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ORIGINAL RESEARCH ARTICLE

Dental cavity analysis, prediction, localization, and quantification using computer vision

Muhammad Aqeel[1], Payam Norouzzadeh[2], Abbas Maazallahi[1], Salih Tutun[3], Golnesa Rouie Miab[4], Laila Al Dehailan[5], David Stoeckel[6], Eli Snir[3], and Bahareh Rahmani[1]*

[1]Computer Science, Saint Louis University, St. Louis, Missouri, United States of America

[2]Professional Studies, Saint Louis University, St. Louis, Missouri, United States of America

[3]Data Analytics Area, Olin Business School, Washington University in Saint Louis, St. Louis, Missouri, United States of America

[4]Pacific Dental Services, St. Louis, Missouri, United States of America

[5]Department of Restorative Dental Sciences, College of Dentistry, Imam Abdulrahman Bin Faisal University, Dammam, Saudi Arabia

[6]Department of Dentistry, Saint Louis University, St. Louis, Missouri, United States of America

***Corresponding author:**
Bahareh Rahmani
(brahmani@slu.edu)

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Abstract

Dental health assessment is a critical component of overall well-being, and advancements in computer vision and deep learning have opened new avenues for automating and enhancing this process. In this study, we present a comprehensive approach to dental cavity analysis, spanning localization, quantification, and visualization. Our methodology leveraged a diverse dataset of colored dental images that had been meticulously augmented and annotated. The You Only Look Once model was employed for precise dental cavity localization, providing bounding box predictions. Remarkably, these results were obtained based on images from standard device cameras. Subsequently, we introduced the use of the segment anything model segmentation model, known for its zero-shot generalization capabilities, to focus on the exact areas of dental cavities. This approach enhanced the granularity of our analysis, providing dental professionals with detailed visualizations for precise diagnosis. During the quantification phase, we extracted cavity areas from bounding box coordinates, enabling accurate measurement of cavity sizes. The model achieved a notable mean average precision of 0.732, an accuracy of 0.789, and a recall of 0.701. Moreover, the model converged quickly, with most metrics achieving near-optimal results after 100 iterations. This quantitative data augments traditional diagnosis methods, facilitating more informed treatment decisions.

Keywords: You only look once; Segment anything model; Segmentation model; Dental cavity

1. Introduction

Many may not be aware that our oral well-being can provide insights into our overall health. The truth is that problems in our mouth can potentially impact the rest of our body. Similar to other parts of our body, our mouths harbor mostly harmless bacteria.

However, some of these bacteria have the potential to cause health problems, as they serve as a gateway to our digestive and respiratory systems.

The body's own defense typically keeps these germs in check, along with basic dental hygiene habits like frequent brushing and flossing. However, without proper oral hygiene, bacteria levels can rise and cause ailments such as tooth decay and gum disease. Research indicates that certain medical conditions may be impacted by oral bacteria and the inflammation brought on by chronic gum disease, also known as periodontitis. Our oral health might contribute to various diseases and conditions, including endocarditis, cardiovascular disease, and pneumonia.[1]

According to the Global Burden studies in 2019, dental caries is the most common oral disease, affecting around 3.5 billion people, of whom 2 billion have permanent dental caries.[2] Moreover, 1.45 million of the 6 million patients with dental caries who visited dentists in the Republic of Korea in 2020 were children (0 – 9 years old).[3] Therefore, it is important to study tooth caries.

Caries formation is affected by a host of preferential habits, systemic disorders, and congenital anomalies. Incipient carious lesions are frequently overlooked by patients. Dentists treat them conservatively using techniques of minimally invasive dentistry. As a result, there are many instances of misdiagnosis and poor care, particularly among young practitioners conducting visual and radiographic investigations. Caries mismanagement can be expensive and leave the patient exposed to future periapical, osseous, and fascial space spread of the infection.[4] These challenges are particularly noteworthy in areas with limited access to advanced dental facilities and trained practitioners. Early detection and ongoing monitoring of these problems are proposed in this article using a low-cost automated system that does not differentiate patients based on their sociodemographic status.

Since cellular technology has expanded globally, even to rural areas, the use of mobile portable devices like smartphones has increased exponentially in emerging economies.[5] As a result, biomedical research can harness functionality in smartphones to offer cost-effective solutions to challenging issues in oral treatment.

In this research endeavor, we define several core objectives, each serving as a pivotal milestone in our pursuit of advancing dental cavity analysis through computer vision techniques. These objectives collectively constitute the foundation upon which our study is constructed, steering our research toward meaningful and innovative contributions to the field. Our first and foremost objective is to pioneer the development of a robust computer vision model dedicated to the precise localized identification of dental cavities within colored images. We recognize that the accurate identification of cavity locations is an indispensable initial step in streamlining the diagnostic process. Achieving this objective will empower dental professionals with a powerful tool that not only identifies cavities but also provides their exact spatial coordinates.

Building upon the success of our initial objective, our second key goal is to introduce a methodology for the quantification of dental cavity areas within these localized regions. Accurate area quantification is paramount in assessing the severity of cavities and can significantly aid in treatment planning. With this objective, we aim to automate and standardize the area measurement process, thereby enhancing the precision of dental health assessments. Furthermore, it is noteworthy to establish a subtle connection between our current study's objectives and our prior research endeavors. In our earlier work, we endeavored to forecast dental cavities utilizing convolutional neural networks (CNNs). While that research focused on predicting the occurrence of cavities, the objectives of the current study extend beyond prediction. Here, we embark on the critical task of geospatial mapping them within images, quantifying their extent, and subsequently facilitating a more comprehensive understanding of their impact on oral health. This intrinsic linkage between our research pursuits underscores the holistic approach we adopt in addressing the multifaceted challenges in dental cavity analysis, paving the way for a more comprehensive and integrated solution.

In this study, we collected a dataset of colored images containing dental cavities and manually annotated this dataset using Roboflow annotation. We then trained the "You Only Look Once" (YOLO) v5 model to detect and locate dental cavities in these images using a bounding box. Once we identified the exact cavity area with a bounding box, we used the coordinates of the bounding box to calculate the area of the cavity. Applying image segmentation on the cavity highlighted the cavity area, and cavity masks were obtained from segmentation for further analysis of the dental cavity shape.

2. Literature review

In our prior research endeavor, entitled "Forecasting teeth cavities by CNNs," we conducted a comprehensive exploration into predicting dental cavities using CNNs. The dataset in this previous investigation consisted of X-ray images. To augment the dataset's size and diversify its content, we applied a series of sophisticated augmentation techniques. To further enhance the accuracy and efficacy of dental cavity prediction, we methodically incorporated segmentation techniques into the research framework. Four distinct segmentation methods were evaluated, namely segmentation with the thresholding method, segmentation with the contouring method, segmentation with the Canny-edges method, and segmentation with a combination of these techniques. The best performance among all methods was obtained by the Canny edge-CNN mode.[6]

In response to the inefficiency and complexity of traditional dental disease detection methods, a study introduced a novel approach utilizing deep learning.[7] The study employed the YOLOv3 model to automate the detection and classification of four common teeth problems: cavities, root canals, dental crowns, and broken-down root canals, using panoramic dental X-ray images orthopantograms. To overcome data limitations, a dental X-ray dataset with 1200 augmented images was created and divided into 70% for training and 30% for testing. The YOLOv3 model achieved a remarkable 99.33% accuracy, outperforming existing models and demonstrating its versatility with other datasets.[7]

Another study indicated that deep learning models can be used to help dentists in planning dental implant placement, ensuring that dental implants are optimally placed and properly aligned with the surrounding teeth and bone.[8]

Dental caries, one of the most prevalent dental conditions in contemporary times, poses significant challenges for early detection in dental X-ray or radiovisiography images. Deep learning has been widely employed across medical domains for predictive and diagnostic purposes. One of the investigations evaluated a K-means clustering approach for image segmentation, underscoring the significance of image enhancement techniques in improving the quality of dental radiographs. The implemented K-means model algorithm demonstrated improved accuracy in the detection of dental caries.[9]

Tareq *et al.*,[10] aimed to pioneer a novel and cost-effective virtual computer vision artificial intelligence (AI) system capable of predicting dental cavitation from non-standardized photographs with reasonable clinical accuracy. They curated a dataset comprising 1703 augmented images sourced from 233 de-identified teeth specimens, captured using consumer-grade smartphones. The methodology leveraged cutting-edge techniques, including ensemble modeling, test-time augmentation, and transfer learning processes. The researchers independently assessed derivatives of the YOLO algorithm, including v5s, v5m, v5l, and v5x, subsequently creating an ensemble model and transfer-learning it with ResNet50, ResNet101, VGG16, AlexNet, and DenseNet. Evaluation metrics encompass precision, recall, and mean average precision (mAP). The YOLO model ensemble achieved a notable mAP of 0.732, an accuracy of 0.789, and a recall of 0.701. When applied to VGG16, the final model demonstrated impressive diagnostic accuracy of 86.96%, with precision and recall values of 0.89 and 0.88, respectively. This performance outstripped all other existing methods for object detection in free-hand, non-standardized smartphone photographs. The virtual computer vision AI system, enriched by an ensemble model, test-time augmentation, and transfer learning techniques, successfully predicts dental cavitations from non-standardized photographs with clinically reasonable accuracy. This innovation holds the potential to enhance access to oral health care in resource-constrained, underserved areas and facilitates automated diagnostics and advanced tele-dentistry applications.

Thanh *et al.*,[11] demonstrated the potential of mobile phone-based diagnostic tools for dental caries detection using deep learning algorithms, highlighting the efficiency of YOLOv3 and Faster R-CNN models. A blog article on innovative applications in dentistry[12] showcased AIs ability to detect caries with high accuracy using image augmentation and transfer learning, emphasizing its role in complementing traditional diagnostic methods. In addition, a GitHub project has been established, aiming to detect and localize various dental diseases, including caries and periodontal diseases, using computer vision in panoramic dental X-ray images.[13]

Nakai and Wei,[14] while focusing on protein localization, highlighted the adaptability of deep learning techniques, such as CNN and long short-term memory, for predictive modeling across diverse fields, including dentistry. Acharya[15] discussed deep learning techniques for image segmentation, including U-Net and SegNet, which are crucial for detailed analysis in medical imaging and diagnostics. Brownlee[16] explored the architectures of Fast R-CNN and Faster R-CNN for real-time object detection, relevant for precise localization and quantification in dental imaging. Fernandes *et al.*,[17] while focused on animal sciences, underscored the importance of machine learning and deep learning algorithms in various computer vision applications, illustrating the multidisciplinary potential of these technologies.

A study on gait pattern recognition for flat fall prediction highlighted the use of computer vision and machine learning in recognizing gait patterns, demonstrating the versatility of these technologies in health diagnostics beyond dental applications.[18] A notable study utilized CNNs to diagnose dental caries from bitewing images, emphasizing the complexity of identifying proximal and interproximal dental caries and the effectiveness of bitewing images in clearly capturing such lesions.[19] Another innovative approach involved classifying tooth caries using quantitative light-induced fluorescence (QLF) images with the help of the Xception deep learning model, underscoring the significance of image augmentation and K-fold cross-validation in training robust models.[20] A systematic review aimed at evaluating neural networks in caries detection highlighted the diverse methodologies and neural network architectures employed across studies, reflecting the dynamic evolution of AI applications in dental diagnostics.[21]

Further illustrating the potential of machine learning in dentistry, a previous study applied several algorithms, notably random forest, achieving high performance in predicting the risk of dental caries from a dataset derived from a children's oral health survey.[22] A systematic review focusing on AI for radiographic imaging detection of caries lesions critically evaluated studies, revealing a preference for CNN models in most research, with a range from 15 to 2900 radiographs used across various studies to build AI models.[23] The use of deep learning for caries detection through tooth surface segmentation in intraoral photographic images has been investigated, employing U-Net for segmentation and ResNet-18 and Faster R-CNN for classification and localization, thereby reducing false alarms and enhancing detection accuracy.[24] Another study developed a CNN model for diagnosing dental caries from bitewing radiographs, demonstrating the utility of deep learning in enhancing dental diagnostic processes.[19]

A research endeavor introduced a novel method for classifying dental caries using QLF imaging combined with CNNs, aiming to improve accuracy in real-time caries detection in clinical settings.[20] Lian *et al.*,[25] utilized deep learning methods to detect and classify caries lesions on panoramic films, comparing performance with expert dentists and showing similar accuracy and reliability. Alharbi *et al.*[26] applied nested U-Net models to dental panoramic X-ray images for caries detection, demonstrating high testing accuracy and robust model performance.

Sikri *et al.*,[27] presented a comprehensive narrative review on the applications of AI in dentistry, detailing how AI integrates into various aspects of dental care, from diagnostics to patient management. Meanwhile, Zhou *et al.*[28] explore a more focused application with their development of a context-aware CNN specifically designed for diagnosing caries in children from dental panoramic radiographs, demonstrating the potential of machine learning to address unique challenges in pediatric dentistry.

These studies collectively underscore the transformative impact of machine learning and AI on dental diagnostics, heralding a new era of precision and efficiency in detecting dental caries. As we delve further into this article, we will explore the mechanics behind these innovations, their practical applications, and the challenges and future directions in integrating advanced computational techniques into dental care.

3. Methods

3.1. Data collection and pre-processing

The image data were sourced from Kaggle (https://www.kaggle.com/datasets/salmansajid05/oral-diseases?resource=download-directory). This dataset comprises a collection of images obtained from multiple health centers and reliable dental websites, ensuring the variety and validity of the dental conditions depicted. Each image in the dataset is thoroughly marked with bounding boxes, accurately representing the dental condition.

3.1.1. Description of the colored image dataset

The colored image dataset used in this study comprises a total of 218 dental cavity images captured using a standard device camera. These images were obtained under casual conditions, featuring open jaws and clear representations of dental cavities. The dataset served as the foundational source of visual data for training and evaluation (Figure 1).

3.1.2. Data augmentation techniques

Data augmentation plays a pivotal role in expanding the dataset and enhancing model robustness. To achieve this, we leveraged the Image Data Generator, an image augmentation API integrated within Keras – an open-source Python library for machine learning. ImageDataGenerator enabled artificially diversifying the dataset by applying transformations such as rotation, shifting, zooming, shearing, and reflection. These augmentations fostered the development of more adept models and improved their ability to generalize across various scenarios. In our experimentation, the augmentation parameters were set as follows:

i. Rotation range: 40°
ii. Width and shifting range: 0.2
iii. Zoom range: 0.2
iv. Shear range: 0.2.

Figure 1. Colored image with a single cavity and multiple cavities

Applying these augmentation techniques expanded the dataset to a total of 2383 images, thereby facilitating a richer and more comprehensive training process.

3.1.3. Manual annotation process

Following the augmentation phase, we proceeded with the manual annotation of dental cavities within the augmented images. For this purpose, we employed the Roboflow annotation tool, which facilitated meticulous annotation of dental cavities (Figure 2). The chosen method for object detection involved bounding box annotation, represented by a rectangular box icon within the annotation tool. In the annotation process, annotators utilized crosshairs to determine the starting point for drawing bounding boxes around dental cavities. Each bounding box served as an annotation for the presence and location of a dental cavity within the image. Furthermore, the Class Selector within the tool allowed annotators to assign the appropriate label to each annotated bounding box, signifying the presence of a dental cavity. This manual annotation process was performed for approximately 400 images, ensuring the availability of accurately labeled data for the subsequent training of the object detection model focused on dental cavity identification.

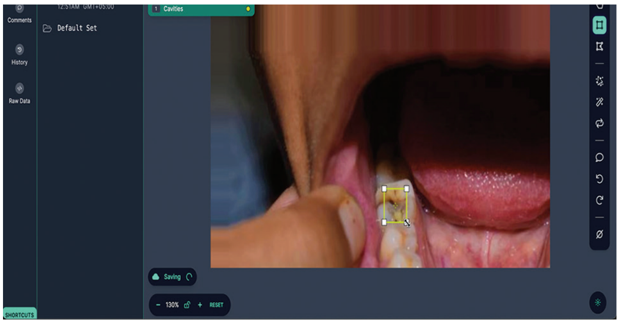

Figure 2. Annotation using the Roboflow annotation tool

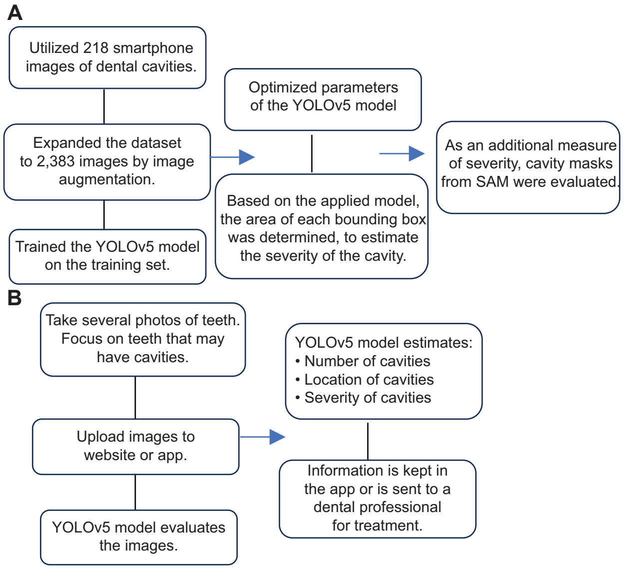

Figure 3. (A) The schematic of the research project. Training set will be trained and optimized by YOLOv5 Model. SAM (Segment Anything Model) will be evaluated. (B) The use of the prescriptive model. The number of cavities, locations and severity of them will be estimated.
Abbreviation: SAM: Segment anything model.

3.2. Dental cavity localization using YOLOv5

The schematic of the research project is shown in Figure 3A. Once the predictive model is developed, its application is straightforward. Implementation can be developed for a smartphone app, where images would be taken by patients or dental assistants, without the need for a dental professional. Figure 3B describes how the prescriptive model would be used.

3.2.1. Introduction to YOLO

In our pursuit of precise dental cavity localization with the augmented dataset, we harnessed the power of the YOLO object detection framework. YOLO represents a groundbreaking approach to object detection, characterized by its remarkable speed and accuracy. Unlike traditional object detection models, YOLO processes images in a single pass, making it especially efficient for real-time applications. The YOLO algorithm divides an image into a grid and predicts bounding boxes and associated class probabilities for each grid cell. This unique methodology enables YOLO to excel in scenarios where objects of interest may vary in size and scale, making it precisely suited for our task of dental cavity localization.

3.2.2. Training YOLOv5 model

The YOLOv5 model, an evolution of the YOLO architecture, served as the cornerstone of our dental cavity localization efforts. Training the YOLOv5 model involved a systematic process aimed at enabling it to accurately predict the presence and location of dental cavities within our annotated images. Our training dataset, enriched by augmentation techniques and manual annotations, was used to train the YOLOv5 model. This training process involved iteratively fine-tuning the model's parameters and optimizing its ability to recognize dental cavities in varying image contexts. The YOLOv5 model's training process was rigorous, ensuring a high degree of accuracy and robustness in detecting dental cavities within the images. The successful training of this model constituted a crucial milestone in our endeavor to automate dental cavity localization, facilitating more precise and efficient dental health assessments.

3.2.3. Bounding box prediction

Following the successful training of the YOLOv5 model, we transitioned to the crucial phase of bounding box prediction and post-processing. This step represents the culmination of our efforts to precisely locate dental cavities within unknown images, a process that significantly contributes to the automation of dental health assessment. The YOLOv5 model, trained on our annotated dataset, acquired the capability to predict bounding boxes around dental cavities with remarkable accuracy. To employ this predictive power, we utilized a streamlined command that swiftly and accurately delineates the region of dental cavities when applied to an unknown image. These bounding boxes serve as visual indicators of cavity presence and location within the image (Figure 4).

Figure 4. Single cavity (left panel) and multiple cavities (right panel) detection using the Yolo V5 model

3.3. Quantification of cavity area

3.3.1. Extracting cavity area from bounding box

In our pursuit of a comprehensive dental cavity analysis, the localization of cavities through bounding box predictions facilitated by the YOLOv5 model marked a significant milestone. With these bounding boxes accurately delineating the regions of interest, the next logical step in our research was to quantify the area encompassed by these bounding boxes, effectively measuring the extent of dental cavities in pixels.

The extraction of cavity area from the bounding boxes generated by the YOLOv5 model is a straightforward yet essential process. The model's coordinates, specifically (Xmin, Ymin, Xmax, Ymax), facilitate straightforward calculation of the area of the contained bounding region.

The following is a brief breakdown of the steps involved (Figure 5):

i. Width calculation (width): We subtract the Xmin coordinate from the Xmax coordinate, where the result represents the horizontal span of the cavity region, to determine the width of the bounding box.

$$Width = Xmax - Xmin \tag{I}$$

ii. Height calculation (height): To represent the vertical extent of the cavity region, we calculate the difference between the Ymin coordinate and the Ymax coordinate.

$$Height = Ymax - Ymin \tag{II}$$

iii. Area computation (area): The final step involves calculating the area of the cavity region by multiplying the width by the height, yielding the area in pixels.

$$Area = width \times height \tag{III}$$

By systematically employing these calculations, we can precisely quantify the area of each dental cavity within the images. This precise quantification empowers dental

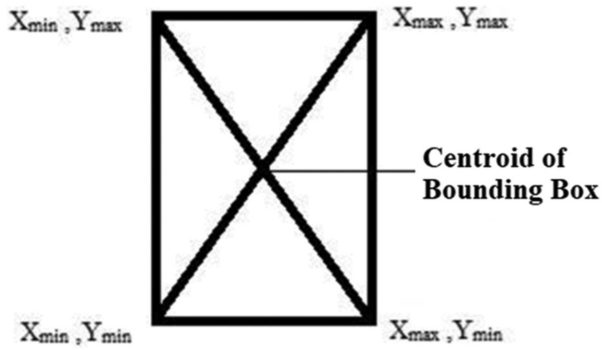

Figure 5. Centroid of a bounding box

professionals with valuable information for assessing cavity severity and planning appropriate treatment interventions.

4. Results and discussion

4.1. YOLOv5 results and limitations

The YOLOv5 algorithm effectively identified cavities through the bounding box process. The algorithm converges quite quickly, enabling implementation in various applications. As expected, object loss in the training set continuously improves with iterations of the algorithm. However, based on the validation set, overfitting starts to become evident after 100 iterations. Other metrics, such as precision, recall, and mAP, converge after 100 trials, indicating that 100 trials are sufficient and desirable to train the algorithm.

From the results, both box loss and object loss are below 0.03 after 100 iterations. The algorithm achieves an accuracy of 0.789, a recall of 0.701, and an mAP of 0.732. These results validate that pictures from smartphones can be an effective 1st step in identifying and treating dental cavities.

There are several limitations in this study, both in terms of the data collected and the modeling. Camera images can only identify cavities that have already formed on the surface of teeth. In addition, it may be difficult to take images within the mouth. To identify issues that are not easily visible, dental X-rays are required. These challenges are inevitable in any visual technique.

The data in this study are based on image augmentation imitating multiple possible alternatives for each original image. While we believe that this is an accurate representation of future images that will be available, it would be more effective to have actual images from multiple angles for teeth and cavities.

More broadly, as AI is applied to more diverse opportunities in modeling and medical diagnostics, several issues may emerge. These relate both to the development of new models and the use of automated diagnostics by individuals and medical professionals. On the modeling side, one can foresee, in the not-too-distant future, the possibility of automated modeling being employed, evaluating a broad set of models on a given dataset. Without supervision and effective parameter tuning, these methods could lead to overfitting or the use of inappropriate models. Similarly, the data used for these automated studies could be suspect. Using available images that are not evaluated by people could be unreliable. Imagine a situation where an autonomous model is developed by images created by AI, for example.

The implications of AI on medical practice should also be considered. Applications like the one proposed here provide effective but limited self-diagnosing opportunities to individuals, especially in areas with limited access to health. However, it is likely that some people who could receive effective diagnoses from medical professionals would also use these tools. Given the noticeable rate of false negative results, these individuals may not receive the necessary treatment. There are also implications for medical professionals. As medical professionals become more reliant on technology, there is a risk of decreased expertise in the profession. This decline in expertise may arise from becoming overly reliant on forecasting tools or from outsourcing diagnostics to low-cost services that rely on technology.

4.2. Image segmentation using the segment anything model (SAM)

The SAM is a promptable segmentation system capable of zero-shot generalization to unfamiliar objects and images without the need for additional training. This capability allows SAM to segment objects into new images; it has never seen before simply by providing it with a prompt such as a text description, a bounding box, or a few clicks on the image.

SAM is trained on a massive dataset of over 1 billion segmentation masks, making it the largest segmentation dataset to date. This extensive training allows SAM to learn a wide range of object appearances and relationships, enabling it to generalize to new images with high accuracy.

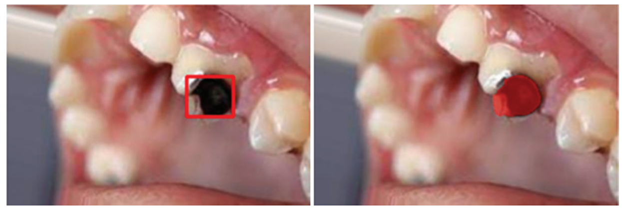

Figure 6. Source image and segmented image

Figure 7. Mask image of the cavity

The SAM is also highly efficient, making it suitable for real-time applications. It can generate a segmentation mask for any prompt in real time after precomputing the image embedding.

For instance, given a bounding box around a dental cavity in an image, the SAM can be used to segment only that area using the SamPredictor class. The SamPredictor class takes a bounding box as input and outputs a segmentation mask for the cavity that is enclosed by the bounding box (Figure 6).

4.3. Dental cavity masks from SAM

Image masks are binary images that represent the foreground pixels of an object. These masks were used to analyze the shape of the dental cavities inside the bounding box. Using the SAM, a segmentation mask for the cavities was generated. The segmentation mask was then cropped to the bounding box and analyzed to measure the desired properties of the cavities. For example, the area of the cavities can be measured by counting the number of white pixels in the cropped segmentation mask.

The white pixels in the binary-masked image show the exact shape of the cavity (Figure 7).

5. Conclusion

In this study, we embarked on a journey to revolutionize dental cavity analysis, resulting in a holistic framework that redefines the way we diagnose and assess oral health. The YOLO model ensemble achieved a notable mAP of 0.732, an accuracy of 0.789, and a recall of 0.701. Considering that this method identifies cavities directly from standard device camera photographs, this accuracy is remarkable. Our approach, comprising precise localization, accurate quantification, and nuanced visualization, demonstrates its potential to improve dental health assessments to unprecedented levels of accuracy and efficiency. Through meticulous augmentation and annotation of a colored dental image dataset, we harnessed the power of the YOLOv5 model for dental cavity localization, providing bounding box predictions with remarkable accuracy. The introduction of the SAM brought the ability to focus with surgical precision on dental cavities, enriching our analysis and empowering dental professionals with detailed visualizations for diagnosis. Our innovative quantification methodology, which extracts cavity areas from bounding box coordinates, offers a quantitative edge, enhancing diagnostic insights. The potential of our research is promising. We foresee the continued evolution of dental health assessments through the fusion of technology and health care. In the future, our framework could pave the way for automated dental check-ups, reducing the burden on both patients and health-care professionals. Moreover, as technology advances, we envision our methods becoming even more accurate and efficient. Remote dental diagnostics, tele-dentistry, and improved oral health-care access may become more widespread, particularly in underserved areas.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Mohammad Aqeel, Payam Norouzzadeh, Abbas Maazallahi, Eli Snir, Bahareh Rahmani

Investigation: Mohammad Aqeel, Golnesa Rouie Miab, Laila Al Dehailan, David Stoeckel, Bahareh Rahmani

Methodology: Mohammad Aqeel, Payam Norouzzadeh, Salih Tutun, Eli Snir, Bahareh Rahmani

Writing – original draft: Mohammad Aqeel

Writing – review & editing: Payam Norouzzadeh, Abbas Maazallahi, Salih Tutun, David Stoeckel, Eli Snir, Bahareh Rahmani

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The image data can be obtained from Kaggle (https://www.kaggle.com/datasets/salmansajid05/oral-diseases?resource=download-directory).

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