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Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm

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ABSTRACT

Objectives: Deep convolutional neural networks (CNNs) are a rapidly emerging new area of medical research, and have yielded impressive results in diagnosis and prediction in the fields of radiology and pathology. The aim of the current study was to evaluate the efficacy of deep CNN algorithms for detection and diagnosis of dental caries on periapical radiographs.

Materials and methods: A total of 3000 periapical radiographic images were divided into a training and validation dataset (n = 2400 [80%]) and a test dataset (n = 600 [20%]). A pre-trained GoogLeNet Inception v3 CNN network was used for preprocessing and transfer learning. The diagnostic accuracy, sensitivity, specificity, positive predictive value, negative predictive value, receiver operating characteristic (ROC) curve, and area under the curve (AUC) were calculated for detection and diagnostic performance of the deep CNN algorithm.

Results: The diagnostic accuracies of premolar, molar, and both premolar and molar models were 89.0% (80.4–93.3), 88.0% (79.2–93.1), and 82.0% (75.5–87.1), respectively. The deep CNN algorithm achieved an AUC of 0.917 (95% CI 0.860–0.975) on premolar, an AUC of 0.890 (95% CI 0.819–0.961) on molar, and an AUC of 0.845 (95% CI 0.790–0.901) on both premolar and molar models. The premolar model provided the best AUC, which was significantly greater than those for other models ($P < 0.001$).

Conclusions: This study highlighted the potential utility of deep CNN architecture for the detection and diagnosis of dental caries. A deep CNN algorithm provided considerably good performance in detecting dental caries in periapical radiographs.

Clinical significance: Deep CNN algorithms are expected to be among the most effective and efficient methods for diagnosing dental caries.

1. Introduction

Dental caries are common chronic infectious oral diseases affecting most teenagers and adults worldwide [1]. According to the National Health and Nutrition Examination Survey, the prevalence of dental caries in the United States is 41% among children 2–11 years of age (in their primary teeth), 42% in children and adolescents 6–19 years of age, and approximately 90% among adults ≥20 years of age (in their permanent teeth) [2–4]. Most studies have reported that socially and economically disadvantaged individuals, including low-income minorities, those with lower levels of education, and disability groups, are at higher risk for dental carries. In addition, several epidemiologicaland clinical studies have reported that tooth loss caused by oral disease, including dental caries, is related to detrimental dietary changes, and potentially modifiable risk factors or risk indicators for cardiovascular disease and cognitive impairment [5,6].

Various retention and restoration methods, which have been proposed and improved for the treatment of dental caries, have been successfully developed over the past few decades [7,8]. However, there has not yet been a significant improvement in the diagnostic methodology for detecting dental caries due to various anatomical morphologies of teeth and the shapes of restorations. In particular, when deep fissures, tight interproximal contacts, and secondary lesions are present, it is difficult to detect early-stage disease and, eventually, many lesions are detected in the advanced stages of dental caries. Therefore, although dental radiography (including panoramic, periapical, and bitewing views), and explorer (or dental probe), which are widely used and regarded to be highly reliable diagnostic tools for the detection of

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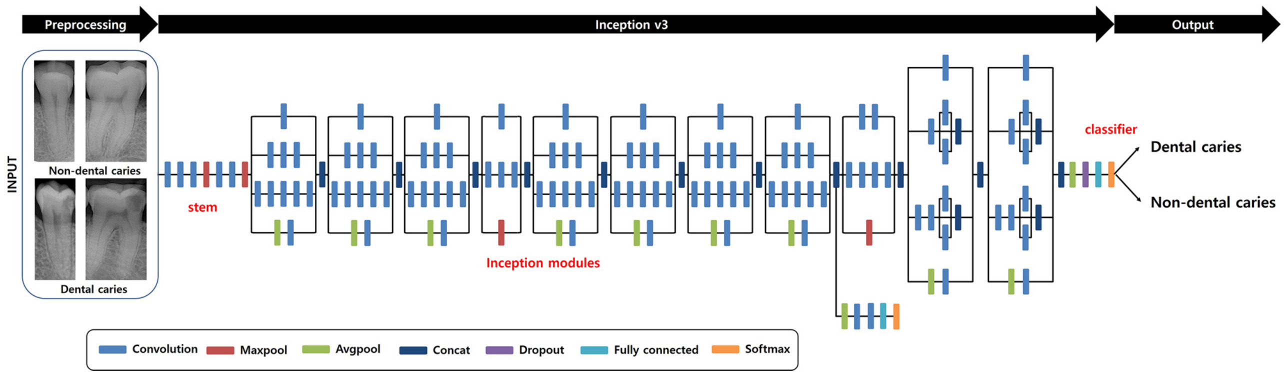

Fig. 1. Overall architecture of the pre-trained convolutional neural network model. The architecture has a total of 9 inception modules, including an auxiliary classifier, and two fully connected layers. The output layer performs binary classification between dental caries and non-dental caries using a softmax function.

dental caries, much of the screening and final diagnosis tends to rely on empirical evidence.

Recently, one aspect of artificial intelligence and deep learning—-convolutional neural networks (CNNs)—has demonstrated excellent performance in computer vision including object, facial and activity recognition, tracking, and three-dimensional mapping and localization [9]. Medical segmentation and diagnosis is one of the most important fields in which image processing and pattern recognition procedures have been adopted. In particular, detection and classification of diabetic retinopathy, skin cancer, and pulmonary tuberculosis using deep learning-based CNN models have already demonstrated very high accuracy and efficiency, with promising clinical applications [10,11]. In contrast, however, there have been few studies based on deep CNN architectures in the dental field, and research investigating detection and diagnosis of dental caries is also more limited [12]. Accordingly, the aim of the present study was to evaluate the efficacy of deep CNN algorithms for the detection and diagnosis of dental caries in periapical radiographs.

2. Materials and methods

2.1. Datasets

This study was conducted at the Department of Periodontology, Daejeon Dental Hospital, Wonkwang University and approved by the Institutional Review Board of Daejeon Dental Hospital, Wonkwang University (approval no. W1804/003-001). Anonymized periapical radiographic image datasets, acquired between January 2016 and December 2017, were obtained from the authors' dental hospital's PACS system (Infinitt PACS, invented by Infinitt Co., Seoul, Korea), and classified and labeled based on electronic medical records (EMR). All images were clearly revalidated, and dental caries, including enamel and dentinal carious lesions (excluding deciduous teeth), were distinguished from non-dental caries by four calibrated board-certified dentists. The dataset excluded all periapical radiographic images in which the diagnosis of the four examiners did not match, and included the periapical radiographic images for which all four examiners agreed to the diagnosis of dental caries.

The dataset consisted of a total of 3000 periapical radiographic images of 778 (25.9%) maxillary premolars, 769 (25.6%) maximally molars, 722 (24.1%) mandibular premolars, and 731 (24.4%) mandibular molars. There were 781 (23.9%) premolars and 772 (25.7%) molars that were diagnosed as dental caries, and 719 (26.1%) premolars and 728 (24.3%) molars diagnosed as non-dental caries. Periapical radiograph images diagnosed as dental caries and non-dental caries were cropped to show only one tooth per image and optimal position. Images with moderate-to-severe noise, haziness, distortion, and shadows, and those with a full crown or large partial onlay restoration were excluded from the analysis. Periapical radiographic images included in the dataset were then calibrated to standardize contrast between gray/white matter and lesions.

2.2. Preprocessing and image augmentation

A total of 3000 periapical radiographic images were finally selected and resized to 299 × 299 pixels and converted into JPEG file format. All maxillary teeth images were reverted to the mandibular teeth form through a vertical flip. A randomization sequence was created using SPSS (IBM Corporation, Armonk, NY, USA), and used to divide the dataset into a training and validation dataset (n = 2400 [80%]), and a test dataset (n = 600 [20%]). The training and validation dataset consisted of 1200 dental caries and 1200 non-dental caries, and the test dataset consisted of 300 dental caries and 300 non-dental caries in the same ratio. The training dataset was randomly augmented 10 times using rotation (range of 10°), width and height shifting (range, 0.1), zooming (range, 0.8–1.2), shearing (range, 0.5), and horizontal flip [13].

2.3. Architecture of the deep convolutional neural network algorithm

A pre-trained GoogLeNet Inception v3 CNN network was used for preprocessing, and the datasets were trained using transfer learning. The Inception v3 architecture, which demonstrated excellent performance in the 2014 ImageNet Large Scale Visual Recognition Challenge, has preliminarily learned approximately 1.28 million images consisting of 1000 object categories. It consists of 22 deep layers, and it is possible to obtain different scale features by applying convolutional filters of different sizes in the same layer. A total of 9 inception modules were used, including an auxiliary classifier, two fully connected layers, and softmax functions [14]. The training dataset was separated randomly into 32 batches for every epoch, and 1000 epochs were run at a learning rate of 0.01. To provide better detection of dental caries, fine-tuning was used to optimize the weights and improve the output power by adjusting the hyperparameters [15,16] (Fig. 1).

2.4. Statistical analysis

The training and validation dataset was used to estimate and create optimal deep CNN algorithm weight factors. All deep CNNs in this study were implemented using the Keras library on top of TensorFlow in Python. The diagnostic accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), receiver operating characteristic (ROC) curve, and area under the ROC curve (AUC) of the test dataset were assessed. P values < 0.05 were considered to be statistically significant, and 95% confidence intervals (CIs) were calculated.

Table 1
Accuracy, sensitivity, specificity, positive predictive value, and negative predictive value for the detection of dental caries in premolars and molars.

	Accuracy (%, 95% CI)	Sensitivity (%, 95% CI)	Specificity (%, 95% CI)	PPV (%, 95% CI)	NPV (%, 95% CI)
Premolar	89.0 (80.4–93.3)	84.0 (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 (81.7–96.8)
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)

3. Results

In the case of premolars, the diagnostic accuracy was 89.0% (80.4–93.3), the sensitivity was 84.0% (75.4–88.3), the specificity was 94.0% (80.4–93.3), the PPV was 93.3% (83.8–98.1), and the NPV was 85.5% (77.7–89.4). In the case of molars, the diagnostic accuracy was 88.0% (79.2–93.1), the sensitivity was 92.3% (83.2–97.1), the specificity was 84.0% (75.2–89.1), the PPV was 85.2% (77.0–89.9), and the NPV was 91.3% (81.7–96.8). In the case of both premolars and molars, the diagnostic accuracy was 82.0% (75.5–87.1), the sensitivity was 81.0% (74.5–86.1), the specificity was 83.0% (76.5–88.1), the PPV was 82.7% (76.1–87.9), and the NPV was 81.4% (75.0–86.4) (Table 1).

A comparison of the training validation, and cross-entropy curves for the pretrained augmented models for premolar, molar, and both premolar and molar is shown in Fig. 2. The blue line represents the accuracy over the course of training, which increased over time, with final accuracies of 99.0%, 100%, and 99.0% for premolar, molar, and both premolar and molar models at the final epoch, respectively. Training was performed for 1000 epochs, with each epoch representing one pass through the entire training dataset. The grey line represents the accuracy over the course of validation, which increased over time, with final accuracies of 92.0%, 91.0%, and 83.0% for premolar, molar, and both premolar and molar models at the final epoch, respectively. The orange curve represents cross entropy on the training and validation datasets, which demonstrated substantial decreases over time.

A comparison of ROC curves for the pretrained augmented models for premolar and molar, as well as both premolar and molar approaches, are provided in Fig. 3. The deep CNN algorithm achieved an AUC of 0.917 (95% CI 0.860–0.975) on premolar, an AUC of 0.890 (95% CI, 0.819–0.961) on molar, and an AUC of 0.845 (95% CI 0.790–0.901) on both premolar and molar models. The pretrained augmented models for premolar provided the best AUC, which was significantly greater than that for other models ($P < 0.001$).

4. Discussion

Fast and accurate detection and diagnosis are important factors in implementing appropriate prevention and treatment in patients with dental caries. When dental caries are not properly diagnosed, the lesion may progressively invade the enamel, dentin, and even pulp tissue, inducing severe pain, and ultimately leading to loss of tooth function. Using a deep CNN based on GoogLeNet Inception v3 architecture, which has superior performance in image detection, classification, and segmentation, compared to any other deep learning algorithm, has been extensively used in the medical field for classifying and diagnosing image and video sources including MRI, CT, microscopy, ultrasound, x-ray, mammography, and color fundus photos. By using this solution, we were able to achieve considerable accuracy and efficiency of detection and diagnosis of dental caries. This finding supports the concept that optimized deep learning architectures can be useful and effective in clinical dental practice.

Alongside clinical examinations, radiography plays an important role in the detection of dental caries, especially for interproximal and root caries [17]. Nevertheless, numerous studies have reported large variations in the reliability and accuracy of detection according to study methodology and the clinician's level of experience, with sensitivities varying from 19 to 92% for occlusal surfaces and 38–94% for proximal surfaces [18]. Another study reported that approximately 20% of non-dental caries are over-diagnosed as dental caries. Because the settings of various parameters, including brightness, shadow and contrast, in radiography vary, it is difficult to objectively diagnose dental caries using radiographs alone [19,20]. Furthermore, enamel caries can be diagnosed only after the lesion has affected more than one-half of the enamel thickness. Furthermore, because the diagnostic and definition criteria for dental caries differ among studies, the prevalence and incidence of dental caries may be biased and inconsistent [21].

Various methods of detection and diagnosis of dental caries that can overcome the limitations of clinical and radiographic diagnosis are being developed and improved. Digital subtraction radiography (DSR), tuned aperture computed tomography (TACT), electrical conductance measurement (ECM), ultrasonic caries detector, laser fluorescence, digital imaging fiber-optic trans-illumination (FOTI), quantitative light-induced fluorescence (QLF) are examples of techniques that are currently being used in clinical settings [22,23]. It has been reported that diagnostic techniques for dental caries demonstrate higher accuracy and sensitivity for occlusal and/or proximal surfaces, respectively, depending on their technical mechanism [24]. Bitewing radiographs and FOTI are useful for the diagnosis of proximal caries. However, bitewing radiographs have a low diagnostic yield for early dental carious lesions, and FOTI also yields low diagnostic sensitivity [25,26]. Ultrasound devices are highly sensitive to proximal caries detection compared with bitewing radiographs. However, the drawback to this technique is that it can detect dental caries only after the tooth has been damaged to a certain extent, and after changes in enamel and dentin structure have already occurred [27]. Laser fluorescence has relatively high sensitivity compared with other methods, and can diagnose early enamel caries [28].

Owing to recent advances in digital radiography and computer systems, computer-assisted diagnostic (CAD) systems are now able to read and interpret radiographs more precisely. LOGICON Caries Detector™ Software (LCDS, Carestream Dental, GA, USA), the only commercially available CAD, was developed to detect and diagnose dental caries based on traditional algorithms consisting of three-layer forward networks [29]. However, it remains controversial whether this system is more accurate than experienced clinical examiners [30,31]. In addition, because detectors using shallow learning techniques are very sensitive to morphology, shape, and location of dental carious lesions, diagnostic accuracy can be significantly influenced by as little as one or two pixel changes; consequently, errors occur [32].

Unlike simple and traditional architecture, deep CNN algorithms perform edge detection very efficiently through multiple convolutional and hidden layers with hierarchical feature representations [33]. Therefore, a deep CNN-based dental caries detector can learn location and morphological changes of dental carious lesions efficiently and detect them conveniently and reliably [33,34]. Deep learning algorithms, such as ResNet and CapsNet, which have deeper or wider layers, or have modified layering methods, are continually being developed and, as a result, the accuracy of object detection and segmentation has been significantly and consistently improved [35,36]. In particular, CapsNet, which has recently been developed, is reported to be very useful for processing visual factors from posture (location, size, and direction), modification, speed, reflection coefficient, hue, and texture, as well as for encoding. Therefore, the use of CapsNet for our dataset may enable more improved and optimized detection and diagnosis of dental caries [36]. In addition, these algorithms have been made available as open-source development projects, and are continually being modified and updated by many researchers in various fields of

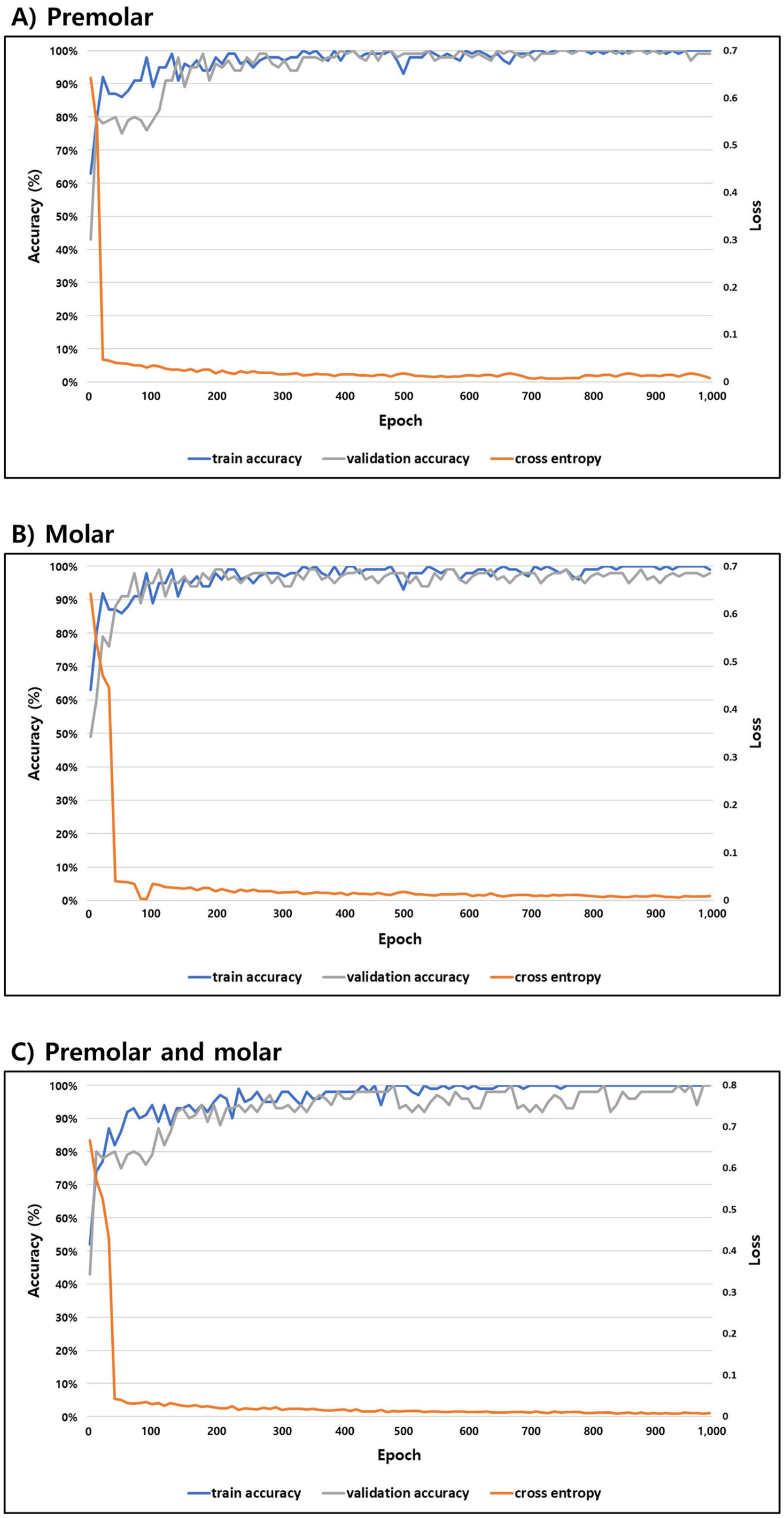

Fig. 2. Comparison of the training, validation, and cross-entropy curves for the pretrained augmented models for premolar, molar, and both premolar and molar. Training and validation was performed for 1000 epochs, with each epoch representing one pass through the entire training and validation dataset.

medicine and science.

Appropriate and accurate diagnosis of dental caries is crucial for long-term maintenance of teeth. Because the treatment process of dental caries is irreversible, specificity is considered to be a more important factor in diagnosing dental caries than accuracy and/or sensitivity. The present study demonstrated that the accuracy between premolars and the molar was only 1%, but the specificity of diagnosis of premolars was higher by 10% than that of molars. In addition, in the

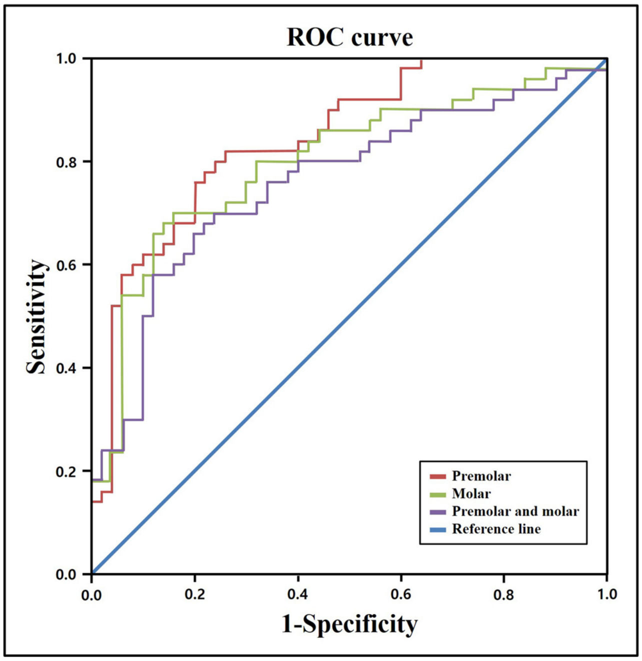

Fig. 3. Comparison of receiver operating characteristic (ROC) curves for the pretrained with augmentation premolar, molar, and both premolar and molar models. The premolar model had an area under the ROC curve that was significantly greater than that for molar and both premolar and molar models.

learning dataset including both premolars and molars, the accuracy was lowered by 6–7% compared with the dataset containing premolars and molars separately. It was shown that the learning for molars—having a more complicated structure than premolars—is a very challenging task for the GoogLeNet Inception v3 architecture. This challenge may be overcome through fine-tuning and transfer learning techniques [37].

Although achieving considerable performance accuracy and efficiency using the deep CNN architecture, there were, nevertheless, several limitations to the current study. The first was that the numbers of periapical radiographic images with/without dental caries were too small to perform conventional and optimal deep learning. To overcome the limited sample size, we used only a high-quality training dataset that was already clearly diagnosed as dental caries by board-certified dentists and randomly augmented 10 times. For more accurate diagnosis of suspected dental caries, the results of clinical examinations, including history taking, percussion and tactile sense, as well as radiographic examinations, should be taken into account, which is also considered to be another limitation because clinical parameters were not included in this study.

We used downscaled low-resolution periapical radiographic images cropped and resized at 299 × 299 pixels as the training and validation dataset due to realistic constraints such as increased computational costs, training time, and operating and storage space. Deep learning-based CNN methods using high-resolution large-scale images demonstrate high accuracy and considerable discriminatory power, which may also be considered another limitation of this study [38]. Finally, the dataset used in the present study included permanent teeth only; it did not include deciduous teeth nor did it differentiate among early, proximal, and root caries.

5. Conclusion

Accurate detection and diagnosis of dental caries reduces the cost of oral health management, and increases the likelihood of natural tooth preservation in the long term. Findings from the present study suggest that a deep learning-based CNN algorithm can provide considerably good performance in detecting dental caries in periapical radiographs. More improved deep-learning algorithms and high-quality and quantity datasets may be useful for dental caries detection and diagnosis in clinical dental practice.

Declaration of interest

The authors declared no conflict of interest.

Acknowledgments

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