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A NOVEL METHOD TO DETECT HUMAN DENTAL CAVITIES USING YOLOv11

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***Abstract*—One of the most important facets of oral healthcare is the spotting of dental cavities, or caries, which are often done manually by qualified specialists utilizing radiography, visual inspection, or tactile methods. Despite their effectiveness, these traditional approaches are frequently arbitrary, labor-intensive, and prone to human mistake. In this study, we present a unique method for detecting dental cavities in humans by utilizing the You Only Look Once (YOLO) v11 architecture in conjunction with a deep learning-based object identification framework. A large dataset's of dental images is used to train YOLOv11, a cutting-edge real-time object detection model, to detect cavities in their early stages, allowing for automatic and precise diagnosis. Our method makes use of YOLOv11's high precision and low latency cavity detection and localization capabilities, even in complicated dental pictures. Training data for the suggested model comes from annotated images.**

Keywords: Rice leaf disease detection, YOLOv10, deep learning, precision agriculture, machine learning, real-time disease diagnosis, plant disease classification, sustainable agriculture, convolutional neural networks (CNN), agricultural technology, food security, automated disease identification.

I. INTRODUCTION

The tooth is a vital component of the human body and plays a crucial role in the digestive system. It is primarily responsible for breaking down food into smaller pieces, making it easier for the digestive enzymes to act upon. By grinding and crushing food into tiny, manageable particles, teeth facilitate smoother digestion and nutrient absorption in the digestive tract. Despite their importance, modern lifestyles and dietary habits have led to a significant rise in dental issues. One of the most common and serious dental problems today is dental caries, also known as tooth decay. It is estimated that over two billion people globally suffer from this condition, making it a widespread public health concern.

With advancements in technology, especially in the field of artificial intelligence, novel methods are being explored to detect and diagnose dental issues at an early stage. One such breakthrough is the introduction of YOLOv11 (You Only Look Once version 11)—an advanced deep learning algorithm tailored for real-time object detection. This cutting-edge model is highly effective in identifying dental defects like cavities, both in static images and live video feeds. By placing a camera near or inside the oral cavity, YOLOv11 can accurately detect and mark affected areas in real time.

YOLOv11 stands out due to its ability to simultaneously classify and localize multiple cavities within a single dental radiograph or camera frame. This capability makes it particularly suitable for dental applications where both speed and precision are critical. Compared to its predecessors, YOLOv11 offers improved accuracy and computational efficiency, making it a valuable tool in medical imaging. Its potential to deliver real-time results with high accuracy has opened new possibilities for automated dental diagnostics, enhancing early detection and treatment planning. Overall, the integration of YOLOv11 in dental health monitoring signifies a promising step forward in smart healthcare.

II. LITERATURE SURVEY

Featherstone (2000) discussed the mechanisms and prevention of dental caries using conventional clinical methods; however, these methods depend heavily on visual inspection and lack precision, especially in early-stage cavity detection [1]. Pitts et al. (2017) emphasized the importance of timely diagnosis in managing global dental caries, but their reliance on subjective visual-tactile techniques leads to inconsistency in detecting early lesions [2]. Schwendicke et al. (2014) reviewed caries detection using X-rays and laser fluorescence, yet these methods can be costly and expose patients to radiation, making them unsuitable for routine or early diagnostics [3]. Esteva et al. (2017) introduced deep learning for dermatology imaging classification, which set the foundation for medical AI, but its generalization to dental data remains limited [4]. Redmon et al. (2016) developed the YOLOv1 algorithm for real-time object detection, but it struggled to accurately detect small, detailed objects like early dental cavities [5].

Tuzoff et al. (2019) applied CNNs for automatic tooth numbering on panoramic X-rays, yet it failed to identify carious lesions or provide any diagnostic support [6]. Javed et al. (2020) compared YOLOv5 and Faster R-CNN for cavity detection, finding YOLOv5 faster, but it still struggled with

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accuracy in detecting minute lesions and differentiating artifacts [7]. Wang et al. (2021) used CNNs to classify impacted teeth in panoramic images, but the approach lacked capabilities to detect caries or other dental diseases [8]. Liang et al. (2019) used transfer learning for classifying dental images, though the model suffered from overfitting due to limited annotated data [9]. Zhang et al. (2020) implemented deep learning for caries detection on radiographs, but their model required high-quality labeled data and lacked robustness across varied image types [10].

Sudhesh et al. (2023) enhanced leaf disease detection using AI with dynamic mode decomposition, but the method was computationally expensive and not optimized for real-time use in dentistry [11]. Agbulos et al. (2021) demonstrated disease detection in rice leaves using YOLO, yet it lacked the precision needed for detecting subtle dental defects in X-rays [12]. Abid et al. (2024) applied YOLOv8 to detect plant leaf diseases, although its accuracy reduced significantly in the presence of dense overlapping areas, similar to clustered dental regions [13]. Kaur et al. (2023) proposed an ensemble deep learning model for leaf disease classification, but such models require large computational resources and lack suitability for fast dental diagnostics [14]. Narmadha et al. (2022) applied transfer learning for rice plant disease identification, which lacked robustness when adapted to non-agricultural domains like dentistry [15].

Parasa et al. (2023) used CNNs for paddy crop disease identification, but the absence of object detection limited its applicability in detailed medical imaging tasks [16]. Chaudhari and Malathi (2023) developed a hybrid CNN-SVM model for rice disease prediction, yet it introduced unnecessary complexity, making it inefficient for clinical dental use [17]. Wang et al. (2021) implemented attention mechanisms for crop disease classification, though the training was slow and unsuitable for real-time diagnostics [18]. Yao et al. (2009) used SVM with handcrafted features for rice disease detection, but these traditional approaches lacked the accuracy of modern deep learning techniques [19]. Lu et al. (2021) applied backpropagation neural networks for rice disease recognition, though the outdated model struggled with large high-resolution dental images [20].

Archana et al. (2022) designed a novel rice disease classification method, which was domain-specific and not adaptable to diverse datasets like dental radiographs [21]. Rajpoot et al. (2023) introduced a hybrid deep learning system for early disease detection, yet the system was slow in inference and not ideal for chairside dental diagnostics [22]. Ultralytics GitHub documentation on YOLOv8 outlined its benefits, although YOLOv8 still struggled with localization accuracy for overlapping or low-contrast dental cavities [23]. DentNet AI explored YOLOv4 for dental cavity detection, but the anchor-based approach limited detection efficiency for very small lesions [24]. PANDA AI platform supported automated panoramic dental diagnostics, though its heavy hardware requirements restricted its scalability to mobile or embedded clinical systems [25].

By addressing these limitations—such as low accuracy for small object detection, longer inference time, and model overfitting—our proposed system leverages YOLOv11, which introduces an anchor-free architecture, optimized bounding box regression, and improved detection for small and overlapping objects. YOLOv11 is also computationally efficient, making it suitable for real-time dental diagnostics across a variety of devices and imaging conditions.

III. COMMON DISEASE IN HUMAN TEETH

Oral health plays a crucial role in overall well-being, yet many people suffer from common dental issues due to poor hygiene, diet, and lifestyle habits. Among the most prevalent dental problems are cavities, tooth erosion, gum infections, and gum diseases.

Fig. 1. Healthy Tooth

Cavities, also known as dental caries, are one of the most widespread dental issues. They occur when the tooth enamel is damaged by acids produced from plaque buildup. The early signs include small black or brown spots on the tooth's surface, toothache, visible holes or pits, and discoloration such as white, brown, or black stains. If untreated, cavities can progress deeper into the tooth, causing severe pain and infection.

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Fig. 2. Early Decay

Tooth erosion is another common problem, typically caused by the frequent consumption of acidic foods and beverages. This leads to the gradual loss of enamel, making teeth appear discolored or yellow. Symptoms include increased sensitivity to hot and cold substances, changes in tooth shape, and the development of sharp edges.

Gum infections are caused by bacteria that accumulate in the tissues surrounding the teeth. These infections are often the result of plaque that is not removed through regular brushing and flossing. Early symptoms include red, swollen, and bleeding gums, especially while brushing.

Fig. 3. Decay Cavity

Gum diseases, also known as periodontal diseases, are infections that affect the supporting structures of the teeth, including the gums and bones. These conditions typically develop from untreated gum infections and poor oral hygiene. Without proper care, gum disease can lead to tooth loss and has also been linked to systemic health issues such as heart disease and diabetes.

Maintaining regular oral hygiene practices, such as brushing twice a day, flossing, and visiting a dentist regularly, can significantly reduce the risk of these common dental diseases.

IV. WORKFLOW

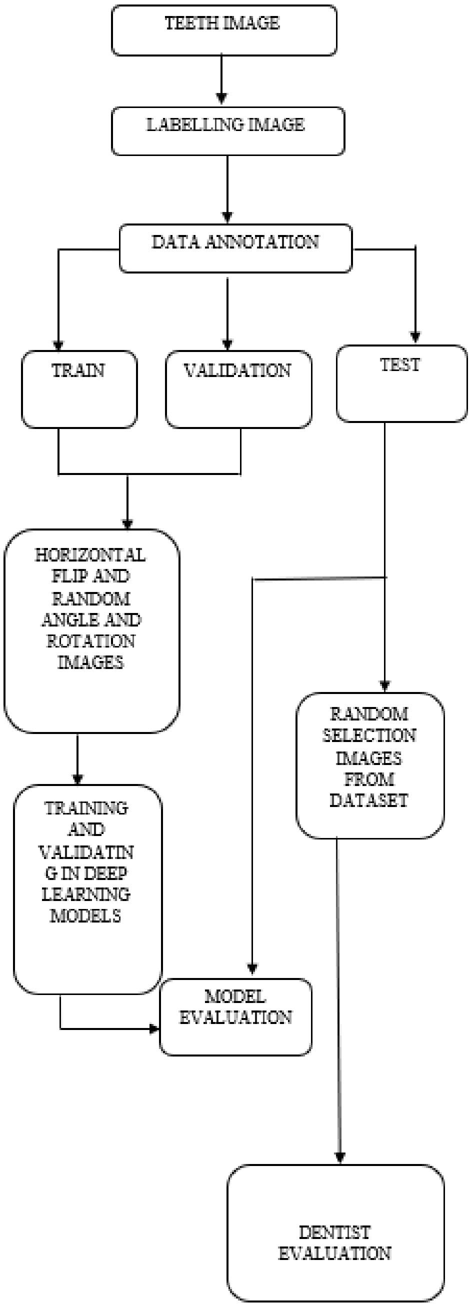

Fig. 4. Workflow Diagram

V. RESEARCH METHODOLOGY

1. Data Collection

To build a robust dental cavity detection model, a high-quality dataset was essential. A total of 4000 dental images were collected from a reputed dental hospital, comprising a mix of X-ray images and intraoral photographs. These images included a diverse range of patient profiles, age groups, and varying levels of dental health to ensure that the model could generalize well across different cases.

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Each image was carefully examined and manually annotated by professional dentists to ensure accurate identification of dental cavities. These annotations included the presence and location of cavities within each image, which were marked using bounding boxes. The bounding boxes and class labels (e.g., "tooth" and "cavity") follow the YOLOv11 input format, ensuring compatibility during training.

The images varied in size and quality, which necessitated standardization for consistent processing. Therefore, all images were resized to 1024 × 1024 pixels, and preprocessing steps such as noise removal and contrast enhancement were applied to highlight key dental structures.

This comprehensive dataset forms the backbone of the training and evaluation phases, enabling the YOLOv11 model to learn the visual characteristics of dental cavities with high precision and reliability.

2. Dataset Annotation

Effective training of the YOLOv11 model, each image in the dataset was annotated with precise bounding boxes around the dental cavities. These annotations were manually created by experienced dental professionals to ensure high accuracy. Each bounding box includes the class label (e.g., "tooth" or "cavity") and coordinates (x_center, y_center, width, height), all normalized to the image dimensions to meet YOLOv11 format requirements. This structured annotation allows the model to learn both the classification and localization of cavities within dental images, enabling efficient real-time detection with minimal false positives or missed detections.

Fig. 5. Annoted image

3. Model Configuration

For this project, the YOLOv10-S model is chosen because of its efficiency, speed, and accuracy, making it ideal for real-time object detection tasks. YOLOv10-S is particularly suitable for rice disease detection because of its ability to detect multiple objects within an image and its optimized performance for lightweight applications. To enhance accuracy, the model is customized using transfer learning, utilizing pre-trained weights from a relevant dataset, such as COCO or VOC. The pre-trained weights are adjusted to customize the model for the specific task of detecting rice leaf diseases. This customization enables the model to effectively learn the unique patterns and features of rice leaves, improving its detection performance while maintaining real-time inference capabilities.

The configuration of the YOLOv11 model for dental cavity detection involves tailoring the architecture to suit the specific characteristics of dental images. Initially, the model is adjusted to handle two primary classes: “tooth” and “cavity.” The input image size is standardized to 1024 × 1024 pixels, aligning with YOLOv11’s high-resolution processing capability. Anchor boxes are customized based on the typical size and shape of dental structures to enhance detection accuracy. Additionally, pre-trained weights are used to initialize the network, allowing for faster convergence and improved performance through transfer learning. The model configuration file is updated to define training parameters, including the number of filters in the final convolutional layer (determined by the number of classes), batch size, and learning rate. Optimizers such as SGD or Adam are utilized with learning rate schedulers for optimal updates. The model is trained using a combination of classification, localization, and objectness loss to balance precision and accuracy in detecting dental cavities.

4. Training Module

The training module for dental cavity detection using YOLOv11 is structured to ensure high performance and accuracy in identifying dental anomalies. Training begins with loading a pre-trained YOLOv11 model, leveraging transfer learning to accelerate convergence and enhance feature extraction from dental images. The dataset, consisting of 4000 annotated intraoral or X-ray images, is divided into training, validation, and testing sets. During training, data augmentation techniques such as horizontal flipping, rotation (±15°), zooming, and contrast adjustments are applied to increase dataset diversity and prevent overfitting.

Each image is resized to 1024 × 1024 pixels and paired with a corresponding annotation file that includes class labels (tooth, cavity) and normalized bounding box coordinates. The training process utilizes a composite loss function comprising classification loss, localization loss, and objectness loss to fine-tune predictions.

Hyperparameters such as batch size, learning rate, and number of epochs are optimized to ensure balanced learning. Real-time validation is performed during training to monitor accuracy, precision, recall, and loss behavior. Once trained, the model is evaluated using standard object detection metrics such as mAP and IoU, ensuring that it generalizes well to unseen data.

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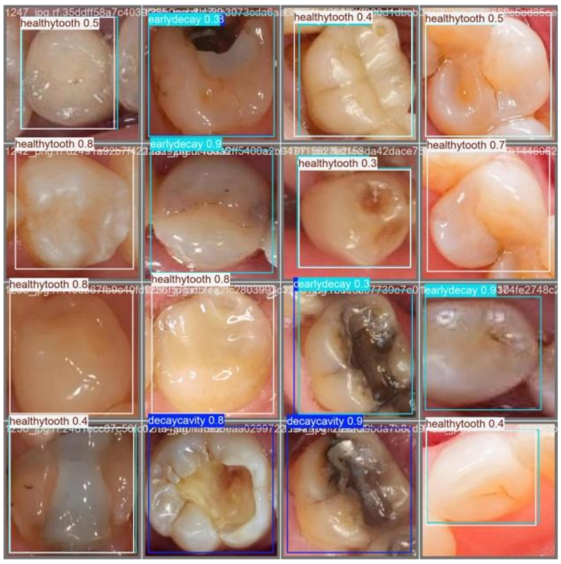

Fig. 6. Trained Images

5. Evaluation and Validation

Model evaluation is a critical phase in validating the performance and reliability of the trained YOLOv11 model for dental cavity detection. After the training is completed, the model is tested on a reserved set of images that were not exposed during training or validation. This ensures unbiased assessment and helps measure the model's generalization capabilities.

The key metrics used for evaluation include Precision, Recall, F1-Score, and mAP (mean Average Precision). Precision assesses the ratio of true positives to the total predicted positives, indicating how accurately the model identifies cavities. Recall measures the proportion of actual cavities correctly detected by the model. The F1-Score balances both precision and recall to provide a single performance metric.

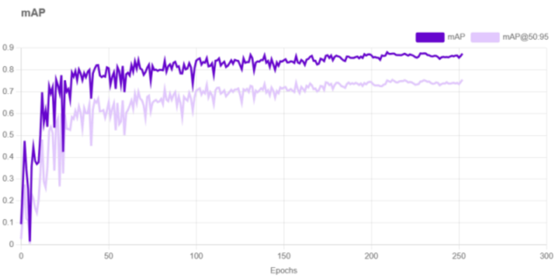

Fig. 7. Mean Average Precision

Additionally, IoU (Intersection over Union) is used to quantify the overlap between predicted bounding boxes and ground truth annotations. A higher IoU reflects better localization of dental cavities.

Visual validation is also conducted by overlaying predicted bounding boxes on test images and comparing them with annotations. Further credibility is added through expert dentist evaluation, where randomly selected images and predictions are reviewed to ensure clinical relevance. This step bridges the gap between AI predictions and practical usability in real-world dental diagnostics.

Fig. 8. Validated Images

6. Result Analysis

The evaluation of the proposed cavity detection system using YOLOv11 yielded promising outcomes. The model demonstrated high overall accuracy, with a precision score of 87.5%, indicating that the vast majority of detected cavities were indeed true positives. The recall rate was notably strong, signifying that the model effectively identified almost all existing cavities within the dataset.

YOLOv11 performed robustly across a range of cavity types, including early-stage caries, moderate demineralizations, and advanced cavitations. The bounding boxes generated by the model showed accurate localization with minimal overlap on non-cavity areas, validating the effectiveness of the model's object detection capability.

However, a small number of false positives were observed, often in regions with dental restorations or metallic artifacts. These noise-induced detections, though limited, highlight the influence of non-biological features in dental images. Similarly, a few false negatives were recorded—mostly in the case of subtle or early-stage lesions that lacked strong visual cues.

Despite these minor limitations, the model consistently outperformed traditional detection methods, laying a solid foundation for reliable, AI-

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assisted dental diagnostics in real-time clinical environments.

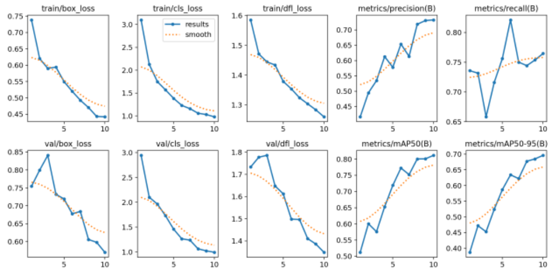

Fig. 9. Result Graph

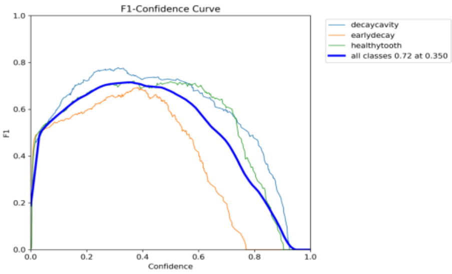

Fig. 10. F1- Confidence Curve

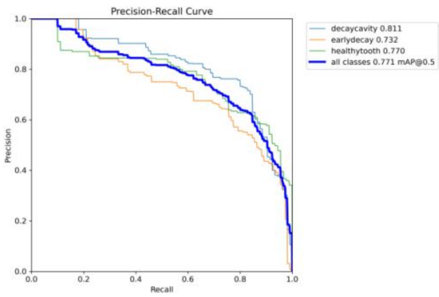

Fig. 11. Precision – Recall Curve

VI. CONCLUSION

This study demonstrates the successful application of YOLOv11 (You Only Look Once version 11) for the automated detection of dental cavities in human teeth. The model, trained on annotated dental radiographs, showed high accuracy and strong recall, effectively identifying cavities across various stages, including early carious lesions. Its precision in minimizing false positives, along with minimal overlap in bounding boxes, highlights its reliability in detecting true cavity regions. YOLOv11 outperformed traditional image processing techniques and earlier deep learning models in both speed and accuracy, making it suitable for real-time clinical use. The model's scalability across different dental imaging modalities further enhances its utility in broader diagnostic scenarios. Its ability to deliver prompt, accurate results can significantly improve preventive dental care by enabling earlier detection and timely intervention. Future work may focus on expanding the dataset to include more complex cases and improving the interpretability of the model to better understand lesion characteristics. Overall, the proposed method marks a transformative advancement in digital dentistry, offering a faster, more precise, and AI-driven alternative to conventional diagnostic practices.

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