Dental Image Analysis for Caries Recognition
Domain: AI/ML

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Abstract-- Dental caries, an infection affecting the tooth and its supporting structures, is the leading cause of tooth loss. This issue occurs due to insufficient dental care. Initial signs can include persistent bad breath or an unpleasant taste, bleeding, or other indicators of gum disease, as well as toothaches or mouth discomfort and heightened sensitivity to hot or cold food and beverages. Identifying caries early in children is beneficial, as advanced cases can lead to severe pain and infection, often requiring tooth extraction. This research aims to create a simpler and quicker method for diagnosing dental cavities through deep learning and soft computing techniques, focusing on early detection with computer vision and digital colour images. The study will utilize Roboflow for data annotation and preprocessing while employing the YOLOv8 model, which is a convolutional neural network, to determine the stages of caries. This model uses machine learning algorithms to detect and classify objects in real-time scenarios, enhancing dental image analysis. Data annotation will be carried out on Roboflow, a platform used to manage, annotate, and create datasets for computer vision tasks. Two labels, namely Healthy and Decay, will be created and annotated manually on all images in the dataset for the detection of dental caries. Medical imaging in oral health can prevent complex dentistry. This non-invasive approach, which relies on digital colour images, aims to improve the comfort of patients undergoing diagnosis without sacrificing the precision of the outcomes.

Keywords-- dental caries, computer vision, convolutional neural network (CNN), machine learning algorithms.

1. Introduction

Over the past few years, Machine learning has advanced in various fields, including the medical domain. These technologies that are created using machine learning are used for planning treatment, diagnosis, and prognosis. Image analysis is an application that is used in the medical field to detect and classify objects and enhance diagnosis by improving accuracy and efficiency. Image analysis is used in various fields, such as the detection of cancer, brain abnormality, cardiac conditions, assessment of bone fracture, etc. Dental image analysis is another application that is used to detect oral health issues, such as cavities and alignment issues, with speed and precision.

Dental caries, otherwise known as tooth decay, is one of the most prevalent chronic diseases of people worldwide; individuals are susceptible to this disease throughout their lifetime [9]. The damages caused by dental caries are toothaches, bad breath, gum diseases, etc. Traditionally, caries were detected using radiographic imaging and dentist's inspection, which was time-consuming and not often accurate. Hence, machine learning came up with models that detect caries using image analysis, which helps prevent errors and deliver precise results.

In "Dental Image Analysis for Caries Recognition," a machine learning-based model is used to recognize dental caries. A combination of a real-time dataset consisting of digital images of teeth and a machine-learning model with an object detection algorithm will give precise results. This study will be helpful for demonstrating the potential of the machine learning model in advancing diagnosis and assisting dental professionals by providing them with efficient and accurate results.

The remainder of the paper is arranged as follows: Section 2 outlines the related work done in this field. Section 3 explains the methodology used in this study. Section 4 presents the analysis and results. Section 5 summarizes the work done and presents avenues for further extension.

2. Literature Review

Several authors and researchers have explored machine-learning approaches for detecting dental caries through various techniques based on deep learning and object detection models. These studies are focused on enhancing the accuracy of detection and diagnosis. Some works are outlined in this section.

Abdou [1] proposed the advancements made by Deep neural networks applied in image analysis. This paper represents the significant progress of Deep neural networks by highlighting the crucial role of Convolutional neural networks in image analysis. The initiation of ImageNet in 2010, with an extensive dataset of 14 million annotated medical images, became a huge turn for deep neural networks in the medical domain. Medical image analysis by deep neural network addresses various issues in images, such as classifying a normal image with an infected image and focusing on the region of the target in the given image. It also helps doctors by giving prescriptions based on the health condition detected in the image. Deep neural network-based models can be applied to CT, MRI, X-rays, ultrasounds, and digital images. This paper also addresses the drawbacks of deep neural networks, such as prolonged execution time, complicated training, etc. This paper also gives hope with necessary comparisons that deep neural networks can be the future of image analysis in the medical field.

Shen et al. [2] elaborated on the impact of deep learning in image analysis for the medical field. Their paper explains the fundamentals of deep learning, focusing on its ability to learn the representation of features on its own without manually building features. It has several applications, such as adjusting the size and time of medical images, which is also called image registration. It also enhances the classification of images and identifies the required object from various scans like X-rays, CT, etc. Deep learning also helps in the segmentation of tissues, where it colors different parts of the organs to identify tissues. However, with these advantages, there are also some challenges deep learning-based algorithms face during the establishment of models. Lack of labeled datasets, model compatibility being short with the dataset, and excessive training that makes the model decrease its accuracy are a few. This paper also addresses the progress of semi-supervised and unsupervised models that are being made.

Nawaz et al. [3] proposed the enhancements made by deep learning through object detection algorithms. This paper highlights how a Convolutional neural network is used across all digital images to recognize and detect objects. This paper elaborates on the MedYOLO framework, which mainly works on 3D digital images. It detects various organs like liver, heart, etc. However, there are some constraints, such as not being able to detect unseen structures and patterns. Convolutional neural networks have also been able to detect and provide a count of blood cells in a body through Faster R-CNNs. It ensures a faster analysis of the issue. Other applications of convolutional neural networks are U-Net and DenseUNet. These models help detect and segment the cellular structures of the human body, which is important for analysis. Despite these advancements, CNN still faces challenges like a lack of large annotated datasets.

Ragab et al. [4] discussed the advantages, applications, and drawbacks of YOLO (You Only Look Once) object detection algorithms in medical images. This study was conducted to research 124 articles written by relevant peers on YOLO. It highlights the improvements made by YOLO in the detection of lesions of different cancers, cavities in teeth, heart abnormalities, categorization of tissues in the brain, and abnormalities in the retina. This research helps us understand that YOLO is quite better than any other object detection algorithm. YOLO helps us retrieve datasets where multiple classes can be made and annotated. This paper revolves around the several versions of YOLO and compares them. It provides an elaborate insight into the workings of various versions. The drawbacks mentioned in this study include complex algorithms, massive demand for YOLO models, partially annotated datasets, etc. This paper shows how YOLO is a productive choice for object detection in the medical field.

Palet al. [5], along with his team, reviewed the advancements by deep learning-based models for object detection and tracking of objects along with their applications in diverse fields like medical fields, surveillance, etc. This paper explains how a model addresses multi-object situations. Models like YOLO, Faster R-CNN, and SSD (Single Shot Multi-Box Detector) work to detect objects. SSD model detects objects not only accurately but also with proper balance. The object tracking model mentioned in this paper is DeepSort, which is a combination of object detection and real-time tracking with motion information. Datasets like MS COCO are used for object detection, and MOT (multi-object tracking) is used for tracking. These combination models have various applications, such as in the medical field; these models keep track of patient diagnosis in terms of postures, movements, etc. In non-medical terms, these models are used on automobiles, pedestrians, and vehicles. Deep learning-based models are also used in cyber security to provide security algorithms to avoid and detect security threats. It mentions future advancements like increasing robustness through improved models.

Datta et al. [6] proposed a technique for early detection of dental caries lesions using image analysis. According to a report by the World Health Organization, around 60-90% of children and nearly all adults worldwide experience dental cavities, exacerbating concerns that this could soon become an epidemic. Furthermore, there is no single method that can accurately detect caries across every tooth surface, including enamel and dentin. Regular monitoring and treatment are essential to curb the progression of caries. Dentists often find it difficult to monitor the growth of each carious lesion. Although X-ray images can help, they also carry health risks. Therefore, an optical image-based caries monitoring system offers a safer alternative for observing the growth of these lesions. This method poses no health threats. The image analysis technique involves filtering the optical images of teeth, identifying carious lesions, and segmenting the regions of the tooth.

Ahmed et al. [7] proposed a study for the detection and classification of dental caries using artificial intelligence, in which they trained a deep learning model to identify and categorize dental caries. Bitewing radiographs were taken at a resolution of 1876×1402 pixels and processed using radiographic image analysis software for segmentation and anonymization.

These images were labeled and classified according to the revised classification system of King Abdulaziz University (KAU) for dental caries. The methodology employed supervised learning algorithms tailored for semantic segmentation tasks. The model achieved an average intersection-over-union score of 0.55 for proximal carious lesions across a five-category segmentation scheme, along with a mean F1 score of 0.535 based on 554 training samples. This research demonstrated the potential for creating a precise caries detection model, which could have faster identification of caries and enhance clinicians' decision-making processes.

Kumar et al. [8] proposed a technique for isolating the restoration area in dental X-ray by combining fuzzy clustering with an iterative set active contour method. Median filtering was applied during the preprocessing phase to remove noise from the X-ray images, which made further analysis easier. Subsequently, fuzzy clustering was used for image segmentation to identify different clusters. Finally, the level-set active contour was used to extract the restoration area from the teeth. Apurva Sonavane and her group introduced the Image Data Generator from Kera'spre-processing. Image in Python, utilizing 20% of the training images for validation while incorporating random horizontal flipping. They developed a model based on deep transfer learning for identifying dental diseases and evaluating their effectiveness for detection tasks in dental images. The results showed notable enhancements in the model's accuracy, convergence speed, and resilience to interference due to deep transfer learning.

Ezzati et al. [9] assessed the function of YOLO in medical imaging, noting the rapid and precise delivery of services compared to SSD and RCNN. Although improved precision and lowered false positives are beneficial, other challenges, such as localization mistakes, high-quality data set requirements, and excessive computation, hinder many real-time applications. In the same manner, Ezzati et al. researched the global disease burden attributed to risk factors, including undernutrition, tobacco use, and high blood pressure, drawing attention to disparities between regions. Yet, policy ineffectiveness, data contradiction, and complexity of multi-risk factors pose great challenges. Both emphasize the need for more advanced and precise models as well as focused public health efforts.

Inthiyaz et al. [10] discussed YOLO (You Only Look Once) in medical imaging for purposes like object detection, image classification, etc. This paper elaborates on the unique system architecture of YOLO, its ability to process images with multiple classes and predict accurate output when images have multiple bounding boxes. YOLO has the ability to work on an image in a single pass and predict output. YOLO has proven to be better than SSD (Single Shot Multi-Box Detector) and RCNN (Region Based CNN). YOLO is able to execute and run three times faster than SSD. The various versions of YOLO have been worked on, and it has been found that YOLO minimizes false positives and increases precision by having high percentages. YOLO depends on its training weights. The more the training weights, the higher the performance of the model. This paper successfully proves that YOLO is a better object detection model than others in terms of the medical domain. As there are always constraints, this paper addresses those concerns, too. YOLO can have many localization errors, but this can be solved by some methods, such as improving the quality of the dataset or using preprocessing techniques like data augmentation.

3. Methodology

The primary aim of this paper is to develop an effective caries recognition model that is capable of accurately detecting the cavities in teeth**.** A dental image analysis project for caries detection leverages the potential of artificial intelligence (AI) and machine learning to improve the accuracy, efficiency, and speed of caries detection. Dental caries, being a very common oral disease, usually needs to be diagnosed early and accurately in order to avoid further development and expensive treatments. Yet, conventional diagnostic techniques like visual inspection or radiographic analysis are subjective, time-consuming, and susceptible to human error.

This seeks to overcome these constraints by creating an automated system that can analyze dental images and detect caries with high accuracy. Through the use of advanced methods such as deep learning, the system is able to pick up even minute or incipient caries, allowing for early intervention. The ultimate vision is to develop a tool that assists dentists in clinical decision-making, minimizes diagnostic errors, and enhances patient care overall. This technology can potentially transform dentistry by making diagnostics more available, consistent, and effective.

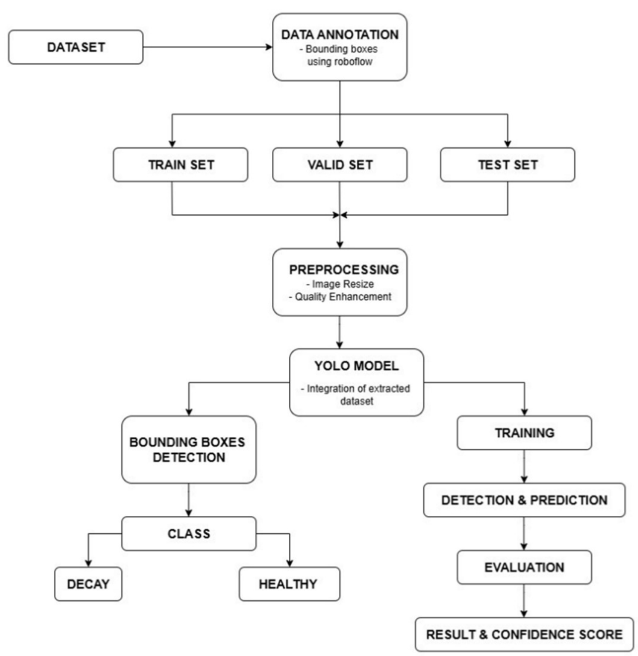


Figure 1: System Architecture

Figure 1 outlines the workflow for detecting tooth decay using the YOLO model. It starts with a dataset that is annotated with tools like Roboflow, which creates bounding boxes around areas of DecayDecay and healthy tissue. This dataset is then divided into training, validation, and test sets. During preprocessing, images are resized and enhanced to improve their quality for model input. The YOLO model uses this preprocessed dataset for training, allowing it to detect bounding boxes for both Decay and Healthy classes. Once detection is complete, the model is evaluated, generating results that include confidence scores to indicate its performance. This setup ensures precise classification and localization of dental issues.

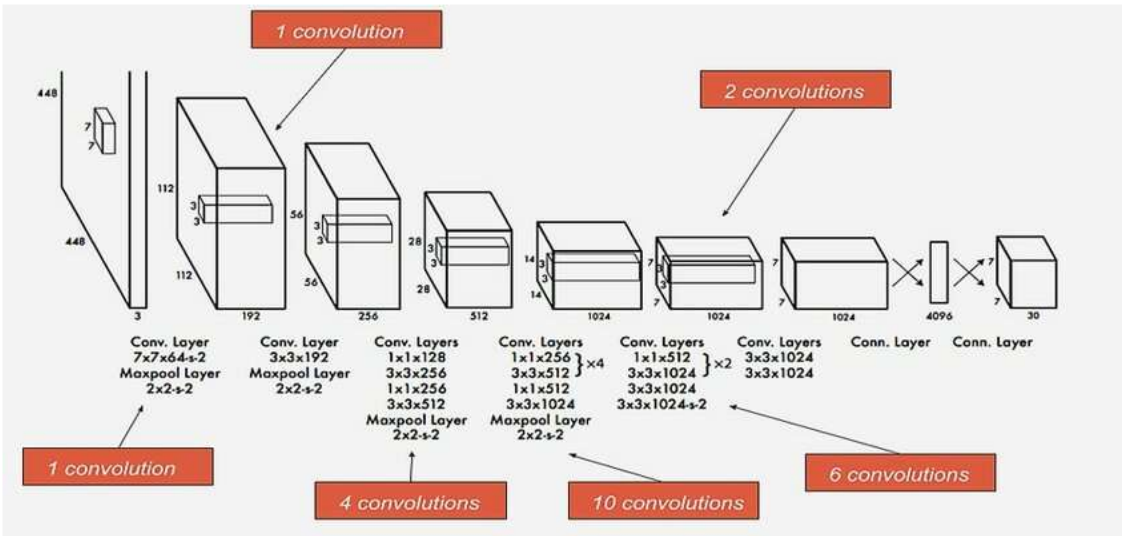


Figure 2: YOLO Architecture

The YOLO model architecture, shown in Figure 2, takes a 448x448 input image and passes it through a sequence of convolutional layers to extract features and then fully connected layers for prediction. It begins with an initial 7x7 convolution and max-pooling layer, followed by repeated blocks of 1x1 and 3x3 convolutions for feature refinement, with downsampling via max-pooling. The last layers produce bounding boxes, confidence scores, and class probabilities. This architecture allows YOLO to detect objects in real time with high efficiency by processing the entire image in a single forward pass.

Using YOLO's object detection framework, a YOLO.v8-based dental image analysis system was developed to detect and classify regions as either Healthy or Decay.

The images are annotated and grouped up into three sets: train set, valid set, and test set. The dataset is then preprocessed in YOLO.v8-compatible format, including bounding box coordinates and class IDs.The model was trained using an augmented dataset. The dataset was randomly split into training (89 out of 145), testing (18 out of 145), and validation (33 out of 145) groups. The training data was augmented through an online strategy. The model parameters were optimized using only the training data to avoid errors. The final performance of the model was then evaluated using just the test set. The YOLO.v8 pre-trained model was trained for 75 epochs (taking about 45 minutes) with a 640*640 image size on a CPU. The entire process was carried out using Anaconda Jupyter Notebook, and all implementations were developed in Python.

4. Results and Discussion

A total of 145 photos were manually annotated, which were then split into the train, valid, and test sets, each having two categories of images and labels. The photographs are in the jpeg format and have two classes in the dataset, i.e., decay tooth and healthy tooth.

Data annotation and initial preprocessing are done in Roboflow and Yolo, and a v8 v8-compatible version is extracted. Sample data annotated images are shown below in Figure 3.

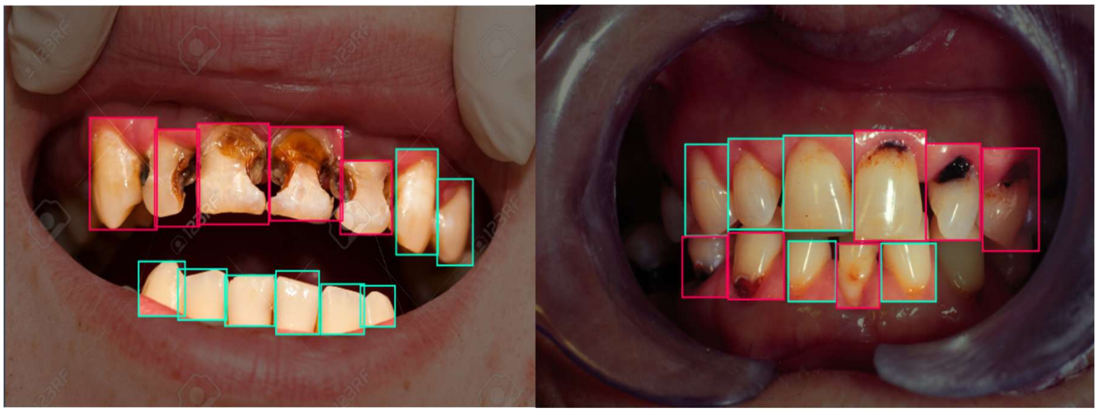
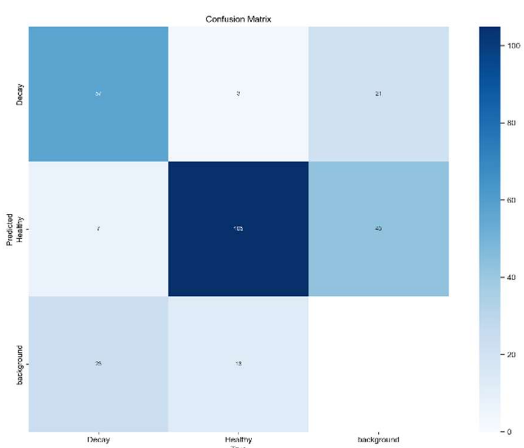


Figure 3: Sample Data Annotated Images from the Dataset



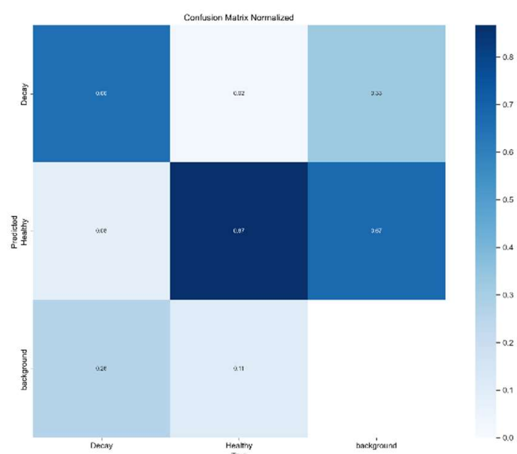


Figure 4(a): Confusion Matrix *Figure 4(b): Confusion Matrix Normalized*

The confusion matrix in Figure 4(a) shows the performance of the YOLO model in classifying dental images into Decay, Healthy, and Background. The model is good at detecting healthy regions (105 correct), but there is some confusion between Decay and Background. Decay was correctly detected 57 times but misclassified as Background 21 times. The Background was correctly detected 43 times, with significant confusion with DecayDecay. This shows that there is a need to enhance discrimination between Decay and Background regions.

Figure 4(b) displays a normalized confusion matrix that illustrates the accuracy of classification for each class. Healthy was correctly predicted at 87%, with 8% classified as DecayDecay and 11% as Background. The Background was accurate to the tune of 67%, with 11% classified as Healthy and 26% as DecayDecay. Decay was 66% accurate, with 2% classified as Healthy and 33% as Background.

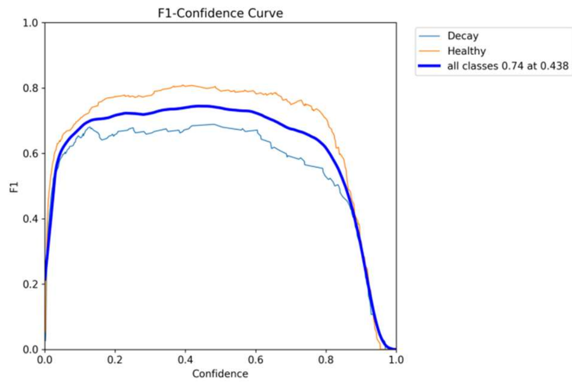


Figure 5: F1-Confidence Curve

The F1-Confidence curve in Figure 5 illustrates how the F1 score changes with different confidence thresholds for Decay, health, and overall performance. The Healthy category, represented by the orange curve, demonstrates higher F1 scores, suggesting more effective classification. In contrast, the Decay category, shown by the blue curve, exhibits lower scores, highlighting difficulties in accurate identification. The overall F1 score reaches its highest point of 0.74 at a confidence threshold of 0.438, representing the optimal balance between precision and recall.

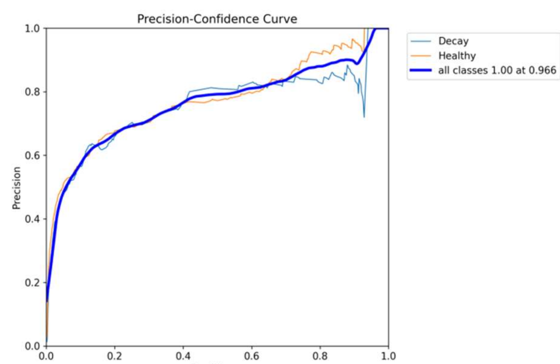


Figure 6: Precision-Confidence Curve

The precision-confidence curve illustrates how well the model can distinguish between dental caries and healthy teeth as the confidence threshold changes. The "All classes" category reaches a precision of 1.00 at a confidence threshold of 0.966, demonstrating its reliability. The smoother curves for each class in Figure 6 suggest that performance remains consistent, with precision improving as confidence rises.

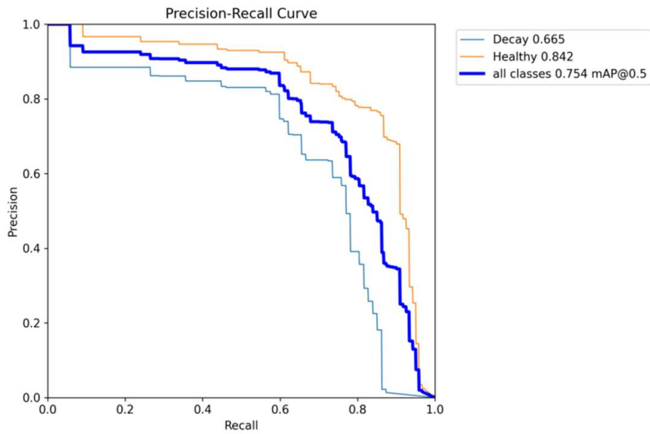


Figure 7: Precision-Recall Curve

The precision-recall curve in Figure 7 above displays how well the model performs in identifying the "Decay" and "Healthy" categories, achieving scores of 0.665 and 0.842, respectively, with an overall mean Average Precision (mAP) of 0.754 at a 0.5 threshold. The curve for "Healthy" demonstrates higher and more consistent precision, whereas the "Decay" curve faces difficulties, showing lower precision at elevated recall levels, which suggests challenges in accurately detecting DecayDecay.

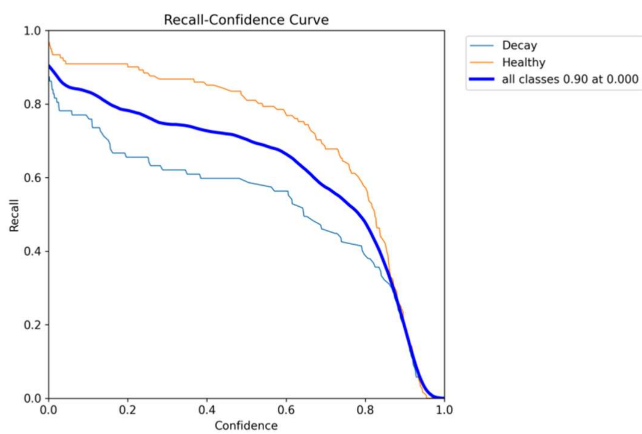


Figure 8: Precision-Confidence Curve

Figure 8 shows a recall-confidence curve that indicates that the model successfully identifies 90% of positive cases in both classes at a 0-confidence threshold. The "Healthy" class demonstrates superior performance, consistently achieving higher recall across various confidence levels. In contrast, the "Decay" class experiences a more rapid decline, highlighting difficulties in accurately detecting DecayDecay with high confidence. Enhancements are necessary for more reliable decay identification.

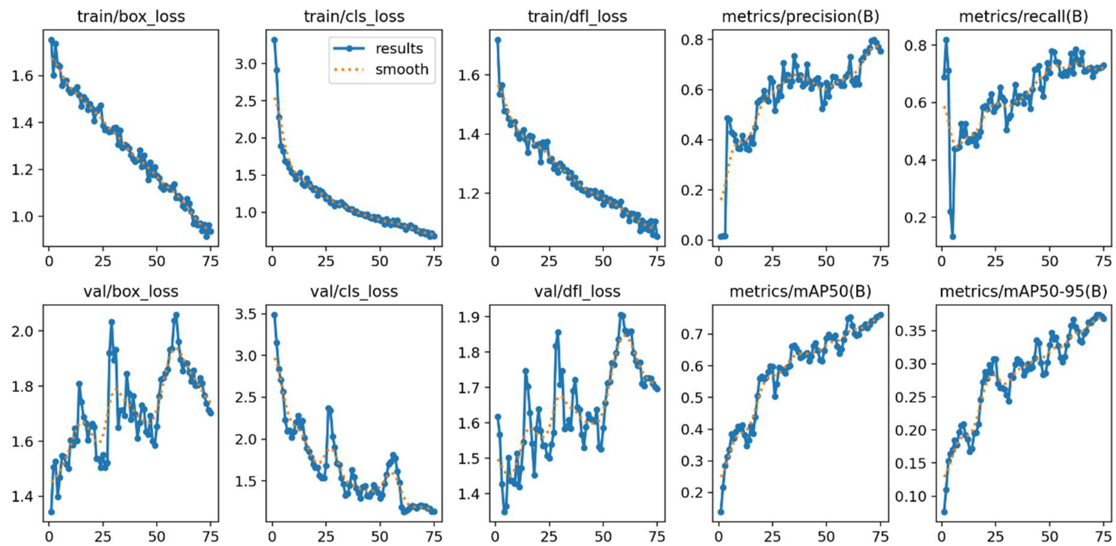


Figure 9: Losses and Performance Matrix

In Figure 9, the training plots for a YOLOv8 model with two classes (DecayDecay and healthy) demonstrate a steady decrease in training losses (box, class, and DFL losses) over the epochs, which indicates effective learning. At the same time, validation losses show some initial fluctuations, but they eventually stabilize, implying that the model is generalizing quite well. Metrics such as precision, recall, mAP@50, and mAP@50-95 show progressive improvement, with recall and mAP@50-95 reaching moderate performance levels. These trends indicate that the model is learning to accurately detect and classify DecayDecay and healthy regions, although additional fine-tuning may be necessary to enhance performance.

CLASS	CONFIDENCE
1	0.86
1	0.80
1	0.80
1	0.79
1	0.78
1	0.76
1	0.74
1	0.63
0	0.48
1	0.43
0	0.36

Figure10: Prediction on Unseen Images

Figure 10 displays model prediction on a new unseen image along with its corresponding class ID and confidence scores. Where class 0 indicates "Decay" and "Healthy" is identified as class 1.

The results show how YOLOv8 can be effectively used to identify tooth decay by examining training and validation metrics acrossdifferent metrics. During training, the box loss, classifi cation loss, and distribution focal loss all decrease over time, which shows that the model is progressively learning to localize and classify regions on the dental images. Validation metrics exhibit almost the same behavior, demonstrating that the model is able to generalize well to new data.

5. Conclusion:

This study portrays the effectiveness of deep learning techniques, particularly the YOLOv8 object detection model, in analyzing dental images for caries detection. Evaluation metrics such as the confusion matrix, F1-confidence curve, and precision-confidence curve indicate strong performance in identifying healthy teeth. However, some misclassification between decay and background areas was seen, which led to further refinement. Despite these minor issues, the study illustrates how AI-driven diagnostic tools in dentistry can provide a quicker method for identifying dental caries. This technology can assist dental personnel by improving the quality of care provided to patients, lessening the manual work required, and increasing the accuracy of diagnoses. In the future, this research can look into enlarging databases, increasing the efficiency of the model, or even looking into live clinical applications to aid in making AI-assisted dental decay detection systems more useful.

None of the alternatives are as efficient as YOLO, which remains unmatched for use in medical imaging. [10] claims that YOLO is much more efficient when compared to Fast R-CNN and Faster R-CNN, as both of these models, at best, only achieve equal levels of accuracy given the significant amount of time it takes to process images one by one. YOLO, in contrast, is much more optimized as it does not need the same amount of time to do computations. Since YOLO, unlike region-based models, directly predicts the bounding box as well as class probabilities

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