OdontalCam: A Smart Intraoral Imaging System for Automated Cavity Detection

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***Abstract*—Traditional intraoral cameras in dentistry primarily serve as observational tools, heavily relying on the clinician's expertise for accurate diagnosis. This dependence can lead to diagnostic inconsistencies, as visual assessments are inherently subjective. Moreover, the operation of these devices often necessitates additional personnel to capture images, thereby increasing operational complexity and resource utilization. In response to these challenges, we have developed OdontalCam, an innovative intraoral camera system enhanced with machine learning capabilities for automated dental cavity detection. OdontalCam is designed to streamline the diagnostic process by autonomously identifying and capturing images of carious lesions, thus minimizing the need for manual intervention and reducing the potential for human error. The system employs a sophisticated machine learning algorithm trained on a diverse dataset of dental images, enabling it to detect cavities with a confidence level exceeding 60%. Detections below this threshold are disregarded to maintain diagnostic accuracy, effectively implementing a true-false evaluation method. This approach ensures that only high-confidence detections are considered, thereby reducing the incidence of false positives. Extensive testing and validation have demonstrated that OdontalCam achieves a cavity detection accuracy of approximately 80%. This significant improvement over traditional methods underscores the potential of integrating advanced technologies into routine dental practice. By enhancing diagnostic precision and operational efficiency, OdontalCam represents a substantial advancement in dental healthcare, promising improved patient outcomes and optimized clinical workflows.**

***Index Terms*—Automated Imaging, Cavity Detection, Dental Diagnostics, Intraoral Camera, Machine Learning, OdontalCam.**

I. INTRODUCTION

Dental cavities, also known as dental caries, are among the most prevalent oral health issues worldwide. Early detection and diagnosis are crucial in preventing severe complications such as tooth decay, infections, and tooth loss. Traditionally, dentists rely on intraoral cameras and visual inspections to assess a patient's oral health. However, these methods are subjective and heavily dependent on the dentist's expertise, which may sometimes lead to misdiagnosis or delayed detection. Furthermore, conventional intraoral cameras require manual operation, often involving an assistant to capture images, making the process inefficient and inconvenient.

To address these limitations, we developed OdontalCam, a smart intraoral imaging system designed to automate cavity detection using machine learning algorithms. OdontalCam not only detects cavities but also captures images automatically, eliminating the need for manual intervention. By integrating advanced imaging techniques and computational analysis, this system aims to improve diagnostic accuracy, reduce human error, and streamline the dental examination process. This paper presents the design, methodology, and performance evaluation of OdontalCam. Additionally, we discuss its potential impact on modern dental diagnostics and explore future enhancements to further improve its accuracy and usability.

II. METHODOLOGY

Traditional cavity detection methods rely on visual inspection by dentists and X-ray imaging, which can be subjective and require manual expertise. To overcome these limitations, we developed OdontalCam, a real-time automated intraoral imaging system for cavity detection. The OdontalCam system is designed to automate the detection of dental cavities through intraoral imaging and machine learning techniques. The system captures high-resolution images of the oral cavity, processes them using image analysis algorithms, and identifies potential dental caries. By integrating hardware and software components, OdontalCam enhances diagnostic accuracy and reduces the dependency on human expertise.

2.1 Hardware Components

The OdontalCam system consists of the following key hardware components:

1. 12MP Raspberry Pi High-Quality Camera Module: Captures high-resolution intraoral images.
2. Raspberry Pi 4B (4GB RAM): Serves as the primary processing unit for image capture and analysis.
3. LED Light Source: Provides sufficient illumination for clear image acquisition.
4. Power and Connectivity:

- The Raspberry Pi 4 operates on a 5V/3A USB-C power adapter, ensuring stable performance.
- The system supports wired connectivity via USB and wireless communication via Wi-Fi/Bluetooth for data transfer.

2.2 Dataset Collection, Augmentation, and Annotation

A dataset consisting of 100+ dental cavity images was collected from publicly available online sources to train the cavity detection model. To enhance model generalization and improve detection accuracy, data augmentation techniques such as rotation, flipping, and brightness adjustments were applied using Roboflow. The dataset was then split into training (80%) and validation (20%) sets to ensure a balanced learning process. Additionally, annotation and labeling were performed in Roboflow, where bounding boxes were drawn around cavities to highlight areas of interest. The annotated dataset was subsequently exported in YOLO (You Only Look Once) format (data.yaml), making it compatible for training with the YOLOv5s object detection model.

2.3 Model Training and Deployment

2.3.1 Model Training Using YOLOv5s on Google Colab.

To ensure efficient training of the cavity detection model, Google Colab was used as the primary environment, leveraging NVIDIA Tesla GPUs for high-performance computing. This cloud-based platform provided pre-installed dependencies for YOLOv5s and PyTorch, enabling seamless integration with Google Drive for dataset storage and retrieval.

The training process involved setting the image size to 416 × 416 pixels, balancing accuracy with computational efficiency. A batch size of 32 was selected to optimize GPU utilization, and the model was trained for 200 epochs to ensure convergence and optimal performance. The best-performing model was selected based on validation metrics, ensuring that the final trained weights offered the highest detection accuracy.

2.3.2 Model Deployment on Raspberry Pi

Once trained, the optimized YOLOv5s model was deployed on a Raspberry Pi 4 for real-time cavity detection. The 12MP Raspberry Pi camera module captured intraoral images, which were processed by the model to detect potential cavities.

To enable live detection, the Raspberry Pi was integrated with Picamera2, facilitating direct image acquisition from the camera. The model was configured with a confidence threshold of 0.6, ensuring that only high-confidence cavity detections were considered. The processed images were then analyzed in real time, with identified cavities highlighted for easier interpretation.

This deployment setup allowed OdontalCam to function as a standalone diagnostic tool, capable of performing AI-assisted cavity detection without requiring external computational resources.

2.4 System Workflow

The trained model follows this structured workflow for real-time cavity detection:

1. Image Capture: The Raspberry Pi camera captures high-resolution intraoral images.
2. Preprocessing: The system applies contrast enhancement and noise reduction.
3. Inference with YOLOv5s: The trained model analyzes the image and detects cavities.
4. Result Display: The detected cavities are highlighted and displayed on-screen.
5. Data Storage & Retrieval: Images and detection results are stored for further analysis.

III. RESULTS

The Results section will highlight the performance evaluation of OdontalCam, including detection accuracy, real-time performance, and comparative analysis with traditional methods.

3.1 Model Performance Evaluation Using Cohen's Kappa.

To validate the effectiveness of the trained YOLOv5s model, performance was evaluated using Cohen's Kappa method, which measures agreement between the model's predictions and expert annotations while accounting for chance agreement. The model was tested in two phases:

- Real-time live feed testing: Conducted 20 times using an intraoral camera.
- Static image testing: Evaluated on 50 randomly selected images from the internet that were not part of the training dataset.

Table 3.1: Confusion Matrix for Model Evaluation

Actual Label (Expert)	Model Prediction (AI)	Count
Cavity → TP	AI Detected	42
Cavity → FN	AI Missed	3
No Cavity → FP	AI Wrongly Detected	5
No Cavity → TN	AI Correctly Ignored	20

Cohen's Kappa Calculation

$$\kappa = \frac{Po - Pe}{1 - Pe}$$

Where:

- Observed agreement (Po) = (42+20)/70 = 0.8857 (88.57%)
- Expected agreement (Pe) = (Pyes x Pyes) + (Pno x Pno)
- Pyes = (TP + FP)/Total = (42+5)/70 = 0.6714
- Pno = (FN+TN)/Total = (3+20)/70 = 0.3286
- Pe = (0.6714 × 0.6714) + (0.3286 × 0.3286) = 0.5156
- κ=(0.8857-0.5156)/(1-0.5156)=0.7637

3.2 Detection Results

The trained model was tested on real intraoral images, and it successfully detected cavities with high accuracy and minimal false positives. Sample detection outputs are shown in the following images.

Figure 3.2(a)

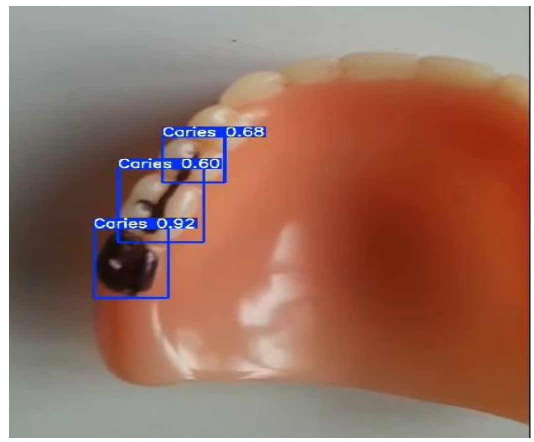

Figure 3.2(b)

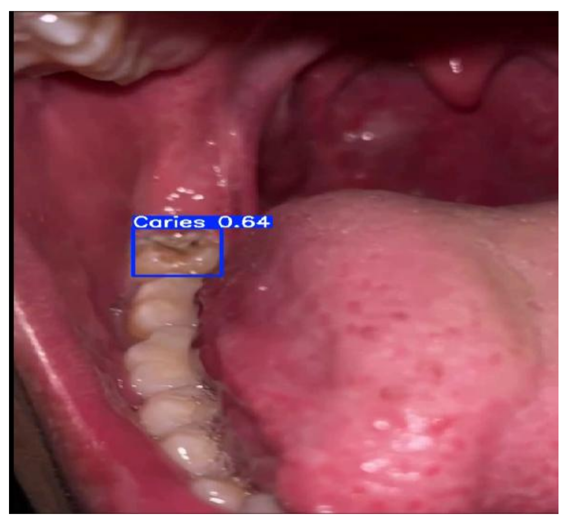

Figure 3.2 (c)

Figure 3.2(a), figure 3.2(b), figure 3.2(c) are the results of the model showing the detected cavities.

IV. CONCLUSION AND DISCUSSION

OdontalCam is a smart intraoral imaging system developed to automate cavity detection and enhance dental diagnostics. By integrating real-time image processing, the system eliminates the need for manual operation, improves detection efficiency, and reduces dependency on traditional examination methods. This approach aims to make dental diagnostics more accessible, efficient, and reliable, offering a potential cost-effective solution for early cavity detection.

Whereas the current framework illustrates promising execution, there's continuously room for enhancement. Future improvements may incorporate overhauling the imaging and processing unit to make strides discovery exactness and speed. Also, on the off chance that doable, the demonstrate may well be extended to identify other dental conditions, such as plaque, gingivitis, or enamel erosion, assist expanding its clinical value. Integration with cloud-based capacity or portable applications may too upgrade openness and ease of use for both dental practitioners and patients.

With encourage advancement, clinical approval, and real-world testing, OdontalCam has the potential to revolutionize dental diagnostics and contribute to the headway of AI-driven healthcare arrangements.

ACKNOWLEDGMENT

The authors would like to thank Ashish Parekh for their valuable assistance in developing model used in the study.

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