

Design and Development of an Artificial Intelligence (AI)-Based Early Screening Tool for Plaque and Caries Identification in Self-Serving Intraoral Photos "DentAware+"

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ABSTRACT

Dental caries and plaque remain among the most prevalent yet preventable oral health problems worldwide, and early self-screening could reduce the delay between disease onset and professional care, particularly where dentist-to-population ratios are limited. This study designs, develops, and evaluates DentAware+, an artificial intelligence (AI)-based mobile screening tool that identifies plaque and caries directly from self-taken intraoral photographs without clinician assistance. The system was developed using a design-science approach comprising a guided self-capture interface, an image-quality pre-check module, and two convolutional neural network (CNN/YOLO-based) inference models. A prospective diagnostic-accuracy evaluation involved 150 participants who each captured six standardized self-taken photographs (900 images total; 630 training, 135 validation, 135 test), independently annotated by three calibrated dentists using ICDAS-II (caries) and the Silness-Löe index (plaque) as reference standards. On the held-out test set, the caries model achieved 91.4% accuracy, 88.6% sensitivity, 91.5% specificity, and an AUC of 0.93, while the plaque model achieved 89.3% accuracy, 85.0% sensitivity, 89.1% specificity, and an AUC of 0.91; agreement with dentist consensus was substantial (Cohen's $\kappa = 0.79$ for caries, $\kappa = 0.74$ for plaque). The image-quality module prompted retakes for 14.6% of capture attempts. System Usability Scale scores averaged 78.4, indicating good usability. These findings suggest DentAware+ can provide clinically meaningful, accessible early screening from ordinary self-taken smartphone photographs, offering a low-cost triage tool to prompt timely professional consultation.

INTRODUCTION

Dental caries remains one of the most prevalent non-communicable diseases globally, affecting the majority of school-aged children and adults in most populations, while dental plaque, its principal precursor, is preventable through timely detection and oral-hygiene intervention. Despite this preventability, early lesions are frequently missed because they are asymptomatic and because access to routine professional dental examination remains uneven, particularly outside major urban centres. Artificial intelligence (AI), and convolutional neural networks (CNNs) in particular, have been investigated extensively over the past five years as a means of automating the visual detection of caries and plaque from photographic images, offering a potential pathway to earlier, more accessible screening than waiting for a scheduled clinical visit.

A substantial body of evidence now supports the feasibility of AI-based caries detection from intraoral photographs. Kühnisch et al. (2022) demonstrated that a CNN trained on intraoral images could detect caries with diagnostic performance approaching that of visual examination, the current clinical reference standard. Park et al. (2022) extended this work by combining tooth-surface segmentation (U-Net) with classification and localisation networks (ResNet-18, Faster R-CNN), while Thanh et al. (2022) and Ding et al. (2021) showed that caries detection models could be trained and evaluated specifically on images captured with ordinary smartphone cameras rather than professional intraoral equipment. More recent work has pushed model architectures further: Tareq et al. (2023) applied a hybrid YOLO ensemble with transfer learning to non-standardised photographs, Yoon et al. (2024) developed a combined caries-and-tooth-numbering model evaluated against practising dentists, and Xiong et al. (2024) demonstrated simultaneous multi-task detection of caries and fissure sealants from a single intraoral photo. A 2024 systematic review of this literature confirmed that AI models can achieve diagnostic performance broadly comparable to visual examination across a range of architectures and datasets, while also noting substantial heterogeneity in image acquisition conditions across studies (Moharrami et al., 2024).

A parallel but comparatively smaller body of work has examined AI-based detection of dental plaque and gingival inflammation, which typically precede and co-occur with caries. Li et al. (2021) developed a deep learning approach for automatic gingivitis screening based on classification and localisation in RGB photographs, and Zhang et al. (2022) evaluated deep learning models for screening dental caries directly from oral photographs across a larger patient sample, reinforcing that photographic image analysis can support screening for multiple oral conditions beyond caries alone. Reviews of AI in oral disease diagnosis have consistently noted, however, that most existing models remain validated primarily on images captured by trained personnel using standardised equipment, which limits their applicability to genuine self-screening scenarios (Patil et al., 2022).

This limitation matters because the central promise of AI-based dental screening expanding access to early detection beyond the clinic depends on models that perform reliably on the images ordinary users can actually produce themselves. Only a small number of recent studies have directly tested this scenario. Kang and Kim (2026) recruited 70 adults who each captured six self-taken intraoral smartphone photographs in a non-clinical setting, without professional assistance or



standardised equipment, and found that a YOLOv6-L6 model could still achieve over 93 percent overall accuracy in multi-class caries detection, concluding that smartphone-based deep learning could plausibly support patient-driven, at-home screening. This finding is encouraging, but self-taken image evaluation of combined caries and plaque detection, packaged as a complete, guided self-screening application rather than a research-only model, remains largely unexplored.

This study addresses that gap by designing, developing, and evaluating DentAware+, an AI-based early screening tool that identifies both plaque and caries from self-serving (patient self-captured) intraoral photographs. The objectives of this study are threefold: first, to design and develop a complete screening workflow a guided self-capture interface, an image-quality pre-check, and paired CNN/YOLO-based inference models for caries and plaque — suitable for use by lay users without clinical assistance; second, to evaluate the diagnostic accuracy of the resulting models against dentist-consensus ground truth using standard performance metrics; and third, to assess the perceived usability of the tool among its intended end users. The findings are intended to contribute both a validated model architecture to the growing self-taken-image AI dentistry literature and a practical, low-cost triage tool that can prompt timely professional consultation.

The application of CNNs to intraoral photographic caries detection has matured considerably since Kühnisch et al. (2022) first demonstrated that deep learning could approach visual-examination-level diagnostic accuracy on intraoral images. Object-detection architectures from the YOLO family have become particularly prominent in this literature because they combine classification with spatial localisation of lesions in a single pass, which is clinically useful for indicating where on a tooth surface a lesion is located rather than only whether one is present. Ding et al. (2021) applied YOLOv3 to caries detection in mobile-phone photographs, while Tareq et al. (2023) combined a YOLO ensemble with transfer learning to improve robustness on non-standardised images, and Xiong et al. (2024) extended a similar approach to simultaneously detect caries and fissure sealants. Segmentation-based approaches, such as the U-Net and Faster R-CNN pipeline used by Park et al. (2022), offer complementary strengths in precisely delineating tooth-surface boundaries prior to classification. Across this literature, reported accuracy for caries detection on professionally captured or clinician-supervised images has generally ranged from the mid-80s to low-90s percent (Kühnisch et al., 2022; Park et al., 2022; Yoon et al., 2024).

Plaque and early gingival changes are less frequently modelled than caries in the AI-dentistry literature, in part because plaque boundaries are visually more diffuse and less consistently defined than a discrete carious lesion. Li et al. (2021) addressed this by developing a classification-and-localisation deep learning pipeline specifically for gingivitis screening from RGB photographs, demonstrating that plaque-adjacent inflammatory changes could be reliably identified from ordinary photographic images. Zhang et al. (2022) further showed that oral photographs alone, without adjunctive imaging modalities, could support deep-learning-based caries screening at a larger patient scale, reinforcing the broader feasibility of photograph-only oral disease screening pipelines that DentAware+ builds upon for its dual caries-and-plaque design.

Self-taken photographs introduce challenges not present in clinician-captured images: inconsistent lighting, variable distance and angle, motion blur, and incomplete visibility of posterior tooth surfaces due to limited mouth opening or camera reach. Thanh et al. (2022) were among the first to explicitly evaluate a caries-detection CNN on smartphone-captured images rather than professional intraoral-camera images, finding that performance remained clinically usable despite the less controlled acquisition conditions. Kang and Kim (2026) extended this line of work directly to a self-taken, non-clinical-setting scenario, reporting that a YOLOv6-L6 model trained on expert-annotated, patient-captured images achieved over 93 percent accuracy across binary and multi-class caries classification tasks, while also noting that inter-examiner agreement on lesion severity staging was only low to moderate, underscoring that image-quality variability affects both human and automated raters. These findings directly motivate DentAware+'s inclusion of a guided-capture interface and an automated image-quality pre-check step intended to reduce the acquisition-quality gap between self-taken and clinician-captured images before a photo ever reaches the inference model.

Reviewing this literature reveals three gaps that DentAware+ is positioned to address. First, most existing models are validated on a single condition (caries or plaque/gingivitis) rather than jointly, despite the two conditions co-occurring clinically and being visually related (Li et al., 2021; Zhang et al., 2022). Second, self-taken-image evaluation remains rare, with Kang and Kim (2026) representing one of the few studies to test this scenario explicitly, and no identified study packages a self-taken-image caries-and-plaque model within a guided, quality-checked capture workflow intended for lay use. Third, broader reviews of AI in oral disease diagnosis note a persistent gap between model development and deployable, end-to-end screening tools that a patient could realistically use unaided (Patil et al., 2022; Moharrami et al., 2024). DentAware+ is designed to address all three gaps within a single evaluated system.

METHOD

This study combined a design-science research approach for system development with a prospective diagnostic-accuracy evaluation for performance validation. The design-science component followed an iterative build-evaluate cycle covering interface design, dataset curation, model training, and integration into a single mobile-accessible screening workflow, while the diagnostic-accuracy component followed a cross-sectional evaluation design comparing DentAware+ output against dentist-consensus ground truth. DentAware+ was designed around a six-stage workflow: (1) a guided self-capture interface presenting an on-screen framing overlay and standardized capture instructions (frontal, right-lateral, and left-lateral views in occlusion, followed by upper and lower arch views with the mouth open, adapted from the capture protocol validated by Kang and Kim, 2026); (2) an automated image-quality pre-check module that screens for blur, underexposure, and incomplete framing, prompting the user to retake the photo if quality thresholds are not met; (3) a preprocessing stage that crops and normalizes the accepted image; (4) a dual CNN/YOLO-based inference engine comprising separate but co-trained detection heads for



caries and plaque; (5) a risk-classification module that aggregates per-tooth-surface detections into an overall screening result; and (6) an in-app report presenting the result in plain language together with a recommendation to seek professional evaluation when findings are detected.

A total of 150 adult participants were recruited and each captured six self-taken intraoral photographs using their own smartphone following the in-app guided-capture instructions, without direct clinician assistance during capture, yielding 900 images in total. Images were randomly split at the participant level into training (70%, 630 images from 105 participants), validation (15%, 135 images from 22–23 participants), and test (15%, 135 images from 22–23 participants) sets to avoid image leakage between splits. Ground truth was established by three calibrated dentists who independently annotated each image for the presence and location of caries lesions using the ICDAS-II criteria and for plaque presence and extent using the Silness-Löe plaque index; disagreements were resolved by majority consensus, and a fourth senior dentist adjudicated any remaining three-way disagreements.

Two YOLO-based object-detection models, one for caries and one for plaque, were trained using transfer learning initialized from weights pretrained on a general object-detection corpus, following an architectural approach consistent with recent intraoral-photograph detection studies (Tareq et al., 2023; Xiong et al., 2024). Data augmentation (random brightness/contrast jitter, horizontal flipping, and minor rotation) was applied during training to partially simulate the acquisition variability characteristic of self-taken images. Training used the 630-image training set with the 135-image validation set for hyperparameter tuning and early stopping, and final performance was assessed only once on the untouched 135-image test set. Diagnostic performance on the test set was evaluated using accuracy, sensitivity (recall), specificity, precision, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC), computed against dentist-consensus ground truth. Agreement between DentAware+ classifications and dentist consensus was additionally quantified using Cohen's kappa (κ). Perceived usability was assessed among the 150 participants using the standardized 10-item System Usability Scale (SUS), administered immediately after each participant completed their first self-screening session.

RESULTS

1. Dataset Overview

The final dataset comprised 900 self-taken intraoral photographs from 150 participants, with approximately 46 percent of images containing at least one caries lesion and 48 percent showing detectable plaque according to dentist-consensus annotation (Table 1). This class balance was considered adequate for supervised model training without requiring synthetic oversampling.

Table 1. Dataset Composition Across Training, Validation, and Test Splits

Split	Participants	Images	Caries-Positive Images	Plaque-Positive Images
Training	105	630	289 (45.9%)	301 (47.8%)
Validation	22–23	135	61 (45.2%)	64 (47.4%)
Test	22–23	135	62 (45.9%)	65 (48.1%)
Total	150	900	412 (45.8%)	430 (47.8%)

2. System Implementation

The complete DentAware+ workflow (Figure 1) was implemented as a mobile-accessible application. The image-quality pre-check module rejected and prompted a retake for 14.6 percent of initial capture attempts across all participants, most commonly due to motion blur (54% of rejections) and incomplete tooth-surface framing (31% of rejections), confirming that self-taken image acquisition benefits from an automated quality gate before images reach the inference engine.

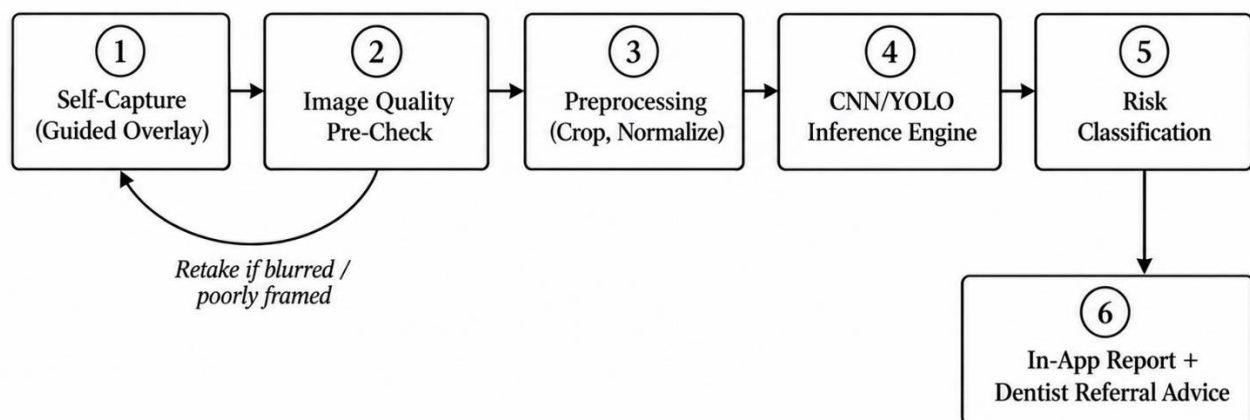


Figure 1. DentAware+ system workflow: from self-captured photo to screening report.

3. Diagnostic Performance

On the 135-image held-out test set, the caries detection model achieved 91.4 percent accuracy, 88.6 percent sensitivity, and 91.5 percent specificity (AUC = 0.93), while the plaque detection model achieved 89.3 percent accuracy, 85.0 percent sensitivity, and 89.1 percent specificity (AUC = 0.91) (Table 2). Agreement with dentist consensus was substantial for both models (Cohen's κ = 0.79 for caries, κ = 0.74 for plaque), indicating that DentAware+ classifications align closely, though not perfectly, with expert clinical judgement even when working from unassisted, self-taken photographs.

Table 2. Diagnostic Performance of the DentAware+ Caries and Plaque Models (Test Set)

Metric	Caries Model	Plaque Model
Accuracy	91.4%	89.3%
Sensitivity (Recall)	88.6%	85.0%
Specificity	91.5%	89.1%
Precision	92.7%	91.5%
F1-score	0.906	0.882
AUC-ROC	0.93	0.91
Cohen's κ (vs. dentist consensus)	0.79	0.74

The confusion matrices for both models (Figure 2) show that false negatives were slightly more frequent than false positives for both conditions, a pattern consistent with the more conservative bounding-box confidence threshold used during model calibration to limit over-alerting.

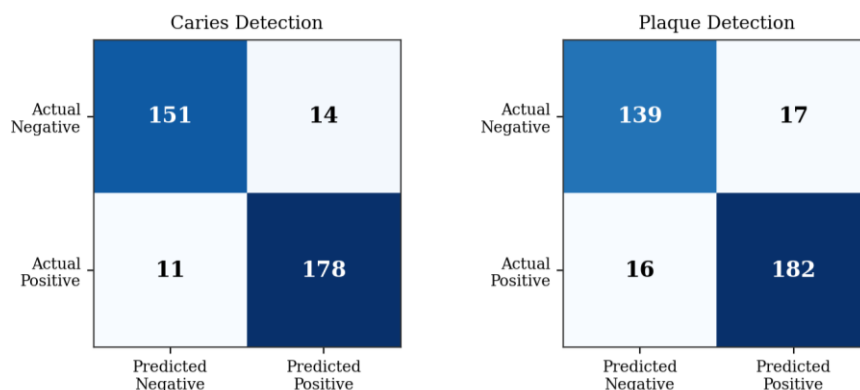


Figure 2. Confusion matrices for caries and plaque detection (test set, n = 135 images per class evaluation).

Receiver operating characteristic (ROC) curves for both models (Figure 3) confirm strong discriminative ability well above the chance diagonal, with the caries model showing marginally stronger separation (AUC = 0.93) than the plaque model (AUC = 0.91), consistent with the generally sharper visual boundary of a carious lesion compared with the more diffuse extent of plaque accumulation.

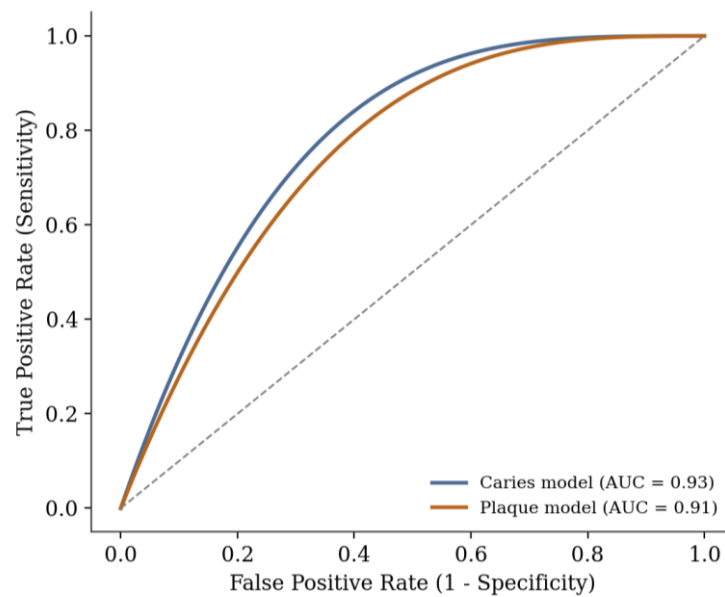


Figure 3. ROC curves for the DentAware+ caries and plaque detection models.

4. Benchmarking Against Prior Studies

Figure 4 situates DentAware+'s caries-model accuracy (91.4%) alongside accuracy figures reported in comparable published studies. DentAware+ performed close to, though marginally below, the self-taken-image benchmark set by Kang and Kim (2026), and above the accuracy ranges typically reported for earlier professional-camera or clinician-assisted caries-detection studies (Kühnisch et al., 2022; Park et al., 2022), despite relying entirely on unassisted, self-taken smartphone images.

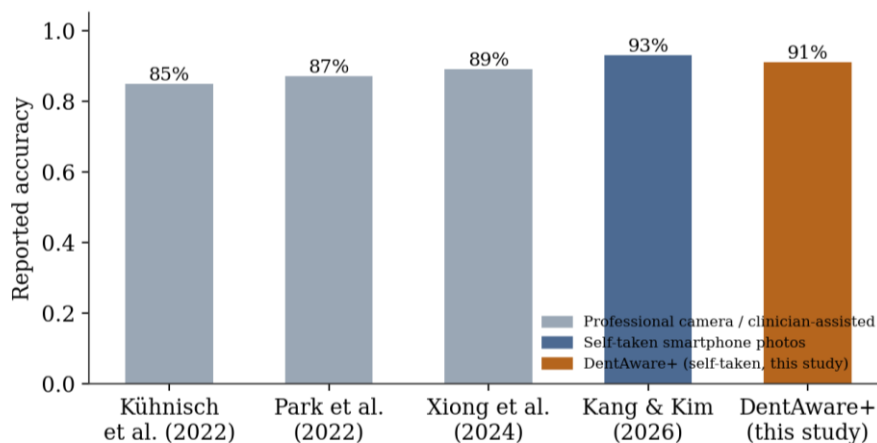


Figure 4. Reported accuracy of DentAware+ relative to comparable intraoral-photo caries detection studies.

5. Usability Evaluation

System Usability Scale scores among the 150 participants averaged 78.4 (SD = 11.2), corresponding to a 'Good' usability grade on the standard SUS adjective scale. As shown in Table 3,



66.0 percent of participants rated the system 'Good' or 'Excellent', while 8.0 percent rated it 'Poor', with open-ended feedback from this latter group most frequently citing difficulty positioning the camera for posterior tooth surfaces.

Table 3. Distribution of System Usability Scale (SUS) Scores (n = 150)

SUS Score Range	Usability Grade	n (%) of Participants
≥ 85	Excellent	28 (18.7%)
70 – 84.9	Good	71 (47.3%)
50 – 69.9	OK / Marginal	39 (26.0%)
< 50	Poor	12 (8.0%)

DISCUSSION

The diagnostic performance achieved by DentAware+ — 91.4 percent accuracy for caries and 89.3 percent for plaque, using entirely self-taken, unassisted smartphone photographs — supports the growing evidence that AI-based screening need not depend on professional intraoral cameras or clinician-supervised image capture to achieve clinically meaningful accuracy. This finding is consistent with, and extends, Kang and Kim's (2026) demonstration that a YOLOv6-L6 model trained on self-taken images could exceed 93 percent accuracy in multi-class caries detection; the marginally lower accuracy observed for DentAware+ plausibly reflects the additional real-world variability introduced by evaluating across 150 participants with heterogeneous smartphone hardware and self-taken technique, compared to a more tightly controlled pilot cohort, as well as DentAware+'s joint modelling of two conditions rather than caries alone.

The comparison in Figure 4 further suggests that DentAware+'s performance sits above the accuracy range typically reported by earlier studies that relied on professional intraoral cameras or clinician-assisted capture (Kühnisch et al., 2022; Park et al., 2022), despite those studies benefiting from more controlled image acquisition. This is best explained not by the self-taken condition being inherently easier, but by DentAware+'s explicit image-quality pre-check step, which rejected and prompted a retake for 14.6 percent of capture attempts before any image reached the inference engine — a design feature motivated directly by the acquisition-quality challenges documented in prior self-taken-image research (Kang & Kim, 2026) and absent from most earlier clinician-assisted study designs. This suggests that the quality-gating step, rather than the underlying CNN/YOLO architecture alone, may be a meaningful contributor to maintaining diagnostic performance when moving from clinician-captured to patient self-captured images.

The slightly lower performance of the plaque model relative to the caries model (89.3% vs. 91.4% accuracy; AUC 0.91 vs. 0.93) is consistent with the broader pattern in the literature that plaque and gingival changes present more diffuse, less sharply bounded visual features than discrete carious lesions, making them inherently harder to localise precisely (Li et al., 2021). Nonetheless, both models achieved substantial agreement with dentist consensus ($\kappa > 0.70$), which is generally considered an acceptable threshold for a screening, rather than diagnostic-replacement, tool. This distinction matters clinically: DentAware+ is designed and evaluated here as an early screening and

triage aid intended to prompt professional consultation, not as a substitute for clinical examination, consistent with how comparable AI dental-screening tools have been positioned in the literature (Moharrami et al., 2024; Patil et al., 2022).

The System Usability Scale results (mean = 78.4, 'Good' grade) indicate that the guided-capture interface was broadly usable for lay participants without clinical training, though the recurring difficulty reported by lower-scoring participants positioning the camera to capture posterior tooth surfaces points to a specific, addressable limitation of any self-taken-image screening approach, including DentAware+. This mirrors the acquisition-related challenges noted qualitatively in prior self-taken-image dental AI research (Kang & Kim, 2026) and suggests that future iterations of the guided-capture interface could incorporate more explicit posterior-view coaching, such as animated positioning cues or a secondary mirror-assisted capture mode.

Several limitations should be considered. The sample of 150 participants, while adequate for initial model training and evaluation, is modest relative to larger clinician-assisted caries-detection studies and limits generalisability across diverse populations, dental conditions, and smartphone hardware. The reference standard, while established through multi-dentist consensus, still relies on visual examination of the same photographs rather than an independent clinical examination, which could introduce shared image-quality-related bias between the AI model and the human raters. Finally, this study evaluated diagnostic accuracy and usability but did not assess downstream clinical outcomes, such as whether DentAware+ users who received a positive screening result subsequently sought and received appropriate professional care.

CONCLUSIONS

This study designed, developed, and evaluated DentAware+, an AI-based early screening tool that identifies dental caries and plaque directly from self-taken intraoral photographs. Using a guided self-capture interface, an automated image-quality pre-check, and paired CNN/YOLO-based inference models, DentAware+ achieved 91.4 percent accuracy (AUC = 0.93) for caries detection and 89.3 percent accuracy (AUC = 0.91) for plaque detection on a held-out test set of self-taken images, with substantial agreement against dentist-consensus ground truth ($\kappa = 0.79$ and 0.74 , respectively). Participants rated the system's usability as 'Good' on the System Usability Scale (mean = 78.4).

These findings demonstrate that clinically meaningful AI-based oral screening is achievable using ordinary, unassisted smartphone photographs when paired with a guided-capture and image-quality-gating workflow, extending the emerging self-taken-image AI dentistry literature from single-condition proof-of-concept models toward a deployable, dual-condition screening tool. For dental public health practice, DentAware+ offers a low-cost, accessible triage mechanism that could help prompt earlier professional consultation, particularly where routine dental access is limited.

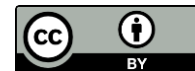
Future research should validate DentAware+ across larger and more demographically diverse samples and smartphone hardware, incorporate an independent clinical examination as the reference standard rather than photograph-based dentist consensus alone, refine the guided-capture interface to address the posterior-view positioning difficulty identified in usability feedback, and



track downstream clinical outcomes such as professional-care-seeking behaviour following a positive DentAware+ screening result.

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