AI-Powered Imaging Technology

Sravani Patlolla, Daun kim, Reshmi

Biomedical Informatics  *University of Nebraska Omaha*

*Omaha, Nebraska, UNO*

[*spatlolla@unomaha.edu*](mailto:spatlolla@unomaha.edu)*,* [*daunkim@unomaha.edu*](mailto:daunkim@unomaha.edu)[*rdeb@unomaha.edu*](mailto:rdeb@unomaha.edu)

*Abstract*— Dental caries remains a significant concern across all age groups, particularly in young children. Although X-ray imaging is widely used for caries detection, it is often time-consuming, uncomfortable for patients, and can be costly. The current study aimed to develop a machine learning-based approach to detect dental caries using images captured with mobile devices and high-resolution cameras, offering a more accessible and patient-friendly alternative.

YOLOv8 and YOLOv11 object detection models were selected for this purpose due to their real-time processing capabilities. A dataset of over 150 dental images was collected from publicly available sources and categorized based on image resolution and Tooth positioning within the oral cavity was considered, including images of both front (anterior) and back (posterior) teeth, captured from different angles such as occlusal (top view), buccal (cheek side), and lingual (tongue side) surfaces. Images were split into training, validation, and testing sets using stratified random sampling. Data labeling was conducted using the LabelImg tool, and Various data augmentation techniques were applied to improve the model's reliability and performance.

Both models were trained on datasets with and without augmentation. Performance evaluation was carried out using standard diagnostic metrics such as true positive, true negative, false positive, false negative, and mean average precision (mAP). While neither YOLOv8 nor YOLOv11 achieved complete accuracy across all lesion types, both demonstrated strong potential in identifying visible carious regions.This approach shows promise in improving diagnostic accuracy, reducing reliance on traditional X-ray methods, and enhancing patient comfort through non-invasive and cost-effective screening tools.

Key Words: Caries; yolo; object detection; radiographs; data augmentation.

1. INTRODUCTION

Dental caries, also known as tooth decay or cavities, is a chronic, progressive disease resulting from the bacterial demineralization and destruction of the hard tissues of the tooth, including enamel, dentin, and cementum. Although it is not life-threatening, dental caries is among the most prevalent oral health conditions worldwide, affecting individuals across all age groups. The disease often progresses silently and remains asymptomatic until it reaches an advanced stage, causing pain, infection, and eventually leading to tooth loss if left untreated. This not only affects the physical health of patients but can also lead to significant financial burdens due to complex treatments and repeated dental visits.

Timely detection and accurate diagnosis of caries are critical for effective intervention and prevention of further complications. Traditional diagnostic methods, including visual-tactile examinations and interpretation of dental radiographs (such as bitewing and periapical X-rays), are the standard approaches used in clinical settings. However, these methods rely heavily on the clinician's experience and judgment, which introduces a degree of subjectivity. Variability in interpretation may result in missed diagnoses, overdiagnosis, or inconsistent treatment plans. Moreover, these conventional techniques can be time-consuming and are not always feasible in community or low-resource settings.

To address these limitations, there is a growing need for innovative, efficient, and more objective diagnostic approaches. In recent years, artificial intelligence (AI), particularly deep learning (DL), has emerged as a powerful tool in medical imaging and diagnostics. Within the field of dentistry, convolutional neural networks (CNNs) have been extensively studied and applied for detecting dental caries on X-rays and images of the oral cavity. These models have demonstrated strong capabilities in recognizing dental anatomy, identifying carious lesions, and differentiating between healthy and decayed tooth structures. Their ability to learn from large datasets and improve over time offers a promising alternative to traditional diagnostic workflows.

One of the most effective deep learning models for object detection tasks is the YOLO (You Only Look Once) algorithm. YOLO is a real-time object detection system that reframes object detection as a single regression problem, directly predicting bounding boxes and class probabilities from full images in one evaluation. Unlike other models that perform region identification followed by classification (e.g., R-CNNs), YOLO is extremely fast and efficient, making it well-suited for clinical applications that require rapid and accurate assessments. Its architecture allows for detecting multiple objects in images with a high degree of accuracy, and recent versions such as YOLOv5, YOLOv8, YOLO NAS, and YOLOv11 have further improved in terms of speed, precision, and usability.

The integration of YOLO models into dental diagnostics opens the door for automated caries detection using not just X-rays but also intraoral photographs captured via high-resolution cameras or mobile devices. This advancement can enable timely diagnosis even outside traditional dental settings, making oral healthcare more accessible and standardized.

This study explores the development and validation of a YOLO-based deep learning system for automated detection of dental caries from clinical images. The goal is to evaluate its performance, analyze its diagnostic indicators, and assess its potential to support and enhance clinical decision-making in dentistry.

While AI-based systems have shown promise in dental diagnostics, one major challenge remains—image standardization. Factors like lighting differences, image quality, and user handling make it difficult to maintain consistent results. Because of these limitations, it’s difficult to use automated tools for cavity detection, and there hasn’t been much research on how accurate AI can be when using images taken with regular cameras under such varied conditions.

This study aims to develop and validate a simple, low-cost system that uses advanced AI techniques, like model combination and transfer learning, to detect dental cavities from non-standard dental images, while still ensuring the results are accurate and clinically useful.

1. LITERATURE REVIEW

Artificial Intelligence (AI) has revolutionized dental caries diagnosis by improving accuracy and efficiency through machine learning (ML) and deep learning (DL) techniques. Traditional methods like visual-tactile examination and radiographic imaging often struggle with early detection and subjectivity, leading to diagnostic inconsistencies (Selwitz et al., 2007). AI-driven approaches, particularly Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), have shown superior accuracy in analyzing dental images, identifying caries with over 90% precision (Yamashita et al., 2018). AI-powered tools such as AssistDent and YOLOv3-based object detection models have further improved real-time detection, reducing false positives and increasing diagnostic efficiency (Ding et al., 2021). However, challenges such as data privacy concerns, model bias, and clinician acceptance remain critical obstacles to widespread adoption (Rischke et al., 2022). Future advancements in federated learning, tele-dentistry integration, and explainable AI (XAI) are expected to refine AI-driven diagnostics, making them more accessible and reliable for dental professionals.

Recent advancements in AI-driven dental imaging have demonstrated promising results in improving diagnostic accuracy and efficiency. AbuSalim et al. (2024) introduced a multi-granularity approach using YOLO-based object detection models for effective tooth detection and classification. Their findings suggest that AI-powered imaging can significantly enhance diagnostic precision, reducing errors associated with manual inspections. Furthermore, Ramírez-Pedraza et al. (2025) explored deep learning applications in oral hygiene, specifically focusing on automated dental plaque detection using the YOLO framework. Their study highlights the potential of AI models in improving preventive dental care by offering real-time detection and quantification of dental plaque using the O’Leary Index. These advancements indicate a growing trend toward AI integration in dentistry, paving the way for innovative solutions that minimize patient discomfort while optimizing clinical workflows.

AbuSalim et al. (2024) explore the application of YOLO-based object detection models for dental image analysis, specifically focusing on tooth detection and classification. The study addresses the limitations of traditional dental imaging techniques and evaluates the effectiveness of AI-driven solutions. The researchers investigate whether YOLO-based object detection can enhance tooth classification accuracy compared to conventional methods. Their methodology involves training a YOLOv5 model on clinically sourced dental images, preprocessing the data, and evaluating model performance using standard accuracy metrics such as mean Average Precision (mAP). The findings indicate that AI-based object detection significantly improves diagnostic accuracy, reducing errors commonly associated with manual inspections. The study demonstrates that YOLO models can efficiently identify multiple teeth with high precision, highlighting the potential for real-time AI-assisted dental analysis. However, the research also notes certain limitations, such as the relatively small dataset size, which may affect generalizability, and the dependency on high-quality image preprocessing for optimal performance. The study contributes to the field by demonstrating the feasibility of AI-powered dental diagnostics and emphasizing the importance of dataset quality in model training. This research is highly relevant to the current project, as it provides a strong foundation for leveraging YOLO-based models in dental imaging. Building on these findings, our study will extend this work by utilizing YOLOv8, incorporating a more diverse dataset, and refining detection accuracy and efficiency for practical clinical applications.

The study by Salahin et al. (2023) focuses on using smartphone images to detect cavities in teeth. It uses the YOLOv5 model for object detection because it is fast and accurate. The model creates feature maps in three different sizes to detect small, medium, and large objects in the images. To see how well the model performs, the study measures accuracy using mean average precision (mAP) by checking true positive and false positive results. The results show that YOLOv5 works well for detecting medium and large cavities but is slightly less accurate with small ones. This research shows that smartphone images can be a simple and affordable way to screen for cavities.

According to Ali and Zhang (2024) gave a detailed overview of how the YOLO model has developed over time and how it’s used in different areas. They explained that YOLO is popular because it’s fast and accurate, which makes it great for tasks that need quick results, like real-time detection. The review also showed how YOLO has been used in many fields, including healthcare, traffic systems, and security. They compared different versions of YOLO with other models and found that YOLO performs well in terms of both speed and accuracy.

1. METHODOLOGY
2. ***Collect data:*** To collect data, we start by gathering dental images from available sources. Some of these images come from public datasets, like those on Kaggle. All the data used is de-identified, containing no patient information and fully compliant with privacy and HIPAA regulations. The dataset should include both healthy teeth images (no cavities) and cavity images (with cavities). Having a large and well-balanced dataset is important because it helps the model learn more effectively.
3. ***Data Augmentation :*** In this project, data augmentation techniques will be used to increase the size of our dataset by applying different transformations to the images. These transformations include horizontal flipping, vertical flipping, cropping, and rotation. By applying these techniques, we can create more varied images, which will help the model learn to recognize caries (cavities) in different situations. This makes the model better at generalizing, so it can work well on new, unseen images.
4. **Data Processing:** We used the NumPy and Pandas libraries to manage and simplify the data. NumPy helped with numerical tasks like handling image pixels and performing operations on them. Pandas are used to organize the data, making it easier to process, especially when dealing with image labels and other related information. These libraries helped make the data processing more efficient and manageable.
5. ***Stratified* *sampling*:** For splitting the images, we used the stratified sampling technique. This method helps ensure that each set (training, validation, and testing) includes a balanced mix of different types of images, such as front, back, upper, lower, and healthy teeth. It also helps prevent repetition and ensures that each set contains a diverse range of examples, helping the model learn more effectively and improving the accuracy of its evaluation.

A diagram of a sampling process

Description automatically generated with medium confidence  
 Figure-1 Stratified sampling method.

1. ***Data Splitting :*** We divided the dataset into three parts. The training set contained most of the images and was used to train the model. This allowed the model to learn how to recognize the differences between healthy and cavity-affected teeth. The validation set included a smaller number of images and was used to check how well the model performed after training. It helped us assess whether the model was functioning correctly and could make accurate predictions on new images. Finally, the testing set was used to evaluate the model’s overall performance.
2. ***Data Labeling*:** Data labeling is important for training the model because it helps the model understand the differences between healthy teeth and teeth with caries. We will label the images to identify whether they show healthy teeth or cavity teeth. To do this, we used labeling tools like LabelImg. Each image had a label assigned to it, such as healthy or cavity, so the model could learn from these labels and make accurate predictions when presented with new images.

A close-up of a person's mouth

Description automatically generated Figure 2: Image Annotation

**Training the YOLOv8 YOLOV11 Model:** We used YOLOv8, a model developed by Ultralytics, to detect cavities in dental images. Initially, the model did not recognize what cavities were. During training, it learned to identify cavities by being shown images repeatedly and adjusting its internal settings (called weights) to improve its accuracy. Training was done in batches, where small groups of images were processed at a time, and this process was repeated over several epochs. With more epochs, the model’s ability to detect cavities improved. After completing the training, we tested different versions of the YOLO model and evaluated their performance.

**Model Evaluation:** After training, we evaluate the model's performance using the validation set. The goal is to see how well the model can detect cavities. We use metrics like Accuracy, precision, and recall to evaluate the model predicts the objects in the image. Precision determines how many of the predicted objects are correct, while recall evaluates how well the model identifies all actual objects in the image. We also analyze True Positive to check if the model correctly identified cavities, and False

REFERENCES

1. Liu, J., Zhang, H., Chen, J., Meng, R., Gao, C., Han, L., Song, Y., Tian, Y., & Wang, Y. (2025). Automated detection and segmentation of dental caries using a novel cascaded learning approach. *Biomedical Signal Processing and Control*, *102*, 107344.

<https://doi.org/10.1016/j.bspc.2024.107344>

1. Salahin, S. M. S., Ullaa, M. D. S., Ahmed, S., Mohammed, N., Farook, T. H., & Dudley, J. (2023). One-Stage Methods of Computer Vision Object Detection to Classify Carious Lesions from Smartphone Imaging. *Oral*, *3*(2), Article 2. <https://doi.org/10.3390/oral3020016>
2. Tareq, A., Faisal, M. I., Islam, Md. S., Rafa, N. S., Chowdhury, T., Ahmed, S., Farook, T. H., Mohammed, N., & Dudley, J. (2023). Visual Diagnostics of Dental Caries through Deep Learning of Non-Standardised Photographs Using a Hybrid YOLO Ensemble and Transfer Learning Model. *International Journal of Environmental Research and Public Health*, *20*(7), 5351. <https://doi.org/10.3390/ijerph20075351>
3. Ayhan, B., Ayan, E., Karadağ, G., & Bayraktar, Y. (n.d.). Evaluation of Caries Detection on Bitewing Radiographs: A Comparative Analysis of the Improved Deep Learning Model and Dentist Performance. *Journal of Esthetic and Restorative Dentistry*, *n/a*(n/a). <https://doi.org/10.1111/jerd.13470>
4. Yilmaz, S., Tasyurek, M., Amuk, M., Celik, M., & Canger, E. M. (2024). Developing deep learning methods for classification of teeth in dental panoramic radiography. *Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology*, *138*(1), 118–127. <https://doi.org/10.1016/j.oooo.2023.02.021>
5. Juyal, A., Tiwari, H., Singh, U. K., Kumar, N., & Kumar, S. (2023). Dental Caries Detection Using Faster R-CNN and YOLO V3. *ITM Web of Conferences*, *53*, 02005.

<https://doi.org/10.1051/itmconf/20235302005>

1. Kadhare, R., Gotmare, Y., Madankar, M., Rathi, H., & Rathi, N. (2024). Deep Learning based Teeth Detection and Numbering System using YOLO. *2024 Asian Conference on Intelligent Technologies (ACOIT)*, 1–6. <https://doi.org/10.1109/ACOIT62457.2024.10939511>
2. Ali, M. L., & Zhang, Z. (2024). The YOLO Framework: A Comprehensive Review of Evolution, Applications, and Benchmarks in Object Detection. *Computers*, *13*(12), Article 12. <https://doi.org/10.3390/computers13120336>
3. Figure1 <https://www.scribbr.com/methodology/stratified-sampling/>
4. Figure2 <https://www.researchgate.net/figure/Example-of-image-annotation-a-Example-of-single-tooth-localization-visualization-blue_fig1_380531104>