed by a board-certified dentist, and images were randomly magnified 10 times to avoid overfitting.¹ The stacked sparse auto-encoder framework was used by Ali et al.¹³ to group dental X-ray photographs into decayed or normal images. This method showed a descendant of the network at a finer local minimum than was achieved using the classic approach. This method also gave excellent results, as shown in Table 4. Choi et al.⁶ employed an automatic proximal dental caries detection method using CNN and crown extraction. This method achieved higher performance than a naïve CNN approach (F₁max 0.74 with FPs of 0.88).

Moutselos et al.⁴ researched 88 permanent molars in vivo using Mask R-CNN, which successfully detected caries among the caries classes of the International Caries Detection and Assessment System. However, the research excluded teeth with occlusal sealants; thus, the efficacy of CNN in teeth with a sealed crown or other conditions still remains unexplored. Moutselos's research implemented superpixels in Mask R-CNN, which resulted in a faster identification process and helped correct and solve annotation differences among practitioners. The research team also conducted the imaging without using any pre-processing filters to help detect morphological features of the teeth, indicating the high accuracy of the DNN itself.

Another promising result of DNN-based caries diagnosis

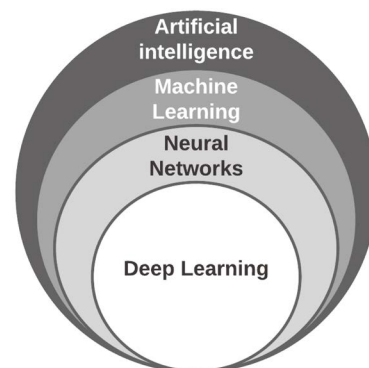


Fig. 4. The basic concepts of artificial intelligence.

was reported by Zhang et al.¹⁴ in 2020. A relatively large dataset of 3,932 photos from patients 14 to 60 years old was examined with ConvNet. This modelling resulted in 81.90% image sensitivity. Consumers' own cameras were used in that study, indicating the success of ConvNet usage among various devices with different camera and image qualities. The researchers also suggested the use of DNN as an inexpensive diagnostic tool for a large population.

This study is limited by the lack of supporting literature, as deep learning studies are still scarce. The reported studies used relatively small datasets to conduct traditional and optimal deep learning. Furthermore, early and root caries were not distinguished. Precise detection and diagnosis of dental caries are needed to reduce the cost of oral health management and increase the likelihood of preserving natural teeth. The findings of this study suggest that deep learning CNN algorithms provide comprehensive, reliable, and accurate image assessment and disease detection, thus facilitating effective and efficient diagnosis and improving the prognosis of dental caries in periapical radiographs. The use of CNNs for diagnosis has yielded promising results that are comparable to assessments by dental experts and radiologists. Improved deep learning and large, high-quality datasets may help improve the output for dental caries detection and diagnosis.

Conflicts of Interest: None

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