Dental Plaque Detection with YOLOv11 Models

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**Abstract.** In the world of dentistry, dental plaque detection and removal is crucial for ensuring healthy teeth and gums, preventing conditions like cavities, gum disease, and bad breath. Regular dental check-ups, professional cleanings, and proper oral hygiene help maintain a plaque-free smile and overall oral health. Early stages of plaque usually hard to detect and requires assist from plaque disclosing agent that highlights the plaque’s location. This requires money, time and energy. This study investigates the performance optimization of the YOLOv11 object detection model to detect plaque and perform segmentation with high speed and accuracy. By leveraging a custom dataset annotated from Roboflow, the model was trained and tested under various augmentation techniques. The performance of the YOLOv11 was evaluated using precision and recall metrics, with 0.857 and 0.433, respectively. This research highlights YOLOv11's capability of demonstrating substantial improvements over baseline results to deliver accurate and fast plaque detection for early prevention.

# INTRODUCTION

Usage of deep learning algorithms in Computer Vision has gained traction in recent years due to more research has been done in this field. Autonomous driving vehicles, robotics and license plate recognition parking system, are some examples of implementation of this technology making our everyday task a lot simpler. However, this technology is not as widespread in the medical sector. Meanwhile there are advanced computer vision machines such as MRI, CT-scan and X-Ray that can detect complex medical conditions, the usage in detecting oral diseases such as plaque is still scarce. This research particularly focuses on segmentation of plaque from the teeth because early detection and prevention are very important before it gets worsen and leads to other diseases such as caries and gum disease. As of today, dentists usually use plaque disclosing agent, a tablet that highlights the location of plaque. However, this method costs time, money and energy. Patients need to travel to the clinic to do inspection. This research aims to utilize You Only Look Once (YOLO) model that is lightweight and takes less time to detect and segment the location that has contains plaque so that the detection process can be done only by using smartphone at home. Therefore, patients do not need to travel to clinic to make early inspection. The identification of challenging image patterns in medical pictures proves superb with Convolutional Neural Networks thus making them ideal for dental plaque detection automation. When combined with these technologies automated systems provide both better diagnostic precision and dental expert workload reduction along with early-stage detection capabilities and timely treatment events. The objectives of this research are to train a YOLO model for dental plaque detection using publicly available annotated images and perform several augmentation techniques to determine which one will increase the YOLO overall accuracy in detecting dental plaque.

# Literature Review

Researchers in this field employ an array of methods and techniques for dental plaque detection and analysis, each with its own advantages and limitations. Table 1 summarises the reviews of all the papers related to this study.

The study by [1] used images of 86 children's teeth (ages 5-8), with 886 for training, 98 for validation, and 102 for testing. The DeepLabV3+ model achieved a mean intersection-over-union (MIoU) score of 0.726±0.165 using 709 training images and 177 testing images. A separate set of 102 low-resolution images resulted in a MIoU score of 0.724±0.159 during testing. [2] used pictures of the inside of the mouth as their dataset. They used Keras to build the DeepLab V3+ model, which improves the ability to separate different parts of an image and can reach a training accuracy of 93.7%. After that, they changed the tooth outline to the Hue Saturation Value (HSV) color space and adjusted the brightness (V channel) to make the image clearer. This helps to tell the difference between the tooth and dental plaque. The HSV values for dental plaque fall within certain ranges and the plaque is shown in green. Finally, they calculated the plaque index using this improved image to measure how much plaque is present.

**TABLE 1.** Model Accuracy Comparison

|  |  |  |
| --- | --- | --- |
| Paper | Model | Accuracy |
| [1] | DeepLab V3+ | MioU: 0.736 ± 0.174 |
| [2] | DeepLab V3+ | Plaque Index: 56.06% |
| [3] | YOLOv3  Faster-RCNN  RetinaNet  SSD | 83.4%  87.4%  83%  81% |
| [4] | MobileNetV3-Small  ResNet34 | 72.73%  81.82% |
| [6] | DeepLab V3+ | 87.2% |
| [7] | ResNet50 + Channel Spatial Attention | 77.6% |

The study by [3] used 1902 training images from 695 individuals and 750 testing images from 250 subjects to assess dental plaque detection. Among the models tested, Faster R-CNN achieved the highest accuracy (87.4%) and specificity (92.9%) in detecting cavitated lesions, while YOLOv3 showed the best sensitivity (74%). However, early-stage lesion detection was poor across all models, with YOLOv3 performing best at 36.9%, and SSD failing entirely. The study highlights the need for improved datasets and image resolution for better early lesion detection.

The study by [4] used the ODSI-DB dataset with 157 filtered images and the dataset by [5] with 220 images, split into 70% for training, 20% for validation, and 10% for testing. UNet struggled with segmentation due to data limitations, so researchers opted for classification models. MobileNetV3-Small achieved 72.73% accuracy, while ResNet34 performed better at 81.82%, improving mobile-based diagnostics.

The study by [6] analysed 168 teeth from 20 patients (ages 10-15) using plaque-stained images. They trained the DeepLabV3+ model with 140 images and tested it with 28 images over 200 rounds. Performance was evaluated using sensitivity, precision, accuracy, and IoU, comparing AI results with those marked by a dentist and a researcher. The AI model achieved an AUC of 0.922±0.006, while the dentist scored 0.833, showing the AI's strong plaque detection capability.

The study by [7] developed the DeepPlaq detection model by combining ResNet50 with Channel-Spatial Attention. It used images from 70 adults (ages 18-55), with 80% for training, 10% for validation, and 10% for testing. YOLOv8 trained on 210 images at 640x640 pixels over 300 rounds, while Segment Anything (SAM) handled tooth segmentation. Image augmentation included resizing, flips, and rotations to improve model stability. Model performance was evaluated using precision, recall, accuracy, and F1-score.

Although research in dental plaque detection using deep learning is relatively new and not that popular, there are several researchers that already get work and expend the deep learning applications in dental plaque detection field. The most popular deep learning model used by the researchers is DeepLab V3+, followed by ResNet. YOLO is also used although YOLO usually used in early phase where the researchers only use it for dental detection and not plaque detection. The model with the highest and lowest accuracy are Faster-RCNN by [3] and MobileNetV3-Small by [4], respectively. DeepLab V3+ also performs well with accuracy above 70%. However, in this research the model of YOLOv11 will be used. This is because YOLO model is easier to train, have real-time detection algorithm and low complexity compared to Faster RCNN that is highly complex, and slower to operate [8].

# METHODOLOGY

There is no specific project lifecycle involving image processing. Therefore, this project will implement the Cross-Industry Standard Process for Data Mining (CRISP-DM) as in Figure 1. CRISP-DM is the standard lifecycle framework applied in Data Science project. The model is flexible and can be customized easily based on use cases [9].

Problem Understanding

Data Understanding

Data Preparation

Modelling

Evaluation

Deployment

**FIGURE 1.** CRISP-DM framework

## Problem Understanding

The main objective for this research involves creating a deep learning model which is YOLO to detect and perform segmentation to dental plaque in dental images with high-speed precision. The requirement for automated plaque detection emerges because it helps dentists achieve better oral healthcare outcomes together with enhanced opportunities for early diagnosis. Additionally, the research serves to advance the implementation of AI-based dental diagnosis tools in dental practice.

## Data Understanding

Data for this study was collected from a user [10] through Roboflow, a versatile platform that facilitates the creation of datasets, labeling of data, model training, and deployment of computer vision applications. The dataset consisted of images that were classified by the original author into three distinct classes: teeth, plaque, and gum. These images, saved in JPG format, feature a high resolution of 2048 × 1536 pixels, ensuring clear visual details for accurate analysis. Notably, some images of teeth exhibited purple discoloration caused by the application of plaque-disclosing agents, which highlight plaque buildup on the tooth surface. Other images contained visible plaque without the use of disclosing tablets, offering natural variations within the dataset. Additionally, certain images lacked labels, introducing unannotated data to the collection. The annotations accompanying the images were provided in text files. These files specified the class labels—0 for plaque, and 1 for teeth—along with precise location coordinates for each annotated region within the images, enabling seamless integration with machine learning workflows.

## Data Preparation

The images were divided into training, validation, and testing sets in an 8:1:1 ratio to ensure a balanced distribution for model development and evaluation. Any unlabelled images originally present in the training and validation folders were transferred to the testing folder to serve as part of the testing dataset. The images were resized to 640 × 640 pixels, as this resolution is optimal for the YOLO algorithm to process effectively while maintaining sufficient detail. To enhance dataset variability and improve model robustness, several data augmentation techniques were applied. The augmentation included horizontal flipping of images, 90-degree rotation, zoom to the teeth up to 20%, auto increase and decrease of saturation from the range of -+20% and brightness has been increased up to 15%. These methods of augmentation is important as it introduce diverse perspectives and reduce potential bias. Additionally, a new set of unlabelled images, sourced from different datasets, was incorporated into the testing dataset to provide complementary data and further evaluate the model's generalization capabilities.

## Modelling

In this study, YOLOv11, the latest iteration of the YOLO family of object detection models, was employed for plaque detection due to its lightweight design, impressive speed, and high accuracy. The model undergo training using the yaml file with 2 classes of the annotation. The task parameter was set to “segment” to indicate segmentation operation for the detection. The optimizer is set to AdamW [11]. This research aims to enhance model variability by training two lightweight YOLOv11 variants, YOLOv11-n and YOLOv11-s, both optimized for use on smartphones.

YOLOv11-n is the most compact and efficient, designed for maximum speed and minimal computational overhead. In contrast, YOLOv11-s offers a balanced trade-off between speed and accuracy, incorporating additional complexity to improve detection performance while remaining relatively lightweight. The model's performance was evaluated using key metrics, including precision, recall, and mean average precision (mAP), which provide a comprehensive understanding of its effectiveness. In addition to these metrics, the F1-score was computed and visualized through graphical plots to further analyze the model's balance between precision and recall. The training process for the YOLOv11 model was carried out over 20 epochs to optimize its ability to detect plaque in the dataset.

## Evaluation

To evaluate the model, this research will use F1-score, Intersection over Union (IoU), precision and recall [12]. Precision is used to measure the ratio between true positive detection to the total positive prediction whether it is positive or negative. Recall is almost identical to precision and is often used side-by side with presicion. F1-Score is combination of precision and recall. Lastly IoU measures the overlap between predicted values and groundtruth values.

## Deployment

The deployment process will be made using Streamlit, a Python-based framework used in web development without the need for extensive experience in web development. Users just simply upload a close-up image of the teeth and wait for a few minutes before the output be displayed. The output is the original image with segmentation of the teeth and plaque have been highlighted.

# RESULTS AND DISCUSSION

Table 2 compares the performance of two YOLOv11 models (YOLOv11-n and YOLOv11-s) under different augmentation conditions for detecting plaque on teeth. The YOLOv11-n model is recommended for use in smartphones due to its available performance metrics under various augmentation conditions. The model is performing best under 90-degree rotation augmentation, yielding the highest precision (0.857), and Zoom +20% augmentation, yielding the highest recall (0.443) as can be seen in Figure 2.

**TABLE 2.** Training results of YOLOv11 on various augmentations

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| YOLOv11 models | Augmentation | Result | | | | |
| Precision | Recall | mAP 50 | mAP55-90 | F1-Score |
| YOLOv11-n | Horizontal Shift | 0.763 | 0.397 | 0.458 | 0.223 | 0.522 |
| 90 rotate | 0.857 | 0.376 | 0.485 | 0.250 | 0.523 |
| Zoom +20% | **0.818** | **0.432** | **0.513** | **0.260** | **0.565** |
| Saturation +- 20% | 0.798 | 0.432 | 0.500 | 0.258 | 0.561 |
| Brighness +15% | 0.856 | 0.405 | 0.504 | 0.261 | 0.550 |
| YOLOv11-s | Horizontal Shift | 0.849 | 0.426 | 0.546 | 0.276 | 0.567 |
| 90 rotate | 0.888 | 0.440 | 0.578 | 0.289 | 0.588 |
| Zoom +20% | 0.812 | 0.475 | 0.594 | 0.307 | 0.599 |
| Saturation +- 20% | **0.843** | **0.479** | **0.581** | **0.303** | **0.611** |
| Brighness +15% | 0.838 | 0.459 | 0.575 | 0.301 | 0.593 |

To implement the YOLOv11-n model, it is essential to optimize the model for mobile devices using techniques such as quantization and pruning to reduce the model size and improve inference speed. By implementing the 90-degree rotation and zoom augmentation techniques as part of the preprocessing pipeline, it may enhance detection accuracy. Preprocessing allows receiving consistent and high-quality inputs for the model to ensure the model can process images in real-time robustly for providing immediate feedback to users. With extensive validation and testing of real-world use cases, having various augmentation may assist with the model's robustness and reliability.

|  |
| --- |
| (a) |
| (b) |

**FIGURE 2.** (a) 20% zoom using YOLOv11-n (b) +-20 saturation using YOLOv11-s

# CONCLUSION

This research concludes its analysis by examining how deep learning models detect dental plaque. The early appearance of dental plaque does not indicate danger until left untreated because it develops into severe dental problems such as tooth decay and tartar accumulation. Dental plaque remains difficult to identify without special aids since it has a non-distinct appearance that keeps it invisible to naked eyes. The process of using disclosing agents demands high expenses and takes a lengthy amount of time. The need exists for developing a completely free method which people can easily access to detect plaque. The research proposes YOLOv11 for important dental image detection by focusing on teeth areas. YOLO being lightweight and has high speed makes it easy for segmentation task of dental plaque to be done in shorter time. Online access to the dataset enables training of YOLOv11 model for this research. We hope this paper serves as a motivational factor for researchers to take on more studies in this field. The research demonstrates how deep learning models create opportunities for dental healthcare by offering an inexpensive and fast dental plaque detection methodology. The research implements YOLOv11 as cutting-edge methods to establish new pathways for dental diagnostic innovations. The positive findings from this work emphasize the need to further investigate this field because it will direct the advancement of dental disease prevention and oral health treatment

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