AI-Powered Cavity Detection: Leveraging Transfer Learning in Dental Images

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Abstract:

Dental cavities are a prevalent concern regarding one's dental health; untreated dental cavities can lead to pain, infection, and tooth loss. The conventional approaches employed in the diagnosis are radiographic evaluation and visual examination, which are limited by subjectivity and the risk of user error. This work demonstrates the diagnosis of dental cavities in dental images through automation with artificial intelligence (AI) using deep learning and transfer learning techniques. The proposed model is based upon an ensemble YOLO architecture for real-time detection of cavities and then leverages test-time augmentation to improve accuracy. The identified dental pathology is subsequently classified into observable changes with and without cavitation using transfer learning. Performance assessments using metrics demonstrated improved accuracy and efficiency in diagnosis. The challenge of the model differentiating cavities exposes the need for more precise optimization, despite the model's superior performance in caries detection. This work illustrates the positive implications AI-dental diagnosis systems can have on patient care, potentially decreasing diagnostic errors and improving early detection. Future work can strategically focus on expanding datasets and refining AI models to assist in the accurate and reliable identification of dental disease.

Keywords: *Dental caries detection; Deep learning; Transfer learning; Artificial intelligence; Dental image analysis; Oral health diagnostics; Smart dentistry*

Introduction:

Dental cavities are a prevalent condition that can impact individuals of any age. If left unprocessed, it can result in tooth loss, infection, and oral pain (Selwitz et al., 2007). Understanding the various parts of the tooth and its location is essential for the segmentation and identification of dental caries (Majanga & Viriri, 2022). Human teeth consist of canines, molars, incisors, and premolars. The front of the mouth contains incisors. These consist of two front teeth and two back teeth. Canines Compared to other teeth, they are sharper. Each quadrant has four canine teeth that most people have. Premolars are between canines and molars are premolars, often

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known as bicuspids. Between canines and molars, or back teeth, are premolars. Molar teeth are found on the back side (Baranova et al., 2020).

1.1 Anatomy of the tooth: The two main parts of a tooth are the crown and root. The crown is a visible portion overhead the gum line. The roots protect the tooth (Asrorovna et al., 2022).

1.2 Common diseases: The following conditions are common causes of tooth damage: Bruxism (teeth grinding). Teeth that have been compressed and clenched lose enamel and become less resistant to harm (Peres et al., 2019). Heat and cold sensitivity in teeth is caused by either damaged enamel or exposed roots. Trauma: Broken or chipped teeth can result from car crashes, sports-related injuries, and other hardships. Tea, coffee, and cold drinks are among the beverages that might discolor teeth over time. Some medications can also lead to staining on the teeth. Impacted teeth: Teeth may become impacted under the jawbone or gums when they erupt improperly (Linner et al., 2021). Any tooth can be affected. By far the most common example is wisdom teeth impaction. An orthodontic issue can be a tooth that is malaligned, spaced, crowded, or rotated. The ability to chew and maintain good dental health may be negatively impacted by these diseases (Hirschfeld et al., 2019). Abscessed tooth: Bacteria can sometimes attack the tooth's innermost layer. This may cause to experience painful swelling (Loureiro et al., 2023).

Gum disease can lead to tooth loss, even though it begins in the gums.

1.3 Dental cavity: Cavities are small holes or gaps caused by decaying tooth structures. Cavities arise from the weakening of oral acids (Warreth, 2023) enamel. Cavities can affect everyone. Cavities can be prevented with frequent brushing and good dental hygiene. The alternate term for dental cavities is dental caries.

Figure 1:

Dental Cavities

Cavity types: the following are typical varieties: Surface smoothness: Tooth coating melts because of a slowly increasing hollow. It can be prevented by regularly cleaning the teeth. This problem often occurs in the 20s (Gonsalves, 2017). Pit and fissure decay are cavities on the top part of the teeth used for chewing. The degradation of pits and fissures tends to begin in adolescence and accelerates. Root decay: Root decay is more common in adults whose gums are thinning. Teeth roots are exposed to dental plaque and acid due to gum decline. It is challenging to prevent and treat root deterioration (Garver, 2008). The deterioration of teeth can occur at any age, even though cavities are more common in youngsters, many of them prefer to eat more sugary foods and beverages, and do not brush properly or consistently. Too many individuals suffer from cavities. Sometimes, cavities that were treated as children get new deterioration around their edges. Additionally, receding gums are more common in adults, and the tooth roots are exposed to plaque in this situation, which can lead to cavities.

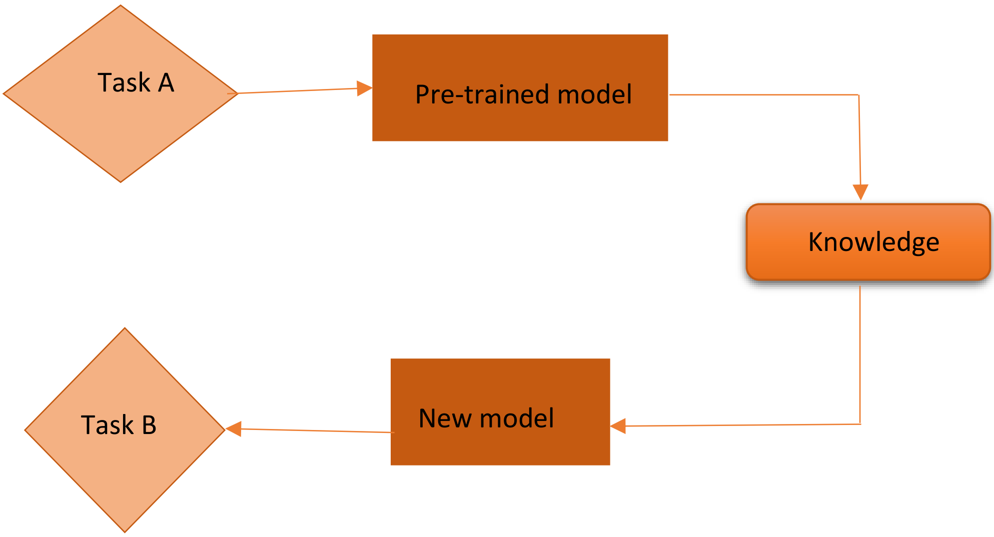
1.4 Signs and Reasons: Usually, tooth decay on the outside of the enamel doesn't create pain or symptoms. Symptoms of cavities include tooth discomfort, facial swelling, tooth sensitivity to hot or cold foods or beverages, bleeding gums or other indications of gum disease, and an unpleasant odor or taste.

Tooth decay stages: Every layer of the tooth is impacted by cavities. There are five primary stages of dental deterioration. Demineralization: Small, white, chalky patches on the teeth are visible at this time. This is a result of the minerals in tooth enamel failing. Enamel decay: If treatment is not received, dental decay will eventually spread and continue to erode enamel. At this stage, holes or cavities may start to show. White spots may become pale brownish. Below the tooth enamel is the dentin layer, which is where dentin decay occurs. Compared to enamel, it is much merciful. Consequently, cavities begin to develop more rapidly once plaque and bacteria have invaded this layer (Asadi, 2024). This is when the tooth starts to feel sensitive. In addition, white spots may appear in darker areas of brown. Involvement of the pulp: The pulp is the innermost layer of the tooth, and it is where the blood vessels and nerves are located that provide nourishment and maintain the health of the tooth. When the pulp is affected by cavities, it becomes painful. Signs of redness and swelling are also present in the gums surrounding the tooth. The spots may become black or darker brown. Abscessed tooth: A deep cavity can lead to infection if left untreated. One of the symptoms could be pain radiating to the face or jaw. Additionally, the neck's lymph nodes and face swell. At this stage, a tooth blister may spread to nearby tissues and other bodily parts. Infections can occasionally spread to the brain or cause blood sepsis.

Science and technology have transformed every aspect of life in recent years, including education, healthcare, finance, and agriculture. In the healthcare sector, science and technology are used to create safer operational systems, monitoring tools, online patient records, and even surgical robots. Technology and science have greatly changed dentistry. For example, cavity detection using digital sensors instead of film X-rays produces better images for more precise diagnosis (Rodriguez-Salvador & Ruiz-Cantu, 2019). It is believed that the AI subfield of deep learning (DL) will help clinicians make quick and precise diagnoses. Deep learning systems accurately analyze dental images, spotting subtle deterioration indicators that people might overlook (Corbella et al., 2021). The previously learned models are replaced by transfer learning. Transfer Learning is the best method to detect the cavity. Because deep neural networks can be trained with very small data, this is beneficial in data science because most real-life situations do not have lots of categorized examples to train compound models. In essence, transfer learning aims to increase generalization in one activity by utilizing knowledge gained from another. The weights that a network has learned at "task A" are transferred to a new "task B" (B. & R., 2020).

Figure 2:

The Weights Diagram



The combination of advanced transfer learning and deep learning models with the diagnostic practices of dentistry could radically revolutionize the early detection and treatment of oral health issues like dental caries. While advanced technologies would streamline the accuracy and effectiveness of diagnostic practices, such technologies would also allow providers to take a more personalized, patient-centered approach to oral health care. As we continue to advance in our new technological landscape, clinicians need to remain current with the most up-to-date developments in artificial intelligence (AI) diagnostic technologies and approaches to improve patient outcomes and a broader understanding of the global factors that are related to oral health issues.

Artificial intelligence simplifies physicians' and patients' lives by automating all tasks, including prescribing medication and diagnosing conditions. We integrate artificial intelligence through machine learning (ML), natural language processing (NLP), deep learning (DL), and other technologies to make the professionals' and patients' experience better. Artificial intelligence can help physicians assist patients with more precision. Intelligently applied deep learning models have shown particularly promising results for mitigating physician workloads where illness diagnosis has been used with artificial intelligence (Schwendicke et al., 2020). The results of various AI models vary depending on factors, including image recognition methods, ailment types, and dataset creation. Dental illnesses can be accurately detected using deep learning models with little additional work on the part of the dentist. Deep learning techniques allow for a more objective evaluation of dental pictures that reduces the possibility of human mistakes and interpretational unpredictability. This may result in more accurate and consistent diagnoses from various medical professionals (Agrawal et al., 2022).

To improve oral health for people all across the world, this research is a first step towards further examination into AI-powered treatments for a wider variety of dental issues. There is a small gap in oral health check-ups. Use of AI to understand intricate dental images, in addition to the conventional dependence on X-rays and radiography. While current approaches have established a solid basis for dental imaging, they provide little opportunity to investigate the use of AI to improve the precision and effectiveness of dental caries detection using several imaging modalities.

Related Work

Recent developments in artificial intelligence (AI) and healthcare are paving the way for progress, specifically in the area of diagnostics in the field of dentistry. Previous detection of cavities is based primarily upon visual inspection and radiography, and AI-enabled detection will provide greater accuracy and efficiency to this diagnostic process. Transfer learning, which involves fine-tuning a neural network already trained on a task to new but related tasks, has become a promising avenue for developing a cavity detection system. This literature review describes the development of AI in dental imaging and particularly focuses on the role of transfer learning in the development of diagnostic imaging. This literature review will summarize and describe the most current literature and development in the area to demonstrate the potential of AI-based cavity detecting systems, and to show that AI-based diagnostic imaging has a place in the future of cavity detection. The paper will conclude with forward-looking descriptions of the next immediate steps for research and practice. In a study by Oztekin et al., a deep learning algorithm was used to autonomously classify dental cavities in panoramic radiograph images. Convolutional Neural Networks (CNNs) were initially trained and later fine-tuned on a group of images that contained annotations classifying the teeth to be carious or non-carious. The Grad-CAM was also utilized to provide support for the decision-making process. Practicing dental clinicians were able to interpret and substantiate the AI's classifications by providing heat maps to indicate areas of importance in the dental images (Oztekin et al., 2023). In 2023, Qayyum et al. developed a semi-supervised learning method utilizing labeled and unlabeled dental radiography images. The authors described a teacher-student design based on self-training, with the student model using a larger number of unlabeled images, and the teacher learning on a smaller labeled dataset. They also employed centroid cropping and other augmentations to help improve training. They evaluated three models pretrained on the annotated set of images, which was reviewed by a physician: ResNet-50, DenseNet-121, and EfficientNet-B0. The authors also created heat maps with Grad-CAM to help explain the AI-based diagnoses by identifying relevant areas of the images. This study demonstrated the importance of transparency in AI-enabled diagnosis and suggested opportunities for future direction toward an improved dataset and models (Qayyum et al., 2023). Lian et al. (2021) explored deep learning architectures to automatically identify and diagnose dental caries on panoramic radiographs. DenseNet121 served as a classification architecture and classified caries into three categories based on the depth of lesions, and nnU-Net was used to create a model to segment lesions in transfer learning. Lesions in the D1 stage are located in the enamel or outside third of the dentin, D2 lesions spread to the middle third, and D3 lesions pierce the inner third of the dentin and may even reach the pulp (Lian et al., 2021). Deep learning algorithms for dental imaging caries diagnosis were systematically reviewed by Mohammad-Rahimi et al. in 2022. The study highlights the problems that dentists face in identifying caries lesions, as well as the potential for deep learning to lessen their variability. It tested a variety of imaging modalities, which are utilized by dentists, such as radiographs, photographs, optical coherent tomography (OCT) images, and near-infrared light transillumination images, to evaluate the performance of AI models in identifying caries lesions. The article categorized deep learning models into three main types: classification models, object detection models, and segmentation models. The retrieval of literature identifies 26 studies focused on making a classification between carious and non-carious teeth utilizing one of the imaging modalities previously identified; the most common type of deep learning model was the classification model. Six studies used object detection models to detect caries lesions and examine the extent of cavities, while ten studies used segmentation models to detect and illustrate caries regions in dental images (Mohammad-Rahimi et al., 2022). In this study, the researchers utilized the You Only Look Once (YOLO) model. YOLO v9 is known for its ability to be used in real-time applications. The model shifts the process and makes it extremely fast and accurate by being able to detect objects in an image at a single glance. YOLOv9 has the potential to significantly enhance diagnosis accuracy in medical imaging, especially dental imaging, by rapidly detecting cavities and other abnormalities. In the field of medical imaging, the YOLOv9 model has the potential to impact the field. Using its real-time detection capacity, YOLOv9 can rapidly and accurately identify dental cavities or other oral abnormalities in an X-ray image, thus potentially reducing the time to diagnosis. One notable feature of YOLOv9 is the use of Programmable Gradient Information (PGI), which expands or allows the model to learn from complex medical datasets. Additionally, the Generalized Efficient Layer Aggregation Network (GELAN) can ensure the model's efficiency and power even with complex medical images. By using these technologies, YOLOv9 combines to be an important tool to utilize for early diagnosis (to a certain extent) and treatment planning for dental conditions, as a whole, providing increased benefits for improving patient outcomes.

Methodology:

Data Collection

The dataset was collected from a famous repository, RoboFlow. The dataset was already annotated and augmented. It provides millions of Computer datasets free of cost to people.

Data distribution:

The downloaded dataset is already distributed by 70% for training, 20% for testing, and 10% for validation.

Figure 3:

Data Distribution

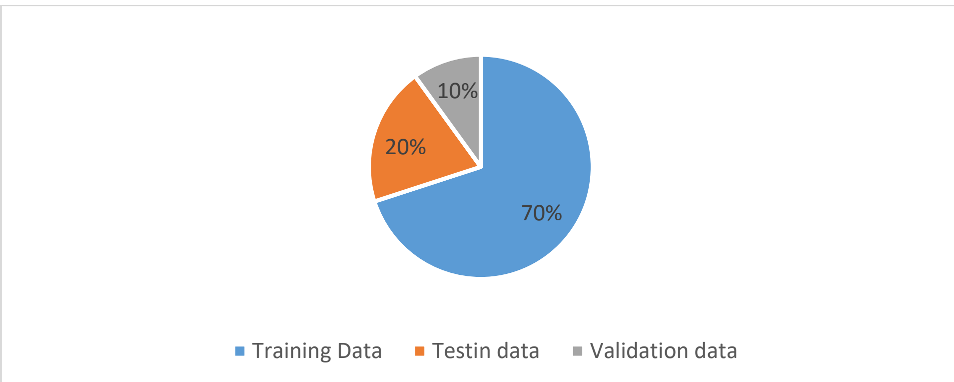
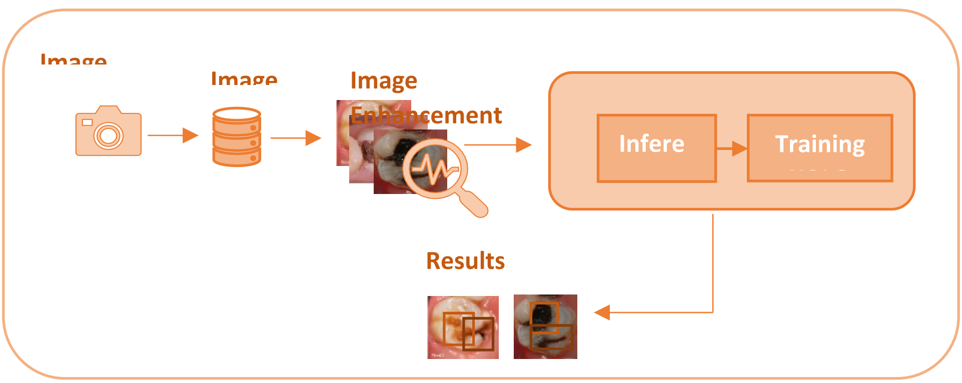


Figure 4:

Proposed Model Constructions and Working



The model shows how automated detection of decay in teeth can occur from computer vision. The first element, "Image Capture," suggests that a picture was taken of a tooth, most likely with a specialized camera. Next, the image moves into the "Image dataset," a collection of images of this type. After that, we have "Image Enhancement," which implies the original image is being processed to improve or enhance the areas of decay, as reflected by a magnifying glass image. After that, the image will move on to the processing stage, which has two parts: "Inference process" and "Training the YOLO model." The "Inference process" means the image analysis that has been completed by the computer software that is analyzing the image that has been enhanced and identifying where there may be decay. The "Training YOLO model" means that the model is learning to reliably identify decays in the images provided in this image dataset. Finally, the "Results" section displays the original tooth image and bounding boxes indicating where the system identified potential decay. Ultimately, this technology enables the automatic detection of dental decay in new images using a YOLO model trained on a dataset of tooth images.

Simulation Results:

Performance Metrix:

The performance of the suggested model is verified using the following metrics, as shown in Table 1.

P=ƿ F=ꜰ T=ʈ N=η

Table 1

Performance Metrics

Metrix	Formula
Precision	$\frac{\text{ʈƿ}}{\text{ʈƿ} + \text{ꜰƿ}}$
Recall	$\frac{\text{ʈƿ}}{\text{ʈƿ} + \text{ꜰ}\eta}$
Accuracy	$\frac{\text{ʈƿ} + \text{ʈ}\eta}{\text{ʈƿ} + \text{ʈ}\eta + \text{ꜰƿ} + \text{ꜰ}\eta}$
F1-Score	$2 * \frac{Precision * Recall}{Precision + Recall}$
FNR	$\frac{\text{ꜰƿ} + \text{ꜰ}\eta}{\text{ʈƿ} + \text{ʈ}N + \text{ꜰƿ} + \text{ꜰ}\eta}$
TPR	$\frac{\text{ʈƿ}}{\text{ʈƿ} + \text{ꜰ}\eta}$
TNR	$\frac{\text{ʈ}\eta}{\text{ʈ}\eta + \text{ꜰƿ}}$

A confusion matrix compares predicted and actual results to evaluate how well a classification model is working. The four primary components of this model are False Positives, when the model calculates positive cases incorrectly when they are negative (Type I error), False Negatives, when the model calculates negative cases incorrectly when they are positive (Type II error), and True Positives when the model calculates positive cases correctly.

Table 2

Confusion Matrix

Predicted \ Actual	decay	gingivitis
decay	114	0
gingivitis	4	5

Table 3

Predicted Values From The Confusion Matrix

Metric	Decay	Gingivitis
True Positives (TP)	114	5
False Positives (FP)	0	4
False Negatives (FN)	4	0
True Negatives (TN)	5	114

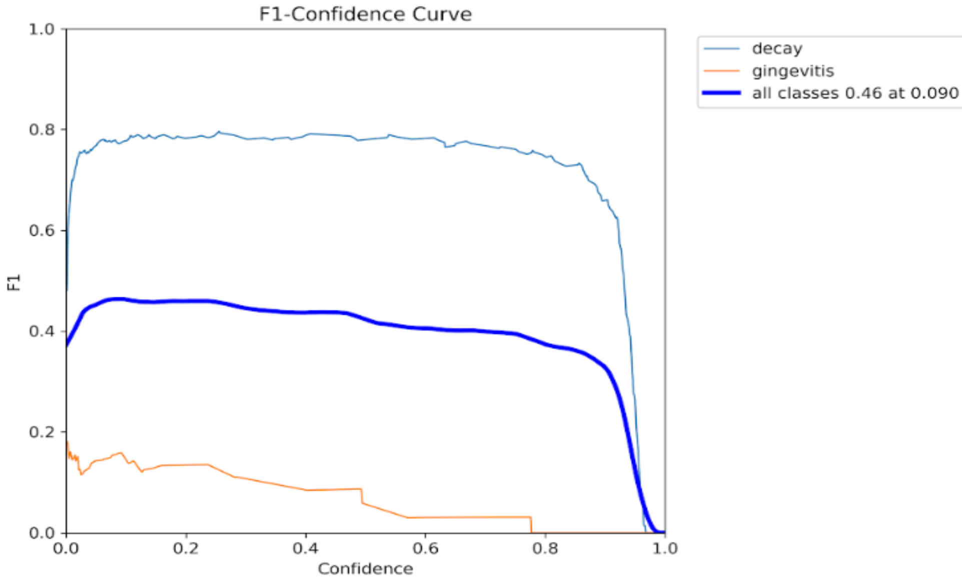
This image of a confusion matrix assesses how well an AI model divides dental photos into three groups: background, cavities, and decay. Whereas the columns show what the model anticipated, the rows show the actual conditions. The frequency of accurate or inaccurate classifications by the model is indicated by the numbers in each cell. The model misclassified 31 decay cases as background despite properly identifying 116 decay cases. Only five cases of cavities were accurately detected, while four cases were incorrectly labeled as decay. The model properly identified 60 instances of background areas. However, it incorrectly identified 30 of these as deterioration. This indicates that while the model does a good job of identifying decay, it has trouble differentiating cavities from other illnesses. Additionally, it frequently incorrectly labels some background regions as decay, indicating that more fine-tuning or better training data may be required to increase accuracy.

F1-Confidence Curve:

It acts as a supporting visualization for the classifier performance across varying confidence levels. The graph shows the F1-score on the y-axis and the confidence threshold on the x-axis, which allows for analyzing the differing predictions of the models with diverging classification thresholds. A higher F1-score is indicative of a better precision-recall trade-off for that threshold. This curve also becomes handy for determining the confidence threshold for maximal performance in the model, while also minimizing the False Positives and corresponding False Negatives.

Figure 5:

F-1 Confidence Curve:



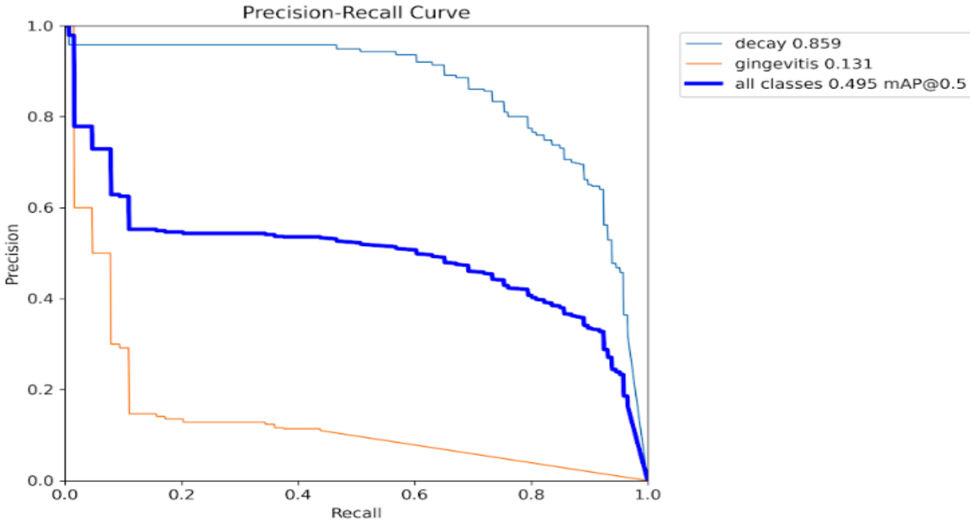
The F1-Confidence Curve illustrated in this figure displays the performance of the model at each confidence level. The model is relatively good at detecting decay, as the blue line, which indicates F1 scores, is high compared to even the lowest confidence level. The orange line denotes the cavities, which are low across the board, demonstrating that the model struggles to accurately classify cavities. The overall F1 score across all classes is indicated by the thick, dark blue line, which has a value of 0.46 at the confidence level 0.090, suggesting the accuracy of the model is typically mediocre to okay across all classifications but could be improved with more precision in the distinction of cavities.

Precision-Recall Curve

A relationship between precision and recall in various classification thresholds. Recall and precision are plotted on the x-axis and y-axis. Better model performance is shown by a larger area under the curve. For imbalanced datasets, where positive cases are uncommon, the PR curve provides more information than the ROC curve, which is helpful for balanced datasets. It assists in choosing the best threshold based on the requirements of the application.

Figure 6:

Precision-Recall Curve



depicts a Precision-Recall Curve, which assesses the relation of precision to recall. It helps to understand how well a model performs in a condition when unbalanced datasets. The light blue line, which has high precision and recall, indicates that the model does a good job of detecting cavities. The model has trouble correctly identifying cases of cavities, as evidenced by the orange line, which depicts cavities and has significantly poorer precision and recall. The values of (mAP) 0.495 at an IoU threshold of 0.5 indicate that the model performance is overall well, recognizing decay far more accurately than cavities.

Results of the Models:

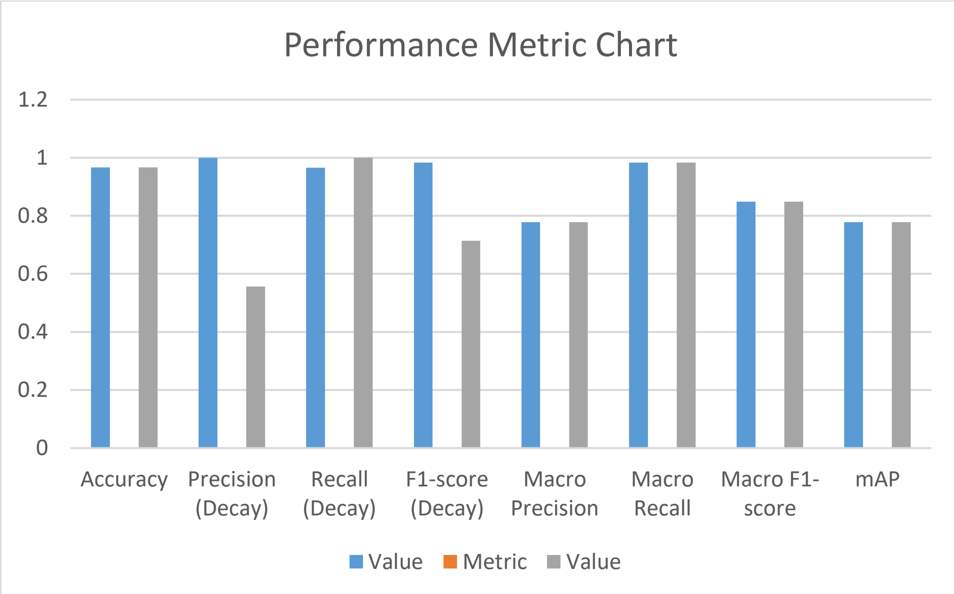
Table 4:

Results Of The Models

Metric	Value	Metric	Value
Accuracy	**0.967**	Accuracy	**0.967**
Precision (Decay)	1.000	Precision (Gingivitis)	0.556
Recall (Decay)	0.966	Recall (Gingivitis)	1.000
F1-score (Decay)	0.983	F1-score (Gingivitis)	0.714
Macro Precision	0.778	Macro Precision	0.778
Macro Recall	0.983	Macro Recall	0.983
Macro F1-score	0.849	Macro F1-score	0.849
mAP	**0.778**	mAP	**0.778**

Figure 7:

Performance Metric Chart



Conclusion:

As the article suggests, artificial intelligence, including deep learning and transfer learning, has altered dental diagnostics. The study demonstrated improved accuracy and precision in the detection of dental cavities using transfer learning-based techniques and AI-enabled models like YOLO. The hybrid approach improves early identification and even reduces diagnostic errors, which leads to improved accuracy in assessments. As such, the study suggests that AI can help reduce human error, improve patient outcomes, and provide a more consistent and objective assessment of dental imaging results. Although the model had robust decay detection ability, it struggled to differentiate cavities. This suggests that further enhancement of the model will involve advanced training methodology and extended datasets. This research also illustrates the opportunity to expand applications to wider dental diagnostics and provides information for future AI-driven dental treatments.

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