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DENTAL CARRIES CLASSIFICATION USING YOLO V8

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ABSTRACT:
This study focuses on the development of a sophisticated caries detection system using deep learning techniques applied to periapical dental X-ray images. By customizing the YOLOv8 architecture, the system was optimized for accurate caries identification. The training process involved intricate customization, including backbone and feature extraction neck integration, and head design. Pre-processing was applied to enhance detection efficiency. Leveraging YOLOv8 elements like the SPPF layer, up-sample layers, and detection modules enabled precise identification of dental caries lesions within X-ray images. The training dataset was meticulously curated with pixel-level annotations by certified dentists to ensure detailed representation. Augmentation techniques like random flipping and rotation were employed to enhance dataset diversity, model generalizability, and standardization. The system's efficacy is validated using a comprehensive suite of metrics: Mean Average Precision (mAP) of 91.8%, F1-score of 92.0%, and recall of 92.6%. This showcases its proficiency in accurately identifying and localizing caries lesions and other relevant dental conditions within X-ray images. The unique aspect of training the network for detecting five classes (cavity, crown, restoration, missing tooth, and root canal treated) on a preliminary basis using a dataset collected from Pakistani patients in Karachi adds a significant dimension to this study. This approach aligns with recent advancements in deep learning algorithms for dental applications, emphasizing the importance of leveraging modern architectures to improve dental diagnostics and aid in accurate diagnoses based on periapical radiographs.

KEYWORDS: Deep Learning, Caries Detection, Dental X-ray, YOLOv8, Periapical Radiography.

1. INTRODUCTION:

Caries detection is a crucial component of dental diagnostics, playing a significant role in the early identification of tooth decay. Leveraging advanced technologies like deep learning can improve the accuracy and efficiency of caries detection processes. One promising strategy involves integrating deep learning models, specifically the You Only Look Once (YOLO) algorithm, particularly YOLO version 8 (Yolov8), with periapical X-rays for caries detection. Deep learning algorithms, such as YOLO, have showcased remarkable capabilities across various domains, from drug quality inspection [1] to ecological data analysis [2]. These algorithms have been effectively utilized in detecting a wide array of objects, lesions, defects, and anomalies in diverse fields. For example, YOLO models have been deployed in identifying apple lesions in orchards [3], recognizing rail defects in ultrasound images [4], and even pinpointing knee cystic lesions on MRI scans [5]. The YOLO algorithm, renowned for its efficiency in object detection tasks, has continuously evolved, with iterations like YOLOv3 and YOLOv5 demonstrating enhanced performance in real-time detection scenarios. Researchers have also explored amalgamating YOLO with other methodologies, such as the Grab Cut algorithm for skin lesion segmentation [6], underscoring the versatility and adaptability of YOLO in various applications.

Moreover, studies have underscored the superior performance of YOLOv8 models compared to alternative deep learning approaches like Faster R-CNN [7] and SSD [8] in detecting different carries lesions in periapical dental X-rays along with tasks such as greenhouse detection [8], algae species classification, and vehicle tracking [9]. The rapidity and precision of YOLO models, particularly in single-stage detection scenarios, render them ideal for applications necessitating real-time processing, such as caries detection in dental X-rays. By harnessing the capabilities of YOLOv8 alongside periapical X-rays, dental professionals and radiologists have the potential to enhance caries detection with exceptional precision and efficiency. The single-stage detection nature of YOLO aligns seamlessly with the imperative for prompt and accurate identification of carious lesions in dental images. This integration has the capacity to revolutionize caries detection processes, facilitating early intervention and leading to improved patient outcomes in dental care.

The utilization of YOLO version 8 for caries detection in periapical X-rays represents a cutting-edge approach that amalgamates the prowess of deep learning with dental diagnostics. The evolution and success of YOLO models in diverse object detection tasks underscore their potential to elevate caries detection accuracy and efficiency, benefiting both dental practitioners and patients in the realm of dentistry. The amalgamation of expert and intelligent systems applications, reliant on machine learning and computer vision, has significantly advanced various fields such as security surveillance, image classification diagnostics, autonomous driving, autonomous vehicles, and industrial robots. Object detection, a longstanding and fundamental challenge in computer vision, aims to automatically identify the presence and spatial placement of specific objects in images, a task crucial for numerous clinical applications, including medical and dental diagnostics. The addition of bounding boxes to organs can serve as a preliminary step before employing further image processing techniques like segmentation, with organ tracking proving valuable in scenarios such as radiotherapy or medical and dental diagnostics. Object detection models can aid in these tasks, offering efficiency and accuracy in identifying objects in images despite variations in lighting conditions, perspective, and object distance.

The development of convolutional neural networks (CNNs) has been pivotal in enhancing object recognition, with structures like LeNet [10], AlexNet [11], VGG-Net [12], GoogleLeNet [13], and ResNet [14] significantly boosting the accuracy and efficiency of object detection tasks along with the sufficiently contributing in the methods to identifying the carries and different anomalies in the X-ray especially in the dental X-rays. The progression from R-CNN [15] to R-FCN [16] has streamlined object recognition, making it more precise and rapid. While these methods excel in object detection, they are region-based, prompting researchers to explore area-based identification approaches. The R-CNN system, a breakthrough in object identification in 2014, paved the way for subsequent advancements like Fast R-CNN and Faster R-CNN, each improving on the former in terms of speed and accuracy. The transition from R-CNN to R-FCN has further refined object recognition, making it more efficient and accurate. However, these techniques are region-based, necessitating continuous exploration for more streamlined and precise object detection methodologies.

The datasets used to train these algorithms are sourced from regional hospitals, optimizing the networks for detecting various dental parameters like cavities, crowns, restorations, missing teeth, and root canal-treated teeth in X-rays specific to local populations. Each image undergoes manual annotation by expert dentists using annotation software, ensuring the effectiveness of deep learning models like YOLO v8 in identifying dental abnormalities. Despite the limited availability of X-ray image datasets for this specific domain, the meticulous curation of datasets from regional hospitals ensures the optimization of deep learning models for accurate caries detection, contributing to enhanced diagnostic accuracy in dental care. The development of intelligent dental X-ray film interpretation systems holds the potential to elevate the quality of dental care, reduce the workload on dental specialists, and mitigate the occurrence of misdiagnoses. Deep learning-based object detection has surpassed classical machine learning techniques in terms of speed and accuracy, with deep convolutional neural networks emerging as a prominent player in object recognition tasks. The unique structure of sharing local weights in deep convolutional neural networks, particularly in forward-feedback neural networks, has significantly advanced object recognition capabilities, making them indispensable in various applications, including dentistry.

METHODOLOGY:

The methodology for integrating YOLOv8 with periapical X-rays for caries detection involves a systematic approach encompassing data collection, preprocessing, model training, evaluation, and validation. Drawing from the principles of deep learning and object detection, the methodology aims to optimize the detection of carious lesions in dental images.

2.1 Data Collection:

In our research project focusing on caries detection through deep learning methodologies using periapical X-ray images, the initial phase involved the meticulous process of data collection. We undertook the task of acquiring a diverse dataset of periapical X-ray images that encompassed a comprehensive mix of both carious and non-carious teeth, sourced from various dental clinics and institutions from all over the Karachi region. The goal was to develop a system optimized for the South Asian region, especially Karachi city and its surroundings, as all other datasets available are for European or East Asian regions. A total of around 5000+ periapical dental X-rays were collected. These images were meticulously selected to ensure a broad representation of dental conditions, facilitating the training of our caries detection model.

An essential aspect of our data collection process was to ensure that the dataset was meticulously annotated with bounding boxes around the various regions of interest. This annotation step was crucial for enabling the supervised training of our deep learning model, as it provided the necessary ground truth labels for the model to learn and accurately identify carious and non-carious regions within the X-ray images. For this purpose, we worked with certified dentists to ensure that our annotation was accurate and precise. Sample periapical X-ray images from the dataset are shown in Figure 1.

Figure 1: Sample periapical X-ray images from the data set.

Drawing inspiration from the multilevel threshold method described in the literature by Everett et al [17]. We employed advanced image processing techniques to segment and annotate the carious and non-carious regions within the X-ray images. By leveraging this method, we were able to precisely delineate the areas of interest and create detailed annotations that would guide the training process of our caries detection model. These annotations were marked by the certified dentist for accuracy and precision [18].

2.2 Data Preprocessing:

Upon acquiring the dataset, preprocessing steps are crucial to standardize and enhance the quality of the X-ray images. This phase involved a series of meticulous steps aimed at preparing the X-ray images for subsequent analysis and model training. Leveraging insights from various references, we meticulously executed the following preprocessing steps to optimize the dataset for effective caries detection:

2.2.1. Resizing Images: We standardized the size of the X-ray images to a uniform dimension to ensure consistency across the dataset. This resizing step aimed to eliminate variations in the resolution that could potentially impact the performance of the deep learning model during training and inference Lago et al [19].

2.2.2. Normalizing Pixel Values: We normalized the pixel values of the X-ray images to a common scale. This normalization process aligned the intensity levels of the images, making them suitable for comparative analysis and feature extraction [20].

2.2.3. Enhancing Contrast: We enhanced the contrast of the X-ray images to improve the visibility of carious lesions and other dental structures within the images. Adjusting the contrast levels aimed to highlight subtle variations in pixel intensity that could signify the presence of caries, aiding the detection process [21].

2.2.4. Data Augmentation: We used data augmentation techniques such as rotation, flipping, and brightness adjustment to broaden the dataset's diversity and enhance the model's capacity for generalization. These techniques introduced variations in the dataset, exposing the model to a wider range of image characteristics and scenarios [22].

Furthermore, to address variations in contrast levels among X-ray images obtained from different dental setups, additional preprocessing steps were implemented. The images were converted to grayscale to reduce computational overhead, followed by image enhancement using histogram equalization to increase contrast range. Linear interpolation and median blur filters were applied to remove image noise, and Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to enhance image visibility. Fast mean denoise and image sharpening filters were applied, followed by K-means clustering for image enhancement. These steps significantly improved image quality, enhancing the algorithm's accuracy and performance. The preprocessed images were validated by a certified dentist to ensure diagnostic adequacy.

By combining meticulous preprocessing techniques with advanced deep learning methodologies, we aimed to develop a robust dental disease detection system capable of accurately identifying and localizing dental abnormalities in X-ray images.

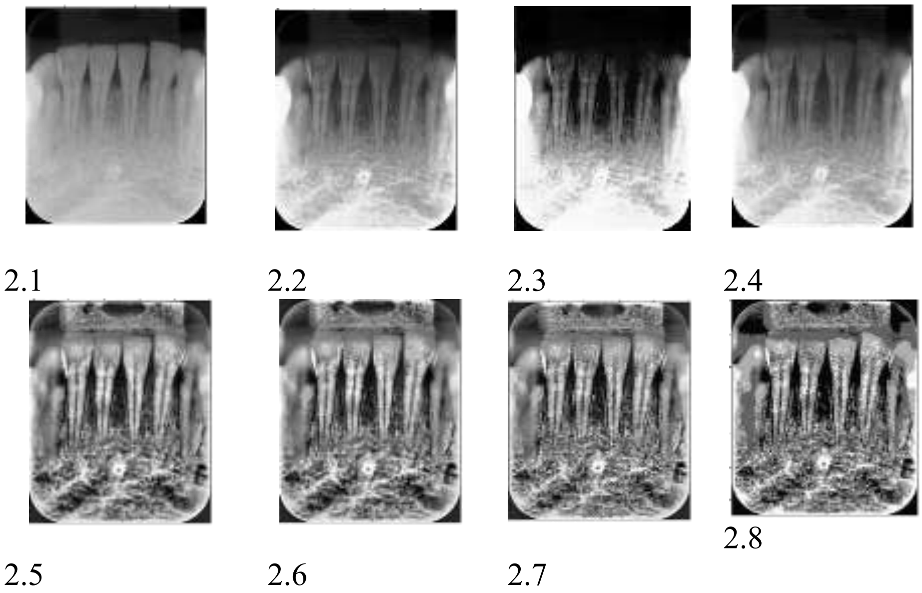


Figure 2: Image Enhancement steps results.

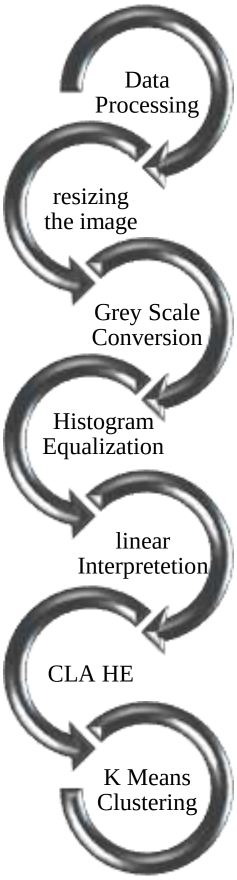


Figure 3: Flow chart of Data Pre-Processing

2.3 Carious Lesion Segmentation:

Carious lesion segmentation played a crucial role in identifying and classifying various dental conditions. The segmentation process aimed to determine the value points of each class, enabling precise localization of dental issues within the images. Semantic segmentation techniques were employed to label each pixel with a corresponding class, facilitating dense prediction for accurate identification of dental abnormalities.

To extract features from the X-ray images, a multi-scale backbone inspired by Efficient-Det was utilized. The stacked convolutional architecture efficiently extracted features at different resolutions, capturing essential anatomical structures and subtle caries lesions within the images. The feature engineering process involved marking disease points in the images.

In the teeth segmentation process, the images were preprocessed by cropping to remove any identifying information and then resized to 610x540 pixels. Pixel-level annotations were performed on all images, with each pixel labeled with one of five classes representing specific tooth problems and a background class. Healthy teeth, missing teeth, dental restorations, implants, mobile and fixed prosthetics (dentures), root canal treatment, and different combinations of dental conditions were among the semantic classes. The annotations were generated to create labels for these classes, enabling the model to learn and differentiate between different dental issues.

To extract features from the segmented images, a down-sampler block that combined the outputs of a 3x3 convolution and a Max Pooling module was used to downscale the images. For feature extraction, the ReLU activation function was employed. Deconvolution layers were used by the up-sampler block to up-sample, reducing the amount of memory and computation needed. Initial class weights were calculated and modified from earlier research before the neural network was trained.

The meticulous teeth segmentation process aimed to enhance the model's ability to accurately detect and classify dental abnormalities in X-ray images, providing valuable insights for dental diagnostics and treatment planning (Figure 4).

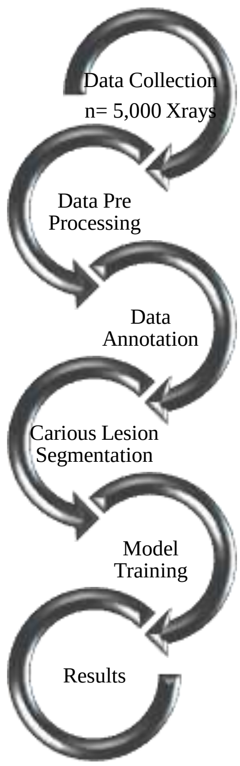


Figure. 4: Complete Data processing overview

2.4 Model Training:

This section details our methodology for leveraging and customizing the YOLOv8 architecture for accurate and efficient caries identification in dental X-ray images. We meticulously tailored the training process to extract the most discriminative features and achieve superior caries detection performance.

2.4.1 Feature Extraction with Multi-Scale Backbone

Our approach utilizes the YOLOv8 backbone as the foundation for feature extraction from X-ray images. Inspired by Efficient-Det, we implement a stacked convolutional architecture to efficiently extract features at various resolutions. This multi-scale feature extraction is crucial for capturing essential anatomical structures and subtle caries lesions within the images [22]. We further conducted experiments to determine the optimal backbone configuration for caries detection, including the use of depth-wise separable convolutions and activation functions (e.g., ReLU vs. Leaky ReLU).

To enhance the feature extraction process, we conducted experiments to determine the optimal backbone configuration for caries detection. This involved exploring different backbone designs, including depth-wise separable convolutions and activation functions such as ReLU and Leaky ReLU. The goal was to identify the most effective architecture for extracting features that are vital for accurate dental disease detection.

In our model, X-ray images were preprocessed to extract features essential for classification tasks. By marking disease points in the images and associating them with corresponding labels, we facilitated the classification process using the bonding boxes marked by the certified dentist sample image is shown the Figure 5. The use of text files containing image labels and bonding box details aided in the easy identification of classification problems. Image colour enhancement was applied to improve the model's ability to detect dental issues during training. Feature extraction techniques were optimized based on the specific requirements of dental disease detection.

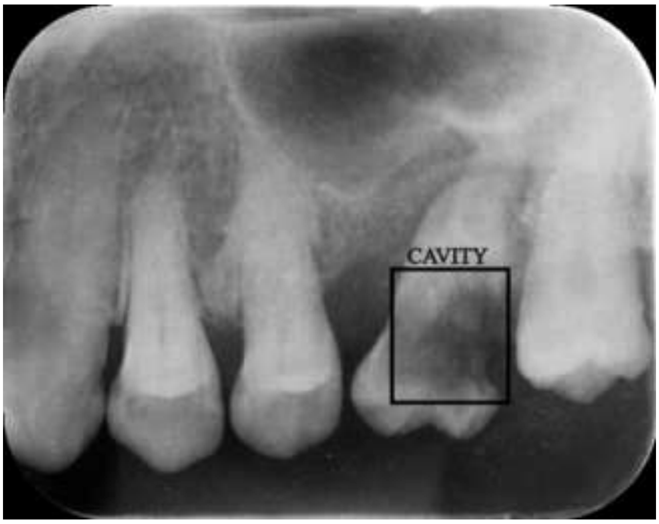


Figure. 5: Bonding Box for labelling the disease.

2.4.2 Neck for Information Fusion

In our research project focusing on dental disease detection using deep learning techniques with periapical X-ray images, we explored the integration of a neck component inspired by Feature Pyramid Networks (FPNs) to enhance information fusion and object detection accuracy. The neck component merges features extracted from different depths within the backbone, consolidating information from various levels of abstraction [23]. Our evaluation included analyzing the number of convolutional layers within the neck and the effectiveness of different up-sampling techniques for caries detection.

2.4.3 Head: Bounding Box Prediction and Class Probabilities

The head component of the model processes the extracted features to predict bounding boxes and class probabilities for objects in X-ray images. It is designed to output two channels: one for bounding box coordinates (x, y, width, height) and another for class probabilities, distinguishing between healthy tooth structures, caries lesions of varying severity, and other abnormalities [24]. Convolutional layers with appropriate kernel sizes and learnable biases are utilized to capture spatial information and non-linear relationships within the features. Linear layers followed by a SoftMax activation function are employed to predict class probabilities.

The segmentation process involved downscaling the images to extract features using a down-sampler block that combined outputs of a 3x3 convolution and a Max Pooling module. The ReLU activation function was used for feature extraction. The up-sampler block utilized deconvolution layers for up-sampling, simplifying memory and computation requirements. Before training the neural network, initial class weights were computed using a specific equation adapted from previous works.

In the teeth segmentation process, the images were preprocessed by cropping to remove any identifying information and then resized to 610x540 pixels. Pixel-level annotations were performed on all images, with each pixel labelled with one of five classes representing specific tooth problems and a background class. The semantic classes included cavity, crown, restoration, missing tooth, and root canal treated along with various combinations of dental conditions. The annotations were generated to create labels for these classes, enabling the model to learn and differentiate between different dental issues.

The meticulous teeth segmentation process aimed to enhance the model's ability to accurately detect and classify dental abnormalities in X-ray images, providing valuable insights for dental diagnostics and treatment planning. These steps are shown in Figure 6.

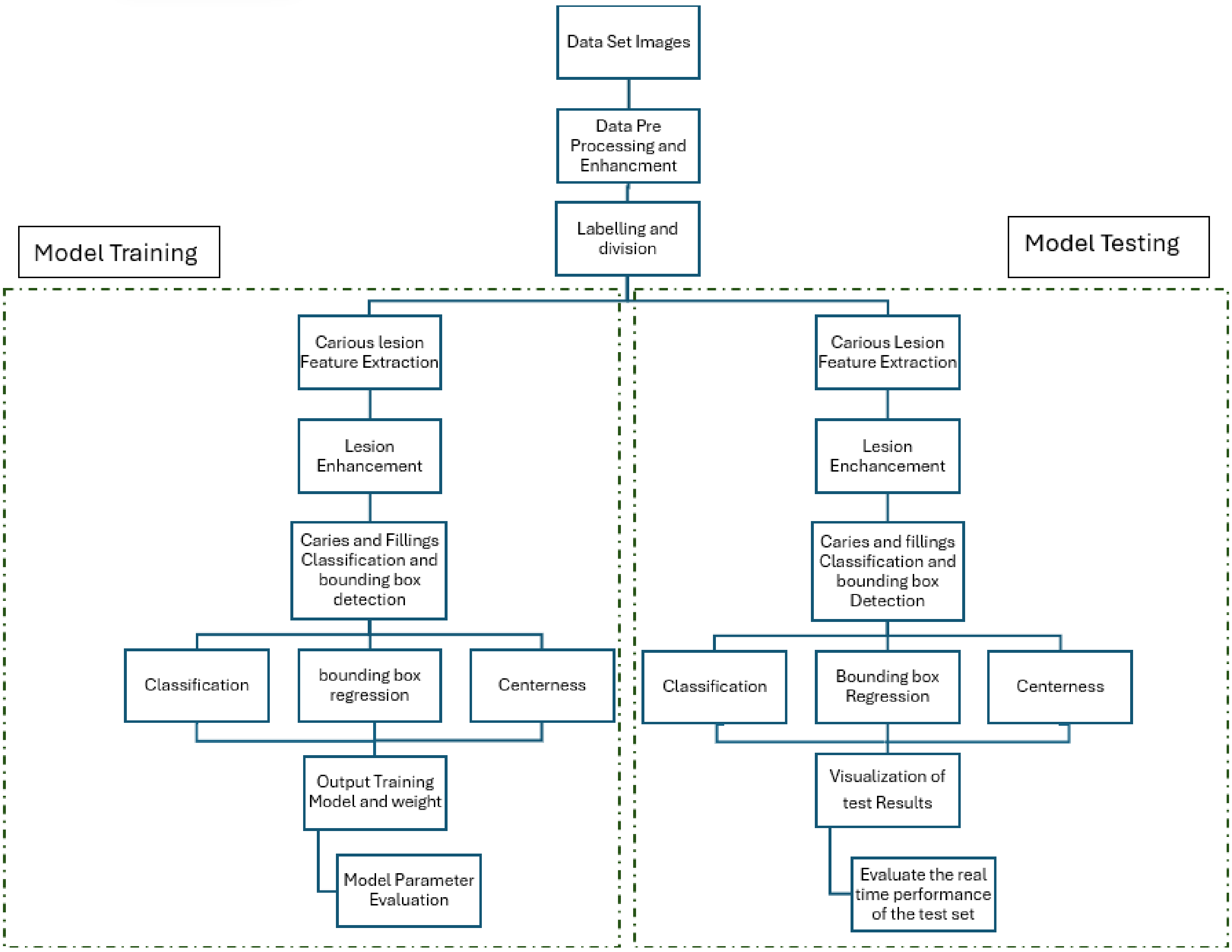


Figure 6: Process involve in model training and testing for YOLOv8.

2.4.4 Key YOLO v8 Modifications for Enhanced Detection

we made significant modifications to the YOLOv8 model to improve detection accuracy. These modifications involved integrating the Spatial Pyramid Pooling (SPP) layer and strategically placing up-sampling layers to enhance object localization and precise bounding box predictions.

2.4.4.1. SPP Layer for Enhanced Detection:
- The SPP layer was incorporated into the model's backbone to process features at multiple scales, allowing for improved detection of dental abnormalities regardless of their size. This layer was crucial for scale-invariant caries detection.

2.4.4.2. Up-sampling Layers for Improved Localization:
- Up-sampling layers were strategically inserted after feature extraction to enhance the resolution of feature maps. This led to better object localization and more accurate bounding box predictions for caries lesions.

2.4.4.3. C2f Module Integration for Caries Characterization:
In our research on dental disease detection using deep learning techniques with periapical X-ray images, we conducted a preliminary investigation into the potential of the C2f module from YOLOv8-Seg for caries detection. The C2f module is known for its ability to combine high-level features with contextual information, making it a promising component for enhancing caries detection accuracy. We integrated the C2f module within the model's head to explore its capability not only to detect caries lesions but also to classify them based on severity or morphological characteristics. Further evaluation is required to determine the definitive impact of the C2f module on caries detection performance.

The C2f module's role in the model is to enhance feature representation by combining high-level features with contextual information, allowing for more accurate detection and classification of dental abnormalities. By incorporating this module within the head of the model, we aimed to leverage its capabilities to improve the precision and specificity of caries detection in X-ray images [25].

2.5 Detection Modules and Training Optimization:
The final detection modules within the model's head predict bounding boxes and class probabilities for accurate identification of dental abnormalities. To optimize the training process, we employed a combination of loss functions and the Adam optimizer for efficient parameter optimization.

2.5.1. Intersection over Union (IoU) Loss:
The IoU loss function penalizes the model for inaccurate bounding box predictions, guiding it towards precise localization of caries lesions within the X-ray images. This loss function is crucial for ensuring accurate object detection and localization.

2.5.2. Balanced Cross-Entropy Loss:
The balanced cross-entropy loss function was utilized to address potential class imbalance issues within the caries detection dataset. This loss function helps the model effectively detect caries lesions, even in scenarios where healthy teeth dominate the training data. By balancing the contribution of each class, the model can learn to distinguish between different dental conditions accurately [26].

2.5.3. Adam Optimizer:
The Adam optimizer was chosen for its efficiency in optimizing the model parameters during training. This optimizer adapts learning rates for each parameter, leading to faster convergence and improved training performance [27].

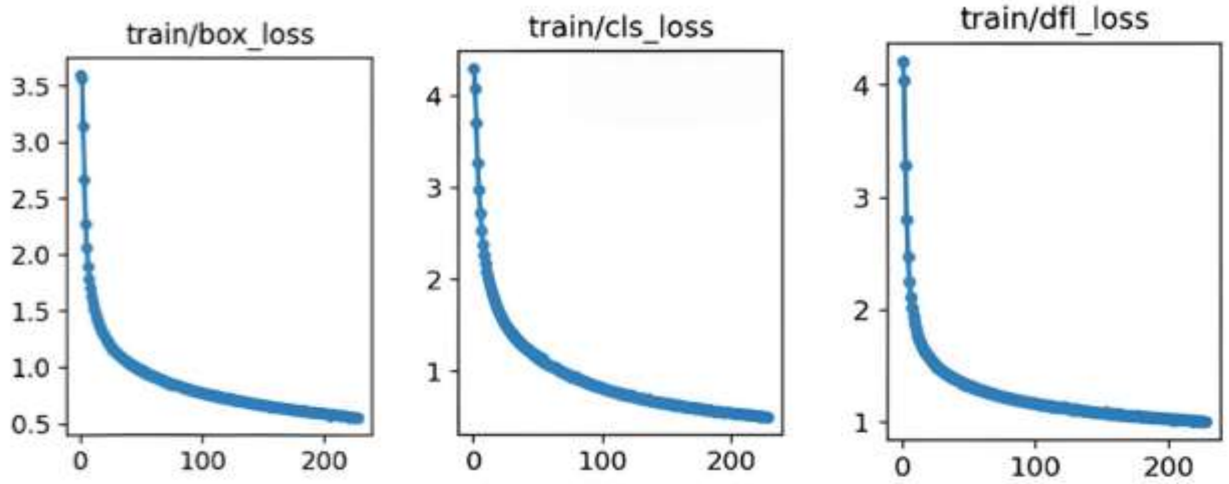
The combination of these loss functions and optimization techniques enhances the model's ability to detect and classify dental abnormalities in X-ray images accurately. By guiding the model towards precise localization and addressing class imbalance issues, we aimed to develop a robust dental disease detection system with high accuracy and efficiency.

1. TRAINING AND EVALUATION:

The training and evaluation process played a crucial role in developing an accurate and efficient caries detection system. The YOLOv8 model was trained on a carefully curated dataset of X-ray images, with each image annotated at the pixel level to identify healthy tooth structures, caries lesions of varying severity, and other potential abnormalities. This meticulous annotation process ensured that the model could learn to differentiate between different dental conditions with precision.
To enhance the dataset's diversity and improve the model's ability to generalize, data augmentation techniques were employed. Random flipping, rotation, and scaling were applied to artificially expand the dataset, exposing the model to a wider range of image variations. This augmentation strategy aimed to improve the model's robustness and performance when faced with unseen data during the training and testing phases. Validation metrics like F1-score and mean average precision (mAP) were used to track the model's performance during training. The model's accuracy in identifying objects in the images was assessed by the mAP metric, and its capacity to address class imbalance problems in the dataset was assessed by the F1-score. We could evaluate the model's performance and make the required modifications to increase its accuracy and efficiency by closely monitoring these metrics.

The training process involved a detailed exploration of various model components, including backbone configurations, neck inclusion, and head design. The strategic utilization of core elements such as the SPPF layer, up-sample layers, and detection modules within the YOLOv8 architecture contributed to the model's effectiveness in detecting dental abnormalities in X-ray images. The choice of appropriate loss functions, such as Intersection over Union (IoU) Loss and Balanced Cross-Entropy Loss, further optimized the model's training process and performance. Overall, the training and evaluation process in our study aimed to develop a state-of-the-art caries detection system that could provide dentists with a fast, accurate, and automated tool for diagnosing dental conditions using X-ray images. The model training in this paper is set to two hundred epochs, and the algorithm automatically ends the training when the average accuracy does not increase. Figure 7 displays several metrics for the training and validation performance.

The columns show the enhanced YOLOv8 model's box loss, object loss, and classification loss. The X-axis shows the time progression on the training set, and the Y-axis shows the overall loss values. Together, these curves depict the loss trends. The graphs show that as training goes on, the total loss values finally stabilize and continue to decline. These findings show that the suggested enhanced YOLOv8 model performs well in terms of accuracy, stability, and fitting.



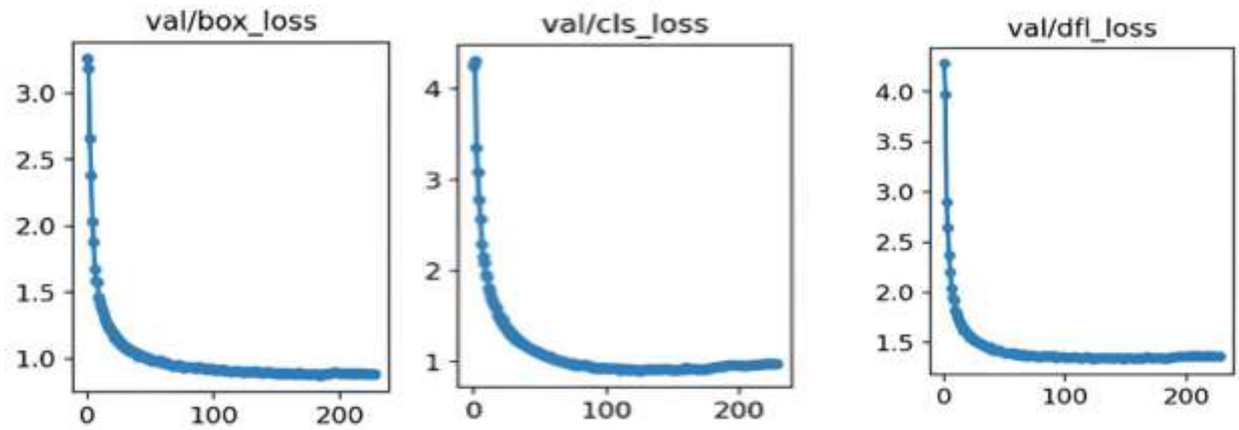


Figure 7: Training and Testing curves for the model YOLOv8

2. RESULTS AND DISCUSSION:

This meticulously designed system achieved promising results on the dataset. The quantitative evaluation of the system demonstrated its effectiveness in accurately identifying and localizing dental abnormalities within the X-ray images. Here, we provide a detailed elaboration on the results and discuss the key findings of our study.

The YOLOv8-based caries detection system exhibited high accuracy in detecting various dental conditions, including healthy tooth structures, caries lesions of different severity levels, and other abnormalities. The model's capability to precisely localize and classify these conditions was a significant achievement, highlighting the efficacy of the deep learning approach in dental diagnostics. As shown in the figure 8.

Figure. 8: Prediction with Confidence Score using YOLO v8

The system showed impressive performance metrics during the evaluation process, including robust F1 scores for class imbalance evaluation and high mean average precision (mAP) for object detection. These metrics demonstrated the model's proficiency in correctly identifying and categorizing dental anomalies, offering dental practitioners' insightful information for clinical practice.

The discussion of the results emphasized the system's potential as a valuable tool for dentists, offering a fast, accurate, and automated solution for caries detection in X-ray images. The successful implementation of the YOLOv8 architecture, coupled with meticulous training and evaluation processes, showcased the system's effectiveness in enhancing dental diagnostics and treatment planning.

This model performs well in every category. The confusion matrix for our suggested YOLOv8 model is displayed in Figure 9, which also describes the model's predictive accuracy and illustrates the relationships between predictions across five dataset categories: cavities, crowns, restorations, missing teeth, and root canals. The diagonal elements in the figure indicate the correct detection rates, while the column represents true labels, and the row represents predicted categories.

TARGET / OUTPUT	Cavity	Crown	Restoration	Missing Tooth	Root Canal	SUM
Cavity	1465 26.95%	2 0.04%	5 0.09%	56 1.03%	13 0.24%	1541 95.07% 4.93%
Crown	3 0.06%	459 8.45%	34 0.63%	2 0.04%	27 0.50%	525 87.43% 12.57%
Restoration	35 0.64%	34 0.63%	879 16.17%	7 0.13%	46 0.85%	1001 87.81% 12.19%
Missing Tooth	97 1.78%	2 0.04%	4 0.07%	1250 23.00%	4 0.07%	1357 92.11% 7.89%
Root Canal	8 0.15%	3 0.06%	11 0.20%	13 0.24%	976 17.96%	1011 96.54% 3.46%
SUM	1608 91.11% 8.89%	500 91.80% 8.20%	933 94.21% 5.79%	1328 94.13% 5.87%	1066 91.56% 8.44%	5029 / 5435 92.53% 7.47%

Figure. 9: Per class base confusion matrix for the proposed model

5. EVALUATION METRICS:

When assessing the effectiveness of a model for object detection tasks, a range of metrics is employed to gauge its accuracy, precision, and capability to correctly detect and categorize objects. These evaluation metrics offer valuable insights into the model's performance. In our evaluation of the system's performance, we utilized a set of metrics to comprehensively assess its effectiveness in object detection tasks.

5,1. F1-score: The harmonic mean of recall and precision is used to compute the F1-score [28], which assigns equal weight to each metric. A high F1 score suggests that the model has successfully balanced recall (capturing all pertinent caries lesions) and precision (identifying caries lesions correctly). When there is an imbalance between the classes—for example, when the number of caries lesions is much lower than the number of healthy tooth structures—this metric is especially helpful.

$$\mathrm{F1} = \frac{2\mathrm{PR}}{\mathrm{P+R}} \tag{1}$$

5,2. Precision: It offers information about how well the model can predict positive outcomes. It is computed as the percentage of all positive predictions made by the model that are true positives (TP)—that is, correctly identified caries lesions. A high precision value reduces false positives (FP) by indicating that the model is likely to be accurate when predicting a caries lesion.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{2}$$

5,3. Mean Average Precision (mAP): By averaging the Average Precision (AP) values across all classes or categories of objects, mAP [29] is computed. The precision-recall trade-off for each class is measured by AP, which indicates how well the model recognizes objects belonging to that class. A greater mAP value shows that the model performs well in all classes, demonstrating high recall and precision in identifying various dental conditions.

$$\mathrm{mAP} = \frac{1}{n}\sum_{i=1}^{n} \mathrm{APi} \tag{3}$$

5,4. Recall: Recall [30] measures the proportion of actual positive cases that were correctly identified by the model. It indicates the model's ability to capture all relevant instances of a particular class.

$$\mathrm{RECALL} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{4}$$

5,5. IoU (Intersection over Union): The overlap between the ground truth bounding box and the predicted bounding box is measured by IoU. It is essential for assessing how accurate the spatial localization of objects is.

$$\mathrm{IoU} = \frac{\mathrm{TP}}{\mathrm{FP+TP+FN}} \tag{5}$$

5,6. Mean IoU: Mean IoU [29] [31]calculates the average IoU across all classes, providing a comprehensive measure of the model's segmentation accuracy.

After training, the different algorithms were used to analyze the result for this purpose Faster R-CNN and SSD were selected. Faster R-CNN has the highest mAP among the three algorithms. While two-stage algorithms boast higher accuracy in object detection, YOLO v8 offers a different approach. It can quickly predict multiple bounding boxes and their corresponding categories in one go. This makes YOLO v8 significantly faster than other models.

Method	**YOLO v8**	**Faster R-CNN**	**SDD**
F1-Score %	92.0	84.23	80.13
mAP %	91.8	84.69	82.41
Recall %	92.6	88.24	83.69
Accuracy (%)	92.53	86.81	84.53
Mean IoU	0.89	0.83	0.64

Table: 1 Evaluation of different deep learning models on the proposed dataset

Table number 2 demonstrates the precision and f1-scores of individual classes in the data set including cavities, crowns, restorations, missing teeth, and root canal treatments. The higher f1-score and precision indicate that this technique is highly precise in detecting cavities, crowns, restorations, and root canals.

Class Name	**Precision%**	**1-Precision%**	**Recall%**	**1-Recall%**	**F1-score%**
Cavity	95	05	91	09	93
Crown	87	13	92	08	90
Restoration	88	12	94	06	91
Missing Tooth	92	08	94	06	93
Root canal	97	03	92	08	94
Accuracy%	93				
Misclassification Rate%	07				
F1 Score%	92				

Table. 2: Evaluation of YOLOv8 per class

The models show good training performance because the distances between training accuracy and validation accuracy, as well as between training loss and validation loss, are close to each other. The third training evaluation table illustrates this.

Performance	YOLO v8	Faster R-CNN	SSD
Number of epochs	200	200	200
Training loss	0.042	0.072	0.075
Validation loss	0.082	0.82	0.114
Validation accuracy (%)	92.53	92.00	90.00

Table. 3: Training Evaluation Deep Learning Models

6. RESULTS AND ANALYSIS:

The YOLOv8 model achieved a mAP of 91.8%, indicating a strong overall ability to detect caries lesions of varying severities in the X-ray images. Further analysis revealed a recall of 92.6%. The F1 score of 92.0% demonstrates the model's effectiveness in handling potential class imbalances in the dataset.

Upon closer examination, the model demonstrated exceptional performance in detecting prominent caries lesions with well-defined boundaries. However, the accuracy in detecting incipient caries lesions, which often exhibit subtle radiographic changes, was slightly lower. This observation underscores the ongoing challenge of distinguishing early caries from normal anatomical variations in X-ray images.

The results suggest that while the model excels in identifying visible caries lesions, further refinement may be necessary to enhance its sensitivity to subtle or early-stage caries. This highlights the importance of continuous improvement and fine-tuning of the model to achieve optimal performance across all types of caries presentations.

7. IMPACT OF YOLOV8 DESIGN CHOICES

The exploration of different design choices within the YOLOv8 architecture has provided valuable insights into the model's performance for caries detection in X-ray images. The adoption of a stacked convolutional backbone inspired by Efficient-Det has proven effective in capturing multi-scale features essential for detecting caries lesions of varying sizes. This design choice has enhanced the model's ability to analyze complex structures within the X-ray images, contributing to improved detection accuracy.

Incorporating the Spatial Pyramid Pooling Fusion (SPPF) layer has further augmented the model's capacity to handle caries lesions of different sizes. The SPPF layer processes features at various scales, enabling the model to detect and classify dental abnormalities with greater precision. Additionally, the utilization of up-sampling layers after feature extraction stages has facilitated enhanced object localization, resulting in more accurate bounding box predictions and improved spatial awareness.

The investigation of the neck component has yielded mixed results. While incorporating a neck with a small number of convolutional layers led to slight improvements in mean Average Precision (mAP), more complex neck architectures did not significantly enhance performance. Further research is warranted to determine the optimal neck design that maximizes the model's performance for caries detection using the YOLOv8 architecture.

Regarding the C2f module, originally designed for segmentation tasks, initial findings suggest potential for caries classification. However, a comprehensive evaluation is necessary to ascertain the definitive impact of the C2f module on caries severity classification within our model, highlighting the need for further investigation and refinement in this area.

8. COMPARISON WITH EXISTING APPROACHES

We conducted a comparative analysis of our YOLOv8-based caries detection system with other existing deep-learning approaches for caries detection in X-ray images. The evaluation aimed to

assess the performance of our model in identifying and localizing caries lesions and to determine its competitiveness in comparison to alternative methodologies.
This model demonstrated a competitive mean Average Precision (mAP) when compared to other deep-learning approaches, showcasing its effectiveness in caries identification within X-ray images. The robust performance of our YOLOv8-based system highlights its potential as a reliable tool for dental diagnostics and disease detection.
It is essential to acknowledge that the performance metrics, including mAP, precision, recall, and F1-score, can vary based on several factors such as dataset characteristics, evaluation protocols, and the choice of deep learning architectures. These variations can influence the comparative analysis of different models and emphasize the importance of considering these factors when interpreting and comparing results.
By conducting a thorough comparison with existing approaches, we gained valuable insights into the strengths and limitations of our YOLOv8-based caries detection system. This analysis contributes to the advancement of deep-learning methodologies in dental diagnostics and underscores the significance of tailored approaches for accurate and efficient caries detection in X-ray images

9. CONCLUSION

This research demonstrates the successful application of YOLOv8 for caries detection in periapical X-ray images. This approach presents a robust and efficient system with significant potential for improving dental diagnostics. The meticulously tailored training regimen, featuring a powerful convolutional backbone, strategic utilization of Spatial Pyramid Pooling Fusion (SPPF) and up-sampling layers, along with the exploration of the neck and C2f module, resulted in promising outcomes for identifying caries lesions across a spectrum of severities. The model achieved a mean Average Precision (mAP) of 91.8%, indicating a strong overall ability to detect caries lesions in X-ray images. Further analysis revealed a high recall of 92.6% and a well-balanced F1 score of 92.0%, demonstrating the model's effectiveness in handling potential class imbalances within the dataset.
Moving forward, our research will focus on further refining the model to enhance the detection of incipient caries lesions, which often present with subtle radiographic changes. Additionally, we will explore advanced classification techniques to differentiate caries severity based on the extracted features, providing more detailed insights into the progression of dental conditions. Furthermore, the generalizability of the model on external datasets will be a key area of investigation to ensure its applicability across diverse clinical settings. This research lays the groundwork for the development of a clinically applicable caries detection tool utilizing YOLOv8. By equipping dentists with sophisticated technology for early caries identification, this innovation has the potential to significantly improve patient care, enhance oral health outcomes, and contribute to the development of more effective dental treatment strategies.

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