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Automated Deep Caries Detection Using Deep Learning: From Data to Diagnosis

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Cover letter

September 26, 2024

Editorial Department of Journal of Dentistry

Dear Editor,

I am submitting a manuscript for consideration for publication in the Journal of Dentistry. The manuscript is entitled "***Automated Deep Caries Detection Using Deep Learning: From Data to Diagnosis***. "

It has not been published elsewhere, and it has not been submitted simultaneously for publication elsewhere.

This study identifies Caries, and deep caries in the clinical environments.. We accurately identify and segment deep caries using advanced deep-learning technique YOLOv8 framework. Our dataset comprises 3,200 RGB images meticulously annotated at the pixel level to differentiate between caries, deep caries and exclusion classes. Training the YOLOv8 model for achieved an average detection accuracy of 75% .

Thank you very much for your consideration.

Yours Sincerely,

Amar Nath

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Title Page with Author Details

Automated Deep Caries Detection Using Deep Learning: From Data to Diagnosis

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Declaration of competing interest

The authors have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

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Automated Deep Caries Detection Using Deep Learning: From Data to Diagnosis

Abstract

Objectives: The study is to address the global burden of dental caries, a highly prevalent disease affecting billions of individuals, including both children and adults. Recognizing the significant health challenges posed by untreated dental caries, particularly in low- and middle-income countries, our goal is to improve early-stage detection. Traditional diagnostic methods, such as bitewing radiography, though effective, have limitations in detecting early lesions. By leveraging Artificial Intelligence (AI), we aim to enhance the accuracy and efficiency of caries detection, offering a transformative approach to dental diagnostics. *Methods*: This study proposes a novel deep learning-based approach using the YOLOv8 model for dental caries detection and classification. Trained on a dataset of over 3,200 images, the model addresses the shortcomings of existing detection methods and provides an automated solution to improve diagnostic accuracy. *Results*: The model achieved a mAP@0.5 of 0.982, demonstrating strong performance across multiple classes, including "Caries," "Deep Caries," and "Exclusion" *Conclusions***:** This high level of accuracy and efficiency highlights the potential of integrating AI-driven systems into clinical workflows, improving diagnostic capabilities, reducing healthcare costs, and contributing to better patient outcomes, especially in resource-constrained environments. *Clinical Significance:* Integrating AI-based models like YOLOv8 into dental diagnostics could revolutionize caries detection by improving early-stage diagnosis and enabling more cost-effective and accurate treatment decisions, particularly in low-resource settings.

Keywords: Dental Caries, Deep Carries, Deep Learning, YOLOv8, Object Detection, Artificial Intelligence

1. Introduction

Dental caries, commonly known as tooth decay, is one of the most widespread health issues worldwide, affecting approximately 3.5 billion people [1]. This disease represents a considerable public health challenge, particularly in low- and middle-income regions, where dental services are often inadequate. According to the World Health Organization (2022), dental caries affects between 60% and 90% of school-aged children and nearly all adults at some point in their lives. Dental caries can cause intense pain, infections, and eventually tooth loss without proper treatment. This burdens healthcare systems significantly, especially in underserved populations where preventive care is often lacking. Early detection and accurate classification of dental caries are essential for preventing the progression of tooth decay, which can lead to complications such as pain, tooth loss, and systemic health issues. Traditional manual caries detection methods, carried out by dentists, are often subjective, time-consuming, and prone to inaccuracies, particularly in the case of early-stage lesions or subtle abnormalities.

Dental caries is a multifactorial disease driven by the demineralization of tooth enamel and dentin caused by acidic by-products from bacterial metabolism. One primary bacteria involved is Streptococcus mutans, which plays a key role in biofilm formation. These biofilms create an acidic environment that accelerates the breakdown of hard dental tissues, ultimately leading to cavities [2]. Detecting caries at an early stage is crucial to prevent disease progression, minimize the need for invasive treatments, and reduce associated healthcare costs. Despite advances in dental technology, diagnosing early-stage dental lesions remains challenging. Bitewing radiography is currently the gold standard for detecting early-stage proximal caries, but it has its limitations in identifying initial lesions [3].

The emergence of artificial intelligence (AI) has the potential to transform dental diagnostics by providing more accurate and efficient methods for identifying carious lesions. AI-powered diagnostic systems can analyze dental images, detect early-stage caries, and highly predict disease progression. Artificial intelligence (AI) advancements have opened new avenues for improving dental diagnostics. Deep learning, a subset of AI, has successfully analyzed medical images, including dental radiographs. Convolutional neural networks (CNNs) have proven effective in image classification, object detection, and segmentation tasks. These systems improve the accuracy of diagnoses and address geographic and resource-related disparities in dental care. In remote or underserved areas, AI tools could provide valuable assistance to healthcare professionals by supporting early diagnosis and timely interventions, thereby reducing the overall impact of dental caries on populations. In deep learning, the quality and size of the dataset play a pivotal role in determining the accuracy and generalizability of the model. A robust, real-world dataset is essential for training deep learning models to perform effectively in clinical settings. To detect dental caries, having a diverse and comprehensive dataset that includes a wide range of cases across different ages, genders, and dental conditions ensures that the model can generalize well to unseen data and perform accurately in varied clinical scenarios.

In this study, we collected a large and diverse dataset of dental radiovisiographic (RVG) images from Postgraduate Institute (PGI) Sangrur, Punjab-India encompassing patients of all ages and genders. This diversity is crucial for creating a model that accurately detects caries across different demographics and dental conditions. The dataset underwent rigorous preprocessing, including normalization, to ensure consistent input values and data augmentation techniques such as rotation, flipping, and scaling. This preprocessing step was essential for enhancing the model's robustness and improving its ability to detect caries in noisy or lower-quality images. A process of data collection to dataset preparation process is depicted in Figure 1

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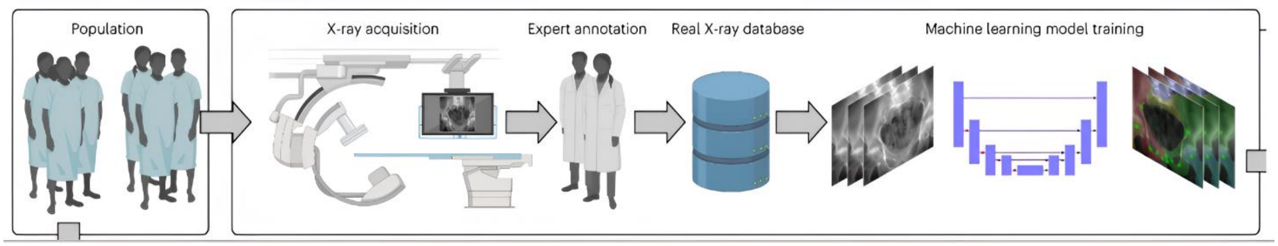

Figure 1. Data collection process for caries identification

Once preprocessed, the dataset was used to train our deep-learning model. By applying the YOLOv8 object detection model, we aimed to enhance the accuracy and efficiency of dental caries detection in RVG images. Combining a real-world, diverse dataset and advanced preprocessing methods ensures that the deep learning model can handle variations in image quality and patient demographics, providing reliable and clinically relevant results. Integrating this dataset into our model not only strengthens its predictive power but also supports the creation of an automated diagnostic tool adaptable to a broad range of clinical cases, offering a significant step forward in AI-driven dental diagnostics.

This study introduces a deep learning-based approach for dental caries detection, leveraging the YOLOv8 model to enhance diagnostic accuracy. YOLOv8, a state-of-the-art object detection algorithm, offers real-time detection capabilities, making it an ideal solution for identifying dental caries in clinical environments. Our model is trained on a diverse and extensive dataset comprising over 3,200 dental images, which have undergone rigorous preprocessing and data augmentation to ensure generalizability and robustness in various clinical scenarios.

This research aims to address existing limitations in dental caries detection by providing a fully automated AI-based solution that can be easily integrated into clinical workflows. By offering real-time analysis of dental images, the proposed system aims to increase diagnostic efficiency, reduce human error, and ultimately improve patient outcomes. This study contributes to the growing field of AI-driven healthcare by demonstrating the potential of deep learning models like YOLOv8 to revolutionize dental diagnostics and enhance access to care in resource-limited settings.

2. Literature Review

Dental caries detection has been a significant research focus in recent years, particularly with the advent of AI technologies. Traditional methods for detecting dental caries include bitewing radiography, fiber-optic transillumination, fluorescence-based techniques, and cone-beam computed tomography (CBCT). While these techniques are widely used, each has limitations, such as high costs or difficulty in detecting early-stage lesions [4]. Despite its drawbacks, Bitewing radiography remains the most reliable tool for diagnosing demineralized proximal caries. AI has emerged as a promising tool for addressing the limitations of traditional methods. Numerous machine learning and deep learning models have been developed to enhance the accuracy of caries detection. For example, [5] introduced CariesNet, an AI-driven model for analyzing dental radiographs and identifying carious lesions with high precision. The system performed pixel-level classification, enabling dentists to pinpoint decay more accurately. Similarly, [6] explored the use of texture features extracted through the Gray Level Co-Occurrence Matrix (GLCM) algorithm, combined with Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) classifiers. While the study achieved promising accuracy rates of 95.7% with SVM and 94.9% with KNN, the relatively small dataset of 396 images raised concerns about the generalizability of the results. Deep learning models have also shown considerable potential in dental diagnostics. [7] employed YOLOv3 and Faster R-CNN models to detect dental cavities from live camera images, eliminating the need for X-rays. The study demonstrated an accuracy of 75% with YOLOv3 and 80% with Faster R-CNN, although the limited dataset of 300 images highlighted the need for larger, more diverse datasets for training.

[8] introduced the YOLOv8 model for automatically detecting and classifying dental issues using Bitewing and Orthopantomography (OPG) X-rays. Their model achieved a mean Average Precision (mAP) of 71.6%, demonstrating the effectiveness of deep learning in dental radiographic analysis but also indicating room for improvement in precision. Our approach builds on these advancements by leveraging the YOLOv8 deep learning model to detect and classify dental caries across multiple classes. We address the limitations of previous studies by utilizing a significantly larger dataset of 3,200 images, augmented through various techniques to enhance model robustness and generalizability. By improving the accuracy of deep caries detection, our system aims to provide a reliable, automated solution that can complement existing diagnostic tools and improve patient outcomes.

3. Materials and Methods

This section outlines the processes and tools used to develop a deep learning-based approach for detecting dental caries using the YOLOv8 model. The study employed a dataset of over 3,200 radiographic images, which were carefully annotated into three distinct classes: "Caries," "Deep Caries," and "Exclusion." Preprocessing techniques, including image resizing and normalization, were applied to prepare the data for training. The YOLOv8 model, known for its real-time detection capabilities and high accuracy, was trained and validated using a split of the dataset, with key metrics such as mean Average Precision (mAP@0.5) used to evaluate performance. This section details the steps taken from data collection to model training and evaluation, ensuring transparency and reproducibility in the study’s methodology.

3.1 Dataset

The dataset utilized in this study was meticulously curated from the Department of Radiodiagnosis at the PGIMER Satellite Centre in Sangrur, Punjab, India, comprising 3,200 high-resolution intraoral periapical radiographs, each representing distinct cases of advanced dental caries. These radiographs were selected to encompass a wide range of clinical presentations, ensuring the representation of various stages and patterns of deep caries involvement across different anatomical sites and patient demographics. The curation process involved selecting cases that accurately depict carious lesions extending into the dentin or pulp, thereby providing a comprehensive learning resource for AI-driven caries detection.

Following the acquisition, a thorough radiographic image preprocessing pipeline was implemented. This included eliminating radiographic artifacts, noise reduction, and removing extraneous anatomical features irrelevant to caries identification, such as surrounding bone structures or soft tissue, to optimize the dataset for training the deep learning model. Each image was then meticulously reviewed by dental professionals to ensure that the radiographs met the diagnostic quality standards necessary for accurate deep caries detection. Representative samples of these cleaned and annotated images are provided in Figure 2, demonstrating the variety and clarity of cases used for model training.

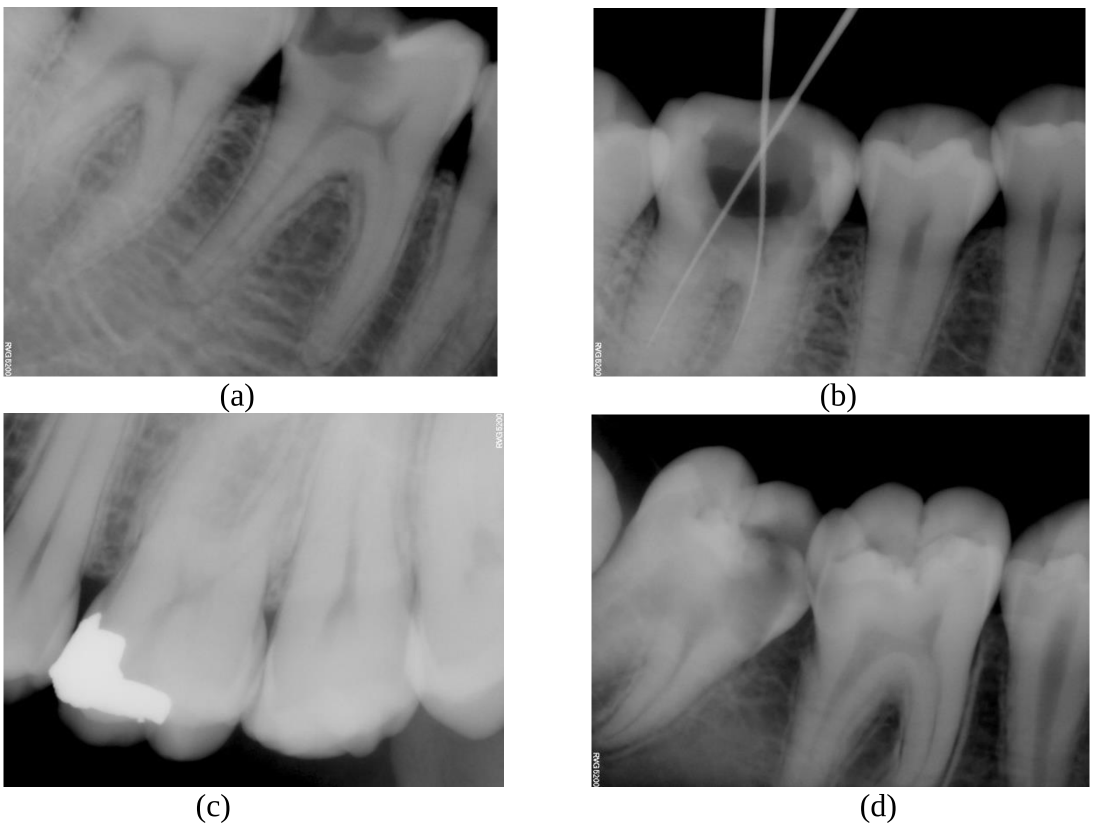

Figure 2 Sample images from the dataset

3.2 Annotation and Augmentation of Dataset

To prepare the dataset for training the YOLOv8 model, a meticulous and comprehensive annotation process was undertaken using the Roboflow platform [9], a widely recognized online tool that excels in data annotation and augmentation. Roboflow's capabilities allow for precise marking of areas of interest, which is essential for object detection tasks. The platform provided an intuitive interface for labeling the X-ray images, streamlining the workflow, and ensuring consistency throughout the annotation process.

The annotation was performed manually by a team of trained annotators under the supervision of experienced dental professionals to maintain the highest level of accuracy. Initially, the cleaned high-resolution X-ray images were pre-processed to remove artifacts and noise and uploaded onto the Roboflow platform. The annotators used Roboflow's rectangular annotation tool to create bounding boxes around regions of interest within each image. These regions specifically included areas presenting caries and deep caries, as the supervising dental experts identified. To ensure precision, each bounding box was carefully adjusted to encapsulate the carious regions tightly, minimizing the inclusion of surrounding healthy tissue or irrelevant anatomical structures. This step was crucial for the model to effectively differentiate between caries, deep caries, and exclusion areas. The annotators also reviewed each image multiple times, refining the bounding boxes necessary to guarantee consistency and accuracy across the dataset. Furthermore, Roboflow's automatic augmentation tools were employed to enhance the variability of the dataset. Techniques such as rotation, zoom, and brightness adjustments were applied to simulate real-world conditions and improve the model's robustness to variations in the data.

Each annotated region was then labeled with one of three classes:

- **Exclusion:** Areas of the image that should be ignored during model training, typically representing irrelevant regions or non-dental structures.
- **Caries**: These Regions exhibit signs of early or superficial dental caries.
- **Deep Caries**: These Regions show advanced stages of caries, which penetrate deeply into the tooth structure.

The manual annotation process was highly rigorous, ensuring that each X-ray image was meticulously labeled to train the YOLOv8 model for dental caries detection with maximum accuracy. Each image underwent detailed scrutiny by trained annotators, working under the supervision of dental experts, to ensure that the various regions were correctly identified. These annotations were saved in XML format, which is a widely accepted standard in the machine learning community, particularly for object detection tasks. The XML format contains information on the coordinates of the bounding boxes, class labels, and image dimensions, making it highly compatible with various machine-learning frameworks, including YOLOv8. The format also facilitates smooth integration into the model's training pipeline, allowing for efficient processing of annotated data. This process was labor-intensive and time-consuming, requiring several hours of careful work to annotate the entire dataset. The annotators drew precise bounding boxes around regions affected by caries and deep caries, and these were meticulously adjusted to ensure they tightly enclosed the areas of interest. Once the annotations were completed, they were thoroughly reviewed for accuracy. Any discrepancies or misalignments were corrected to ensure that the labeled dataset was of the highest quality. This level of attention to detail was vital for the deep learning model to learn effectively from the data and perform well in the task of detecting complex caries cases.

Following the annotation and review process, the data was exported in XML format, ready for use in the YOLOv8 model's training phase. Using XML ensured compatibility and ease of integration with the training algorithms. The annotations were further enhanced by applying various data augmentation techniques to improve the model's robustness to variations in image quality and lighting conditions. These augmentations included transformations such as rotations, scaling, and brightness adjustments, simulating real-world variations, and expanding the dataset's diversity.

The success of this annotation process was essential to developing a reliable model for deep caries detection. Table 1 provides a comprehensive description of the dataset, including the augmentation techniques, parameters used, and the data acquisition setup, highlighting the critical aspects contributing to the model's training efficacy.

Table 1. Dataset overview and augmentation details

Subject	Artificial Intelligence, Computer Vision, Dentistry, and Medical Science
Original Images	2000
After Augmentation Images	3,200
Specific Area	Image Classification, Object Detection
Type of Data	Images, Annotation Files
Data Format	Raw images: .jpg format, manually annotated images: XML files
Data Augmentation	Zooming range: [0.8, 1.2] Shearing: 10 Flipping: Horizontal flip Changing brightness: Between -15% and +15%

	Cropping: px=(0, 10) Image rotation: 20°

Deep learning models typically require large datasets to learn object features and enhance model generalization and robustness. To address this need, data augmentation was performed, expanding the dataset size. The augmentation techniques applied included zooming, shearing, horizontal flipping, adjusting brightness, cropping, image rotation, and noise addition, as shown in Fig. As a result, the dataset grew from 2,000 to 3,200 images.

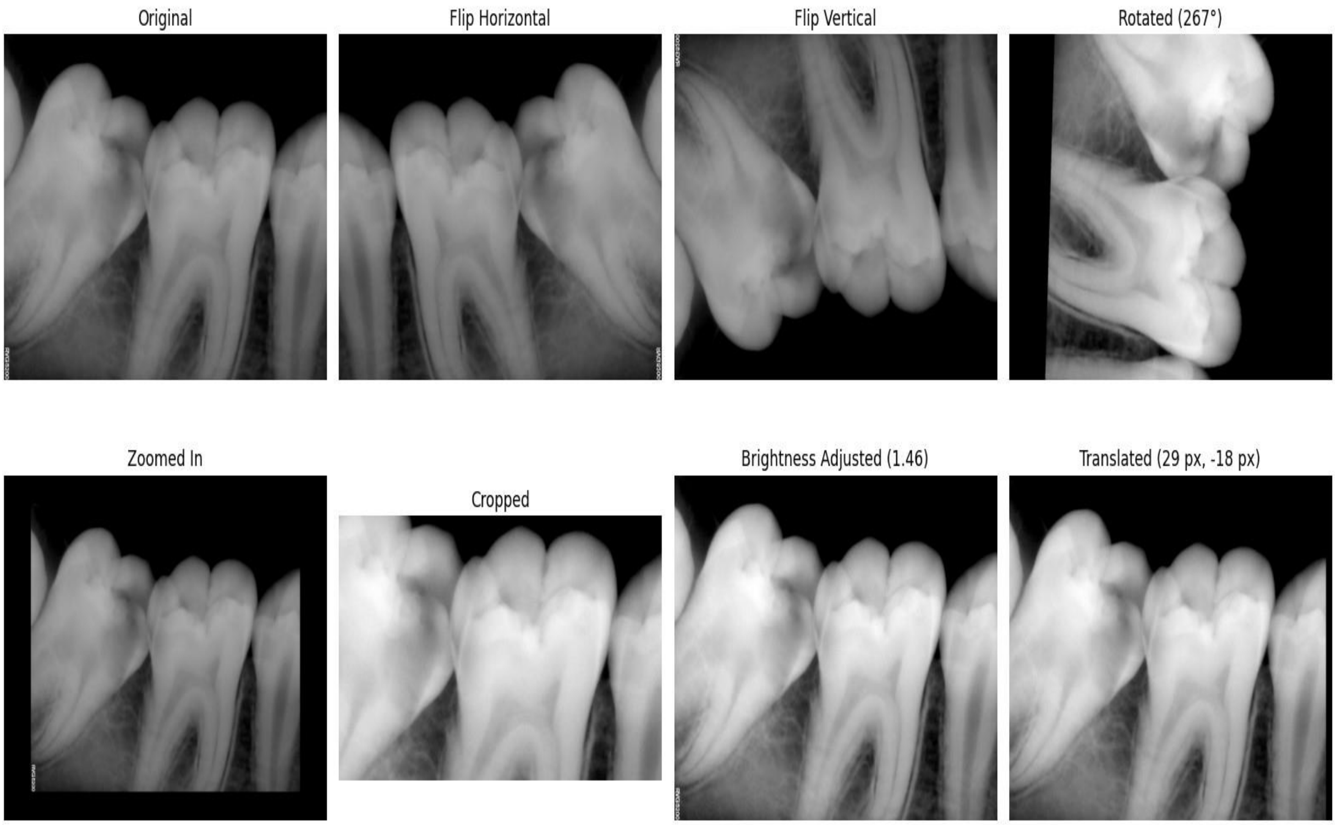

Figure 3. Data augmentation techniques used

3.3 Deep learning Model: YOLOv8

YOLOv8 (You Only Look Once, Version 8) [10] is a state-of-the-art deep learning model designed for real-time object detection, segmentation, and classification tasks. Developed as part of the YOLO family of models, YOLOv8 continues the legacy of its predecessors by offering an even more efficient and accurate approach to detecting objects within images or video streams.

3.3.1 YOLOv8 Architecture

YOLOv8 architecture builds on the core principles of its predecessors but incorporates several enhancements to improve performance, particularly in object detection and segmentation tasks The architecture is represented in Figure 4.

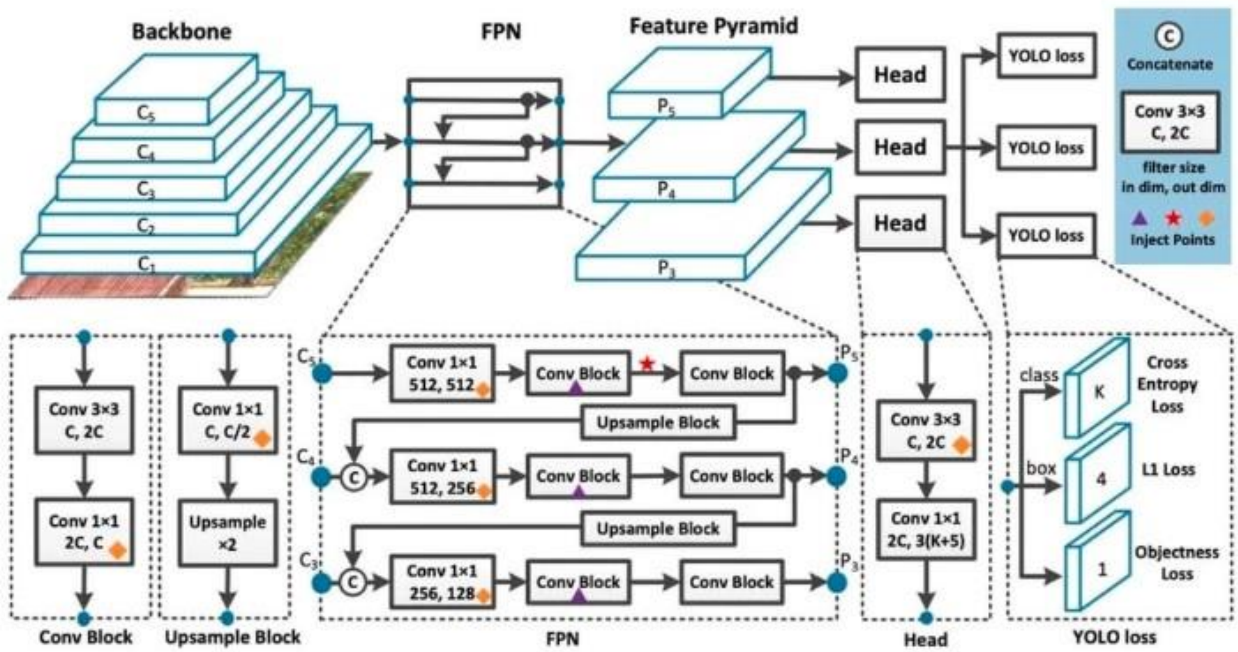

Figure 4. YOLOv8 Architecture [10]

YOLOv8 has three essential blocks: Backbone, Neck, and Head.

- **Backbone**: The backbone of YOLOv8 is responsible for feature extraction from input images. It uses a convolutional neural network (CNN) structure with multiple layers to progressively capture more complex and abstract features, such as edges, textures, and shapes. YOLOv8 typically employs a modern and efficient backbone network that balances speed and accuracy, allowing it to process images in real time.

- **Neck:** The neck is a critical part of the architecture that aggregates and refines the features extracted by the backbone. YOLOv8 often uses a path aggregation network (PANet) or a similar feature pyramid network (FPN) design. This structure enhances the model's ability to detect objects of varying sizes by combining features at different scales, improving the detection of small or overlapping objects.
- **Head:** The head of the YOLOv8 model is where object detection and classification occur. It generates predictions for bounding boxes (regions where objects are located) and classifies the objects within those boxes. The head also includes layers for generating segmentation masks if the task involves object segmentation. YOLOv8 employs anchor-free detection, meaning it predicts object locations directly rather than relying on predefined anchor boxes, which can improve accuracy and reduce computational complexity.

3.3.2 Activation Functions and Loss Functions

YOLOv8 utilizes advanced activation functions like Mish or SiLU (Sigmoid Linear Unit) to improve gradient flow during training, leading to better model convergence. The loss function used in YOLOv8 typically includes components for bounding box regression, object classification, and, if applicable, segmentation mask prediction. These are carefully balanced to ensure that the model learns to prioritize both accuracy and localization.

3.3.3 Post-Processing

After the model generates predictions, a post-processing step applies techniques like non-maximum suppression (NMS) to remove duplicate or overlapping bounding boxes, ensuring that only the most accurate detections are retained.

4 Experimental Evaluation

In this section, extensive experiments are done using the state-of-the-art algorithm YOLOv8. Python-3.10.12, torch-2.2.1+cu121, and GPU (NVIDIA RTX A1000) were utilized to train the model. After fine-tuning the model, we get the best results at batch size 4, image size 800, Optimizer AdamW, learning rate 0.001667, momentum 0.9, and weight decay 0.0005. The various loss and accuracy graphs for YOLOv8 are represented in the Figure 6.

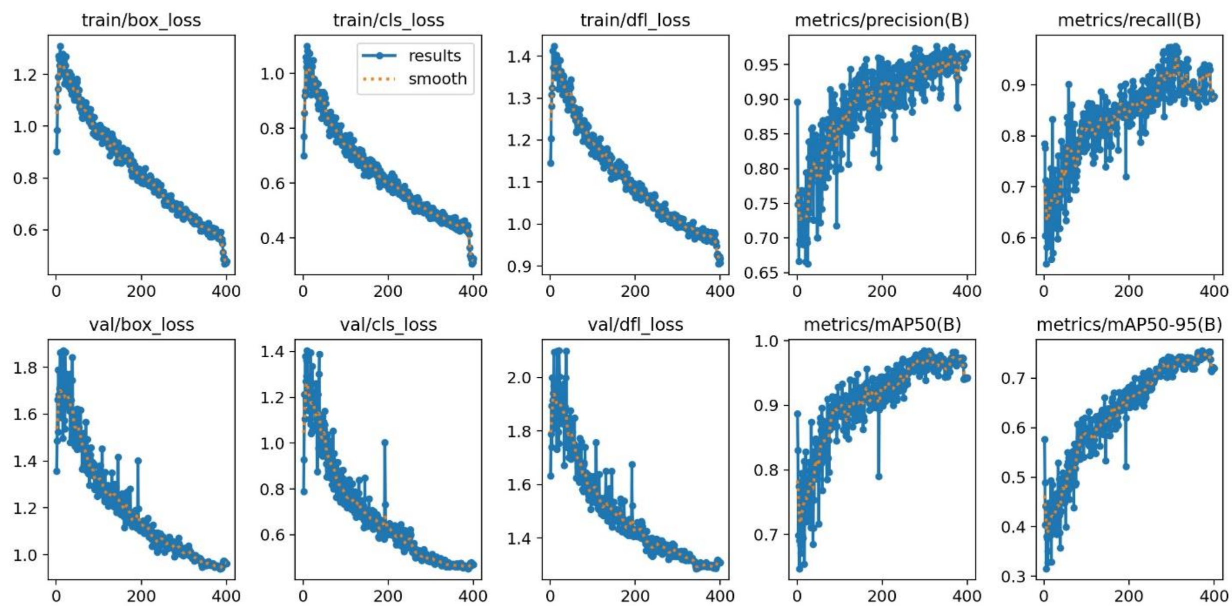

Figure 5. Various Loss and Accuracy graphs obtained after training and validating the model

4.1 Performance metrics

The various performance metrics used to evaluate the performance of an object detection model are Precision, Average Precision (AP), Mean average precision (mAP), F-measure(F1), and Recall [11]

4.1.1 Precision

Precision is the ratio of correctly predicted positive observations to the total predicted positives. It answers the question: Of all instances the model predicted as positive, how many were actually positive?

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

4.1.2 Recall

Recall is the ratio of correctly predicted positive observations to all observations in the actual class. It answers the question: Of all actual positive instances, how many were correctly predicted as positive?

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

4.1.3 F1 Score

The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances both concerns, particularly useful when dealing with imbalanced datasets.

$$F1\ Score = \frac{2.Precision.Recall}{Recall}$$

4.1.4 Mean Average Precision (mAP@50)

Mean Average Precision at IoU threshold 0.5, denoted as mAP@50, is a standard metric in object detection that averages the precision across all classes for a given Intersection over the Union (IoU) threshold, typically set at 0.5. This threshold indicates that a predicted bounding box is correct if it overlaps the ground truth box by at least 50%.

$$mAP = \frac{1}{n}\sum_{i=1}^{n} AP_i$$

The Average Precision (AP) for a single class is the area under the Precision-Recall curve for that class.

4.1.5 Intersection over Union (IoU)

Intersection over Union (IoU) is a measure used to quantify the accuracy of the object detector on a particular dataset. IoU is defined as:

$$IOU = \frac{Area\ of\ overlap}{Area\ of\ union}$$

This metric decides whether a predicted bounding box is a true positive (TP) or a false positive (FP).

5 Results and discussion

The YOLOv8 model performed exceptionally well on our proposed dataset. The results are compiled in Table 2. The "Deep Caries" class has the highest recall (0.84), meaning that the model is good at detecting most instances of deep Caries. The model achieves an overall accuracy of 0.73, indicating a moderate level of performance across all classes. For the "Caries" class, the model is fairly good at correctly identifying positive cases, with a precision of 85%. However, the model somewhat struggles with recall, identifying only 63% of true "Caries" cases. This indicates that some "Caries" instances are being missed.

Table 2: Performance Metrics for Dental Dataset Classification

Class	Precision	Recall	F1 Score	Accuracy
Exclusion	0.97	0.94	0.96	
Caries	0.85	0.63	0.72	-
Deep Caries	0.72	0.83	0.77	-
Background	0.31	0.68	0.43	-
Overall	-	-	-	75

The model achieved a mAP@0.5 of 0.982, indicating excellent performance in detecting and localizing objects such as dental caries, deep caries, and backgrounds with an accuracy of 98.2% across all classes. The model performs well for the "Caries" class, achieving a precision of 85% in correctly identifying positive cases. In the "Exclusion" class, the model demonstrates high precision (0.97), meaning it is highly accurate in predicting this class, and strong recall (0.94), indicating it correctly identifies most true "Exclusion" instances. The F1 score of 0.96 reflects a well-balanced and effective performance in this class. Similarly, for the "Deep Caries" class, a precision of 0.72 indicates that 72% of the instances predicted as "Deep Caries" are correctly identified. With a recall of 0.83, the model captures most of the true deep caries cases, and the F1 score of 0.77 suggests a good balance between precision and recall, highlighting the model's strong ability to detect deep caries. The visual outcomes are represented in Figure 7

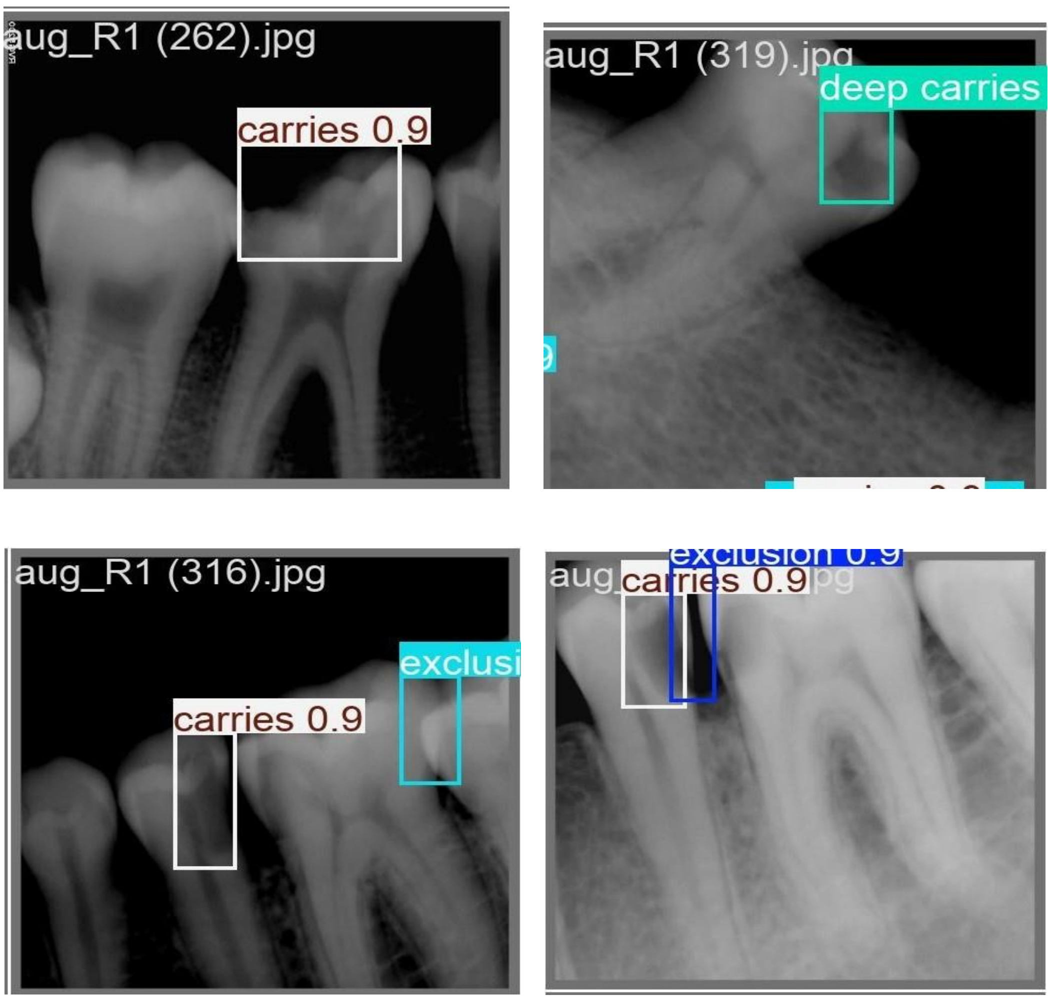

Figure 6. Visual outcomes of YOLOv8 model

The size of the dataset plays a crucial role in deep learning. As given in Table 3, the analysis of various studies on dental caries detection highlights several vital observations. First, larger datasets, such as those used by [8] and the proposed study, generally lead to better performance metrics. In contrast, smaller datasets (112 and 304 images) used in other studies may limit model generalization. Additionally, model evolution plays a significant role, with more advanced architectures like YOLOv8 outperforming older models such as FCNN in both precision and accuracy. This underscores the advancements in deep learning models for object detection over time. YOLOv8, in particular, demonstrates consistently stronger performance across metrics like mAP and accuracy, suggesting its superior suitability for caries detection compared to models like FCNN, ResNet, Inception, and U-Net. Overall, the proposed study shows notable improvements in accuracy due to the larger dataset and the use of YOLOv8, reflecting progress in both dataset acquisition and model sophistication for dental caries detection.

Table 3. Result summary of studied models for dental caries detection

Reference	Year	Dataset Size	DL Model Used	Result
[12]	2017	3000	FCNN	Precision: 61.5%
[13]	2021	112	ResNet+Inception	Accuracy:73.3%
[14]	2021	304	UNet	Precision:65.02%
[8]	2024	1516	YOLOv8	mAP: 71.6%
This Study	**2024**	**3,200**	**YOLOV8**	**Accuracy: 75%**

6. Conclusion

The proposed deep learning approach using the YOLOv8 model demonstrates significant promise in enhancing the detection and classification of dental caries. With a large dataset of over 3,200 images and advanced data augmentation techniques, the model achieved an impressive mAP@0.5 of 0.982, reflecting its strong performance across all dental classes. The model performs particularly well in detecting "Deep Caries" with a precision of 0.72 and recall of 0.83, indicating its effectiveness in identifying true positive cases. While the model shows high precision for the ``Exclusion" class (0.97) and good overall accuracy, there is room for improvement in the recall of ``Caries" cases. By offering a reliable and automated solution, this approach could be an invaluable tool in clinical dental settings, helping to improve early detection and reduce the reliance on invasive procedures.

References

[1] World Health Organization, Oral Health, (2022).

[2] J.A. Lemos, S.R. Palmer, L. Zeng, Z.T. Wen, J.K. Kajfasz, I.A. Freires, J. Abranches, L.J. Brady, The Biology of Streptococcus mutans , Microbiol Spectr 7 (2019). https://doi.org/10.1128/microbiolspec.gpp3-0051-2018.

[3] K. Kamburoğlu, E. Kolsuz, S. Murat, S. Yüksel, T. Özen, Proximal caries detection accuracy using intraoral bitewing radiography, extraoral bitewing radiography and panoramic radiography, Dentomaxillofacial Radiology 41 (2012). https://doi.org/10.1259/dmfr/30526171.

[4] A.D. Al Saffan, Current Approaches to Diagnosis of Early Proximal Carious Lesion: A Literature Review, Cureus (2023). https://doi.org/10.7759/cureus.43489.

[5] H. Zhu, Z. Cao, L. Lian, G. Ye, H. Gao, J. Wu, CariesNet: a deep learning approach for segmentation of multi-stage caries lesion from oral panoramic X-ray image, Neural Comput Appl 35 (2023). https://doi.org/10.1007/s00521-021-06684-2.

[6] Y. Jusman, M.K. Anam, S. Puspita, E. Saleh, S.N.A.M. Kanafiah, R.I. Tamarena, Comparison of Dental Caries Level Images Classification Performance using KNN and SVM Methods, in: Proceedings of the 2021 IEEE International Conference on Signal and Image Processing Applications, ICSIPA 2021, 2021. https://doi.org/10.1109/ICSIPA52582.2021.9576774.

[7] A. Juyal, H. Tiwari, U.K. Singh, N. Kumar, S. Kumar, Dental Caries Detection Using Faster R-CNN and YOLO V3, ITM Web of Conferences 53 (2023). https://doi.org/10.1051/itmconf/20235302005.

[8] M. Razaghi, H.E. Komleh, F. Dehghani, Z. Shahidi, Innovative Diagnosis of Dental Diseases Using YOLO V8 Deep Learning Model, in: Iranian Conference on Machine Vision and Image Processing, MVIP, IEEE Computer Society, 2024. https://doi.org/10.1109/MVIP62238.2024.10491172.

[9] Roboflow, Roboflow. Give your software the power to see objects in images and video., (2020). https://roboflow.com/.

[10] G. Jocher, A. Chaurasia, J. Qiu, YOLOv8, Ultralytics (2023). https://github.com/ultralytics/ultralytics.

[11] R. Padilla, S.L. Netto, E.A.B. da Silva, A Survey on Performance Metrics for Object-Detection Algorithms, in: 2020 International Conference on Systems, Signals and Image Processing (IWSSIP), IEEE, 2020: pp. 237–242. https://doi.org/10.1109/IWSSIP48289.2020.9145130.

[12] Srivastava, Muktabh Mayank and Kumar, Pratyush and Pradhan, Lalit and Varadarajan, Detection of tooth caries in bitewing radiographs using deep learning, ArXiv Preprint ArXiv:1711.07312 (2017).

[13] M. Moran, M. Faria, G. Giraldi, L. Bastos, L. Oliveira, A. Conci, Classification of approximal caries in bitewing radiographs using convolutional neural networks, Sensors 21 (2021). https://doi.org/10.3390/s21155192.

[14] S. Lee, S. il Oh, J. Jo, S. Kang, Y. Shin, J. won Park, Deep learning for early dental caries detection in bitewing radiographs, Sci Rep 11 (2021). https://doi.org/10.1038/s41598-021-96368-7.

Conflicts of Interest Statement

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