Use of artificial intelligence to detect dental caries on intraoral photos

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Dental caries is one of the most common diseases globally. It affects children and adults living in poverty, who have the most limited access to dental care. Left unexamined and untreated in the early stages, treatments for late-stage and severe caries are costly and unaffordable for socioeconomically disadvantaged families. If detected early, caries can be reversed to avoid more severe outcomes and a tremendous financial burden on the dental care system. Building upon a dataset of 50,179 intraoral tooth photos taken by various modalities, including smartphones and intraoral cameras, the present study developed a multi-stage deep learning-based pipeline of artificial intelligence algorithms that localize individual teeth and classify each tooth into several classes of caries. This study initially assigned International Caries Detection and Assessment System (ICDAS) scores to each tooth and subsequently grouped caries into two levels: level 1 for white spots (ICDAS 1 and 2) and level 2 for cavitated lesions (ICDAS 3 to 6). The system's performance was assessed across a broad spectrum of anterior and posterior teeth photographs. For anterior teeth, 89.78% sensitivity and 91.67% specificity for level 1 (white spots) and 97.06% sensitivity and 99.79% specificity for level 2 (cavitated lesions) were achieved, respectively. For the more challenging posterior teeth due to the higher variability in the location of white spots, 90.25% sensitivity and 86.96% specificity for level 1 and 95.8% sensitivity and 94.12% specificity for level 2 were achieved, respectively. The performance of the developed AI algorithms shows potential as a cost-effective tool for early caries detection in nonclinical settings. *(Quintessence Int 2025;56:82–91; doi: 10.3290/j.qi.b5857664)*

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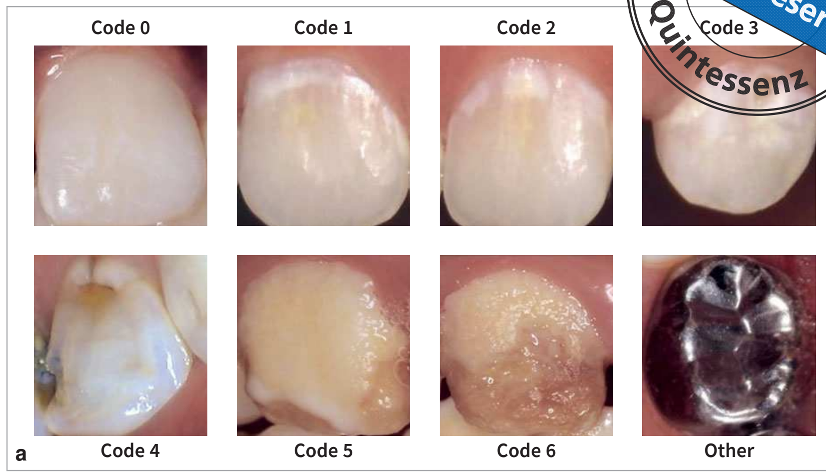
Dental caries is one of the most common diseases globally.[1-3] Children and adults living in poverty who have limited access to dental care are the most affected by dental caries. Dental caries is localized destruction of dental hard tissues (enamel and dentin) by acidic byproducts from the microbial fermentation of carbohydrates.[4] In the very early (subclinical) stages, such as white spot lesion on the tooth enamel surface, caries can be reversed.[4] However, many individuals from low-income families often have poor access to dental services.[5] In this underserved group, dental caries is often diagnosed at a late stage when extensive restorative treatment is needed. Enabling access to dental care and empowering individuals to engage with oral health self-monitoring via mHealth tools is essential.

Intraoral photos have been routinely collected as dental records during dental examinations.[6] Previous research has demonstrated the high accuracy of using intraoral photos[7-10] and live-video tele-dental tools[11,12] to diagnose caries and predict the appropriate treatment modality for pediatric patients. With the advancement of smartphone cameras, photographs of intraoral teeth taken with smartphones offer comparable quality that could be used for caries diagnosis.

Artificial intelligence (AI) systems based on convolutional neural networks (CNN) are promising for caries detection automation since CNN models have been successfully employed in medical fields to detect pathologies using images.[13-15] One way to address the dental health system dilemma is to make the oral disease screening service accessible to individual patients regardless of their socioeconomic status, such as via mHealth or mDentistry tools.[16] AI has been increasingly applied in dentistry for detection of dental caries on radiographs, demon-

Fig 1a and b Example images that demonstrate the ICDAS visual diagnostic criteria and classification used in the AI algorithm. Example images of ICDAS visual diagnostic criteria *(a)*. ICDAS code, criteria, and classes for the AI algorithm *(b)*.



ICDAS Code	Criteria	Classes for AI algorithm
0	Solid tooth surface (no caries yet)	Healthy
1	White spot seen when tooth is dry (no caries yet)	Level 1
2	White spot seen when tooth is wet (no caries yet)	Level 1
3	Caries in the enamel (outer layer of the tooth)	Level 2
4	Caries in dentine (second layer of tooth)	Level 2
5	Caries in enamel and dentin < ½ of the surface	Level 2
6	Caries in enamel and dentin > ½ of the surface	Level 2
Other	Other (stainless-steel crowns, braces)	Other

b

strating high accuracy in identifying early and advanced stages of decay. These AI models analyze radiographic images to assist dental practitioners in diagnosing caries more efficiently and consistently.[17,18] A recent study utilized a smaller internet-sourced intraoral dataset of 506 images to train AI models for detecting dental caries in intraoral photos.[19] In the present study, an AI algorithm was developed with a set of CNN models to conduct caries detection using a large set of 50,179 intraoral photos. This AI algorithm could be integrated into smartphones, allowing users to utilize their phone cameras to capture images of their teeth, ultimately supporting the goal of self-monitoring oral health outside of dental clinics. In particular, these models enable image quality check, tooth localization, and caries classification.

Therefore, the main objectives were to develop a multi-stage deep learning-based pipeline of AI algorithms that localize individual teeth on intraoral photos and classify each tooth into several levels of caries (each level with multiple codes), and evaluate the performance of the AI algorithms on caries detection.

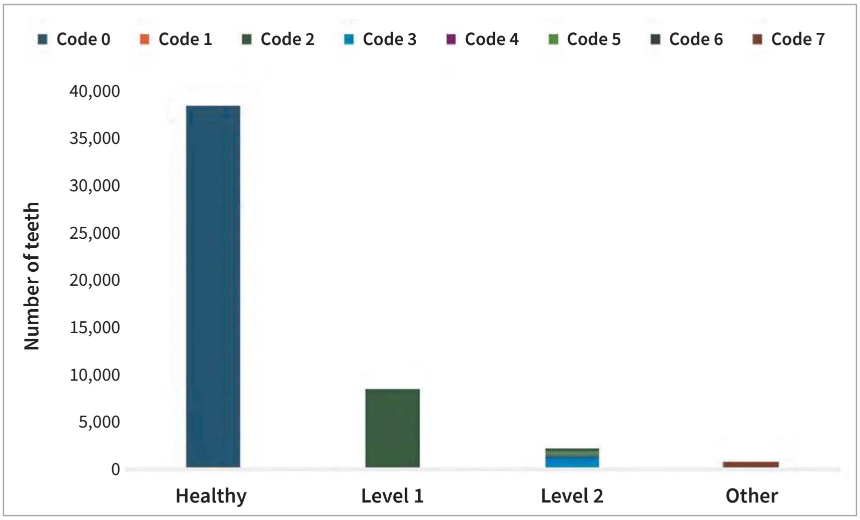
Method and materials

Yolov4[20] was used as the backbone CNN architecture to train a caries detection model. The model can facilitate the localization and detection of caries on intraoral photos for both anterior teeth and posterior teeth with desirable sensitivity and specificity.

Data acquisition

The study was approved by the University of Rochester Institutional Research Board (Protocol # 00003953 and 00005772). The intraoral photo dataset was obtained at the University of Rochester Medical Center, and included two types:

- Annotated set: 5,862 images taken by cameras in the dental clinical setting. These 5,862 intraoral images included 50,179 anterior and posterior teeth (22,975 anterior teeth from 2,851 images and 27,204 posterior teeth from 3,011 images) and have been annotated for dental caries.



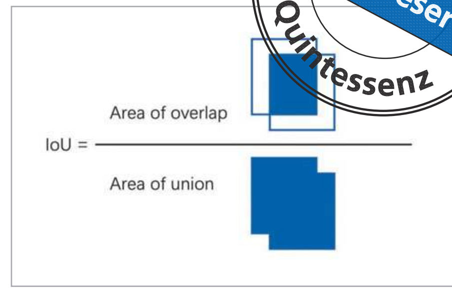


Fig 2 Class distribution and the mapping schema of the annotated datasets.

Fig 3 The definition of intersection over union.

- Unannotated set: 5,143 intraoral images taken by intraoral camera (MouthWatch) in a nondental setting. This set contained a total of 5,273 anterior and posterior teeth and were not annotated.

Dataset and caries annotation

Three trained and calibrated dental practitioners annotated 5,862 images using the International Caries Detection and Assessment System (ICDAS).[21,22] Tooth hard surface is composed of the outer enamel and inner dentin layers. ICDAS is the gold standard caries diagnostic index for scoring caries severity and is routinely used in caries research and epidemiologic studies. ICDAS categorizes dental caries status into seven levels, with 0 indicating a healthy condition and levels 1 through 6 representing varying stages of caries development. Code 1 and 2 indicate initiation of white spots on noncavitated tooth enamel indicated by the arrows, with or without air-drying. Code 3 and 4 indicate caries on cavitated tooth enamel. Code 4 revealing the gray shadow around and underneath the enamel caries indicates more extensive enamel caries. Code 5 and 6 indicate caries involving dentin, with ascending extensiveness from 5 to 6. In addition to the 7 categories defined by ICDAS, another category label has been added to represent dentures that can cover the surface of teeth, such as stainless-steel crowns and braces (Fig 1a and b). In total, there were 50,179 bounding boxes from eight classes: code 0 (38,382), code 1 (2), code 2 (8,547), code 3 (1,213), code 4 (249), code 5 (552), code 6 (264), and code 7 (970). Under the definition, code 1 is white spot seen when the tooth is dry, and there were only two teeth labeled as code 1. The annotation was completed within a span of 3 months. Kappa tests were conducted among the dental practitioners during the calibration process using a set of 24 intraoral images, both prior to and during the ICDAS annotation for the datasets. Inter- and intra-examiner agreement was assessed and evaluated, demonstrating over 85% kappa value.

For each image, there was a corresponding xml file that specified the manual annotation of the bounding box and the ICDAS score of each specific tooth. Upon receiving annotated image files from the dental team, all tooth labels were converted into four classes for training and testing of the caries detection model. All teeth labeled as code 0 were mapped to class “healthy”; teeth with label code 1 or code 2 were teeth with white spots with or without air-drying, and were thus mapped to class level 1; teeth with label code 3, code 4, code 5, or code 6 had cavitied dental caries lesions and were mapped to class level 2; and teeth with dental prosthesis such as restorations like crowns were mapped to class “other” (Fig 2).

CNN architecture

The Yolov4 object detection network[20] with CSPDarkNet53[23,24] was used as the backbone to construct the caries detection model. CSPDarknet53 is an improved version of the Darknet53 architecture, which utilizes the concept of cross stage partial (CSP) connections to improve the flow of gradients and information through the network. CSP architecture reduces the number of parameters and computations by employing a split-transform-merge strategy. Darknet53 is known for its effective-

Table 1 Quantitative detection, sensitivity, and specificity of the AI algorithm on the anterior and posterior teeth testing datasets*

Tooth location	Prediction	Ground truth: Healthy	Level 1	Level 2	Other	Total	Sensitivity	Specificity
Posterior teeth	Healthy	17,106	203	42	5	17,356	NA	NA
	Level 1 (white spots)	2,564	1,878	68	6	4,516	90.25%	86.96%
	Level 2 (cavitated lesions)	1,068	83	958	14	2,123	95.8%	94.12%
	Other	13	0	0	317	330	NA	NA
	Total	20,751	2,164	1,068	342			
Anterior teeth	Healthy	1,871	87	3	4	1,965	NA	NA
	Level1 (white spots)	170	765	5	2	942	89.78%	91.67%
	Level2 (cavitated lesions)	4	7	99	11	111	97.06%	99.79%
	Other	1	0	1	33	35	NA	NA
	Total	2,046	959	108	50			

*The annotated anterior teeth dataset was divided into three parts: 60% for training, 20% for validation, and 20% for testing. The whole annotated posterior teeth dataset is used to test the performance of the model. The results listed in Table 1 are from the testing dataset.
NA, not applicable.

ness in feature extraction, consisting of 53 convolutional layers, which can learn hierarchical features from the input images. It enhances the network's ability to learn and represent complex features from input images.

Data augmentation is a crucial component in training models like Yolov4. Several data augmentation methods, including random crop, random flip, rotation, and scaling, were used to simulate different angles of view in the real-world practice. For each image, one or more of these augmentation methods were randomly applied to an image and the augmented image was added to the training, thus doubling the number of training images.

Implementation details

The annotated anterior teeth dataset was divided into three parts: 60% for training, 20% for validation, and 20% for testing. The whole annotated posterior teeth dataset was used to test the performance of the model by several evaluation metrics, such as intersection over union (IoU; Fig 3), sensitivity, and specificity. For the images in the unannotated dataset, the AI algorithm was used to generate caries predictions, and three calibrated dental practitioners evaluated the AI-detected caries results manually.

Input images were resized to the resolution of 480 × 480 pixels using the bicubic image resizing method, and the value of the image was normalized into the range from 0 to 1 by dividing the pixel value by 255. Since the dataset was heavily unbalanced, a sparse categorical focal loss was employed as the loss function and different weights were set for different classes of data to balance the dataset. It is important to note that even though there were only approximately 1% of the "other" class in each data partition, this was still given a low weight compared to other classes, as the teeth in the "other" class had distinct features and could be easily classified. The aim was to focus more on correctly classifying the healthy, level 1, and level 2 classes. For training, the batch size was set to 32, and the model was trained for 100 epochs.

For the evaluation of the unannotated images, an input image was also resized to the resolution of 480 × 480 and its pixel values normalized. When receiving an image, the algorithm loaded the trained model and then detected caries in the image; the inference process took about 8 seconds on a CPU. When continuously receiving images, the algorithm invoked the model already loaded in the computer memory and then detected caries in images one by one; the inference process only took around 0.9 seconds on CPU. This rapid performance of the developed models provides the technical foundation necessary to run the algorithms on mobile devices for future applications.

Image quality check

To ensure that the quality of the tooth images was adequate for the subsequent caries detection, live image quality check was implemented. To that end, the pre-trained ImageNet weights[25] were loaded to the image quality check model reported in the Vizwiz study,[26] and the model was fine-tuned in two steps. In the first step, the Vizwiz-Image Quality Issues dataset was utilized to fine-tune the model.[21] The purpose of this step was to have the image quality check model learn to predict the image quality-re-

Fig 4a to l Visual results of the model prediction on the posterior teeth dataset: input *(a to d)*, prediction *(e to h)*, ground truth *(i to l)*. Green boxes denote healthy teeth, yellow boxes denote level 1 (white spots) teeth, red boxes denote level 2 (cavitated lesions) teeth, and blue boxes denote other teeth.

lated issues instead of classifying objects as in the original pretrained ImageNet.[20] In the second step, the learning on real-world general objects as included in the Vizwiz-Image Quality Issues dataset was transferred to the tooth image domain. It was assumed that the images included in the annotated anterior teeth dataset had no image quality issues (because they had been inspected by the calibrated dental practitioners). Therefore, artificial images with quality issues were generated based on the dataset. Considering the real-world user scenarios and possible quality issues, three types of image quality issues were generated: too blurry, too bright, and too dark, described below.

Evaluation metrics for AI performance

To produce blurry images, a random integer between 8 and 12 was generated as the blur radius for each image and Gaussian Blur was applied 10 times on the image with the blur radius to obtain the blurred image. To generate darkened and brightened images, a random number between 0.2 and 0.7 and between 1.8 and 2.5, respectively, was generated as the factor for every image, and overall brightness of the image with the factor was modified. Two operations could also be combined (except for the combination of brighten and darken operations) to generate images with more than one image quality issue. The list of the possible scenarios contained none, blurry, too bright, too dark, blurry and too bright, as well as blurry and too dark. In total, 1,800 images were used from the dataset as the training set, 992 images as the validation set, and 254 images as the testing set. When the artificial problematic images were generated, it was ensured that both the training set and the validation set were balanced. Empirically, the image quality check tool was proven effective in that the images passing the quality check allowed the caries detection algorithm to function properly.

IoU, sensitivity, and specificity were chosen to evaluate the performance of the proposed system. IoU is a metric used to evaluate the performance of an object detection algorithm. In the present task, the bounding box of a tooth was annotated by a dental practitioner and the tooth detection algorithm predicted another bounding box. IoU measures the area of overlap between the predicted bounding box and the ground truth bounding box over the area of union between the predicted bounding box and the ground truth bounding box. The IoU score ranges from 0 to 1; the higher IoU score an algorithm gets, the more accurate the algorithm prediction.

Sensitivity measures the proportion of true positive objects that are correctly identified by the model, and specificity measures the proportion of true negative objects that are correctly identified by the model. A high sensitivity score means that the

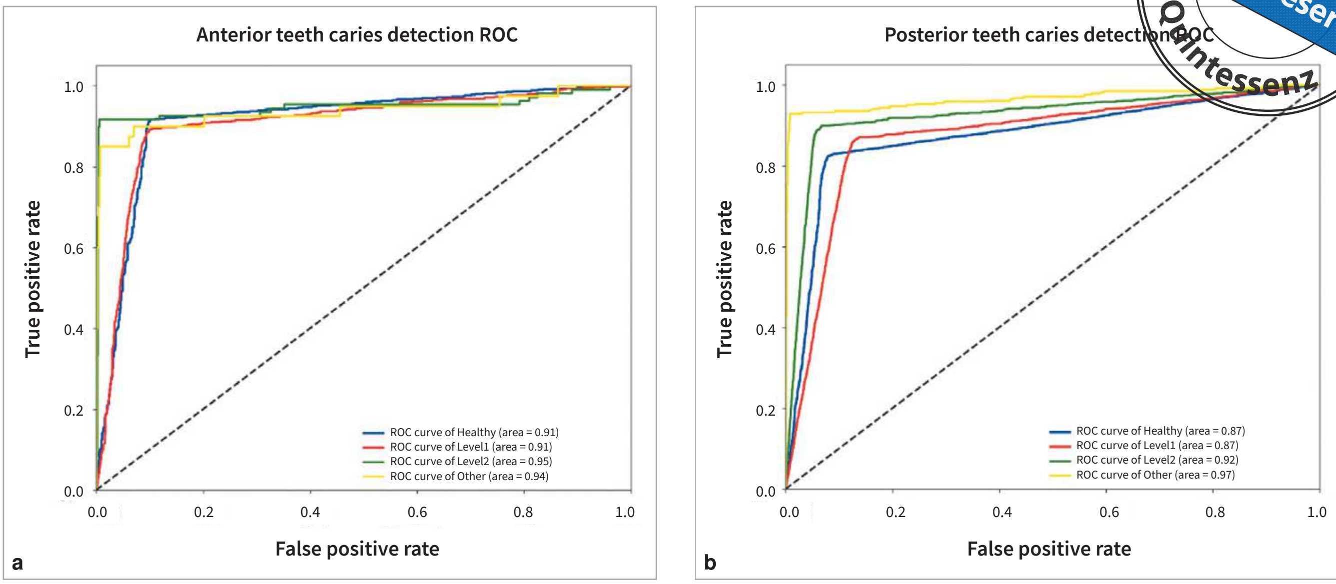


Fig 5a and b ROC curve of the anterior and posterior AI algorithm. Area under the curve of the AI model for anterior teeth *(a)*. Area under the curve of the AI model for posterior teeth *(b)*.

model is good at detecting positive cases, and a high specificity score means that the model is good at detecting negative cases.

Sensitivity = (true_positives)/(true_positives + false_negatives)

Specificity = (true_negatives)/(false_positives + true_negatives)

Results

Performance on tooth segmentation

In total, 24,325 bounding boxes with a 0.8734 IoU from the posterior dataset (27,204 bounding boxes in total) were obtained using the model that was trained. The reason that the number of predicted bounding boxes was lower than that of annotated bounding boxes is that the threshold set for IoU meant that some not accurate bounding boxes were ignored. In total, 3,053 bounding boxes with a 0.8819 IoU were obtained from the anterior test dataset (3,076 bounding boxes in total) using the model that was trained.

The quantitative detection results on the anterior teeth test dataset and posterior teeth dataset are shown in Table 1. The rows represent the predicted class, and columns represent the actual class to which teeth belong according to expert annotation. Elements on the diagonal represent the numbers of true positive teeth for each class.

Performance on caries detection

According to the sensitivity and specificity metrics shown in Table 1, for anterior teeth, 89.78% sensitivity and 91.67% specificity for level 1 (white spots), and 97.06% sensitivity and 99.79% specificity for level 2 (cavitated lesions), were achieved, respectively. For the more challenging posterior teeth due to the higher variability in the location of white spots, 90.25% sensitivity and 86.96% specificity for level 1(white spots), and 95.8% sensitivity and 94.12% specificity for level 2 (cavitated lesions), were achieved, respectively. This performance is comparable to that of dental practitioners, as reported in previous studies,[27] where sensitivity in identifying dental caries ranged from 0.77 to 1.00 and specificity from 0.45 to 0.93, highlighting the potential of this tool as a cost-effective solution for early caries detection in nonclinical settings. Although the ratio of the number of predicted posterior teeth to that of annotation posterior teeth was 89.42%, which is lower than the 99.25% ratio for the anterior teeth, for most clear images even occluded teeth that were not annotated by the dental practitioner could be noticed by the model, as shown in Fig 4. The ROC curves for anterior

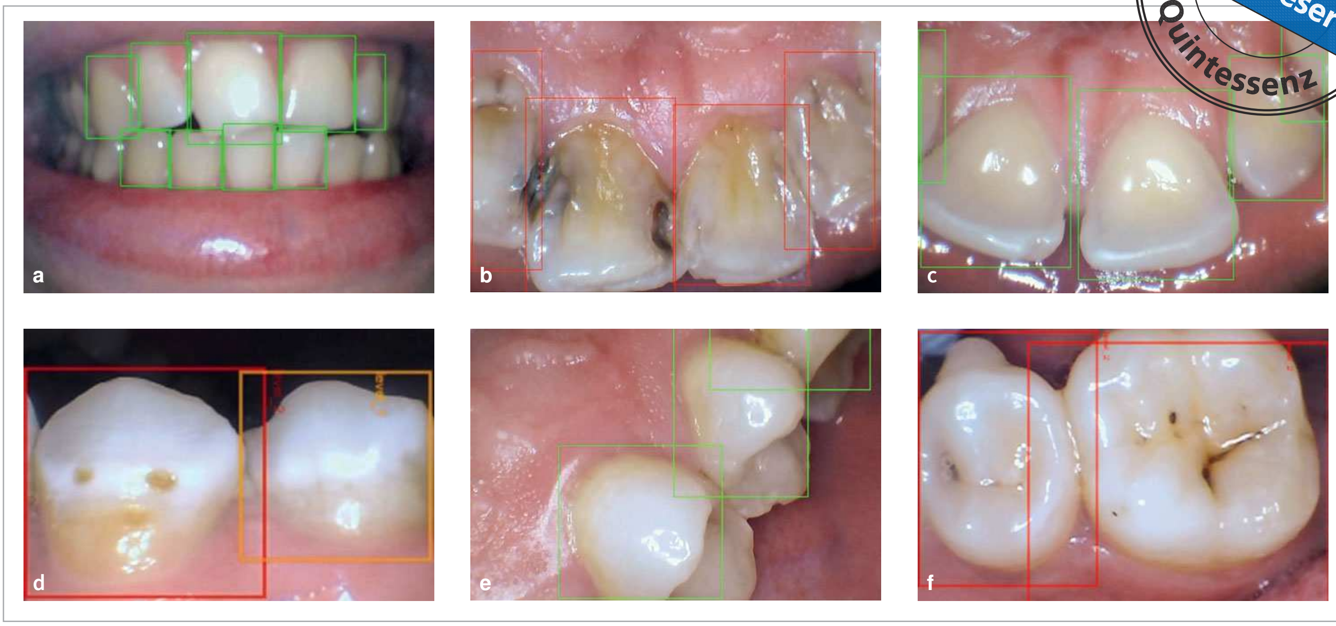


Fig 6a to f Examples of accurately predicted caries status by AI algorithm on anterior *(a to c)* and posterior teeth *(d to f)* from anterior view, buccal and lingual view, and occlusal view.

teeth (Fig 5a) and posterior teeth (Fig 5b) caries status classification demonstrate excellent performance of the classifier, with an average area under the curve (AUC) of 0.9.

The sensitivity of the image quality check model on too blurry, too bright, and too dark categories was 100%, 92.66%, and 97.79%, respectively. The specificity of the image quality check model on too blurry, too bright, and too dark tasks was 90.07%, 92.21%, and 69.49%, respectively. The performance of the present model on the testing set was satisfactory. However, since there was no dataset of labeled real user images with image quality issues, it was not possible to assess how the model performed on real, not generated, images. A small number of tooth pictures were taken using smart phones under different lighting conditions and camera movements to simulate images that the real users may take. The prediction results on the images were generally correct in terms of the too bright and too dark classes.

As seen in Fig 6, the AI algorithm was able to accurately predict normal or caries lesion on the different surfaces (buccal, facial, lingual, and occlusal) of anterior and posterior teeth. Conversely, the AI algorithm demonstrated inaccuracies (predominately false positive prediction), as depicted in Fig 7, under certain conditions: in the presence of dental calculus or surface stains, when assessing retained roots significantly smaller than the average tooth size, or in instances of amalgam restorations.

Discussion

The present study utilized a large set of intraoral photos to develop AI models for caries detection. The study has the following highlights. First, the developed models demonstrated desirable caries detection sensitivity and specificity, which are comparable to the average performance of dental practitioners (reported as 0.84 to 1.00 for sensitivity and 0.92 to 0.93 for specificity).[27] Second, although the caries detection model was trained using only the anterior teeth portion of the dataset, the model showed strong performance in detecting caries across both anterior and posterior teeth. This was confirmed by several metrics, including IoU, sensitivity, and specificity. The performance of the model through extensive testing showed that the model has a strong ability of generalization, which means that it has acquired the ability to process data in a wide variety of datasets even if it is only fed partial data during training.

In addition, the generalizability of the model could facilitate its integration into mobile apps. It can accurately detect teeth in images that are blurry or tilted, allowing for photos taken from various angles and with suboptimal resolution. This adaptability is crucial for implementation in a user-facing system, such as a smartphone app. Patients, who may lack the expertise to take high-quality professional photos of their teeth, need only place their phone outside their mouth and

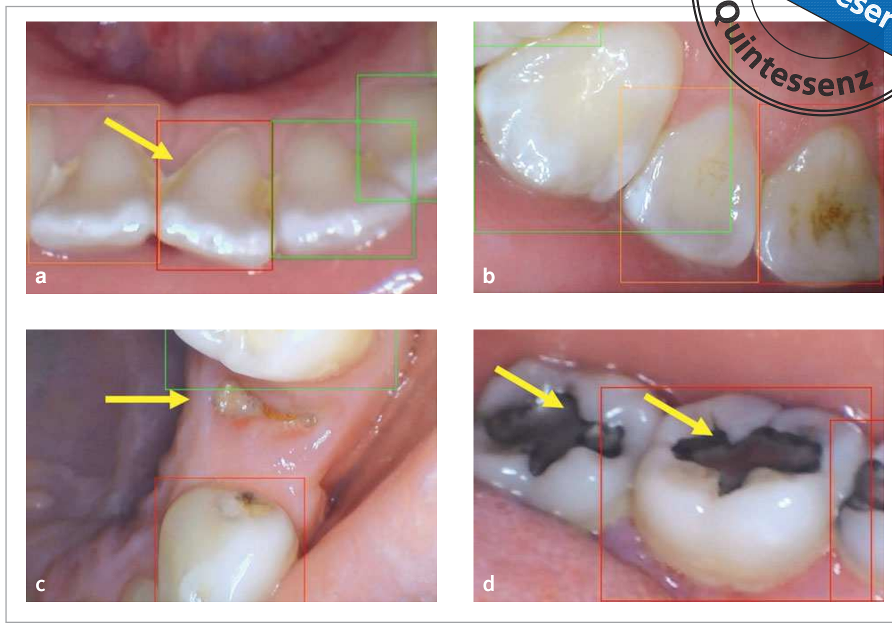


Fig 7a to d Examples of inaccurately predicted caries status. The common reasons for inaccuracy are presence of calculus on tooth surface *(a)*, stains on tooth surface *(b)*, small retained root *(c)*, and existence of amalgam restorations on teeth *(d)*.

snap a picture. Given the variability in photo-taking skills and conditions, the present system can promptly provide live feedback to users, suggesting when a new image might be necessary. If a high-quality image proves unattainable after multiple attempts, users are advised on whether to seek assistance from a dental practitioner or trained dental assistant.

It was observed that the model often predicts more valid bounding boxes than those provided in the annotations by dental practitioners. For example, the clinicians only annotated teeth that were not occluded by teeth from the maxillary and mandibular arches; however, the AI model was able to generate bounding boxes for those teeth with overlayed areas by maxillary and mandibular teeth. The performance depicted in Fig 3 illustrates that the trained model can assist dental practitioners in annotating new data. Clinicians can input images into the model to receive several preliminary bounding boxes. A graphical user interface (GUI) could be developed to enable dental practitioners to select the most accurate bounding box when multiple are available for a single tooth, correct any erroneous labels, or adjust the bounding box to better fit the tooth. This capability could significantly reduce the time required to annotate new data.

The prediction performance on healthy, level 1 (white spots), and level 2 (cavitated lesions) can be improved in several ways. For example, a query could be included in the model to gather data on users' habits of dental hygiene and the relation with the caries, to improve model prediction. The historical scores could be included to make a longitudinal prediction model. Furthermore, work on the UI design and user experience of mobile deployment will continue.

Based on the AI models developed, an artificial intelligence powered smartphone application has been further developed (described elsewhere), AICaries, to promote caries prevention and early detection via mDentistry tool.[28,29] The shell of the AICaries app includes an AI-powered caries detection algorithm, caries risk assessment, oral health literacy assessment, oral health education recourses, and available dental clinic information suitable with user's insurance. The image quality checker is integrated into the AICaries app. If the captured image fails this check, smartphone users are prompted to retake the photo and are notified of the specific issue affecting image quality. The usability of the AICaries app has been pilot tested among 32 parents with young children from low-income families and was well-accepted by the families.[28,29] The AICaries app could empower patients to monitor their own oral health by providing early caries detection and potential management on mobile devices in their own home. Furthermore, the AI-powered caries detection models could facilitate population-based caries screening and monitoring in community settings. Nondental clinicians can leverage the technology for efficient and effective caries diagnosis and treatment, especially for communities lack-

Table 2 Image quality check results on synthesized teeth image quality check dataset

Image quality	Prediction	Ground truth		
		Class 0	Class 1	Total
Blur	Class 0	113	14	127
	Class 1	0	127	127
	Total	113	141	
Bright	Class 0	164	6	170
	Class 1	13	71	84
	Total	177	77	
Dark	Class 0	133	36	169
	Class 1	3	82	85
	Total	136	118	

ing medical resources. Moreover, policymakers may consider integrating this technology into health care systems, promoting accessible and low-cost dental care for all in the community.

Conclusion

This study developed a smartphone application-enabled, machine learning-powered dental caries detection system using intraoral tooth photos. The system's performance was validated across a broad spectrum of anterior and posterior teeth photographs, highlighting its potential as a cost-effective tool for early caries identification in nonclinical settings.

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Disclosure

The authors declare that there are no conflicts of interest.

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