EARLY DETECTION OF DENTAL CARIES USING IMAGE PROCESSING TECHNIQUES

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***Abstract*— Advancements in healthcare technology have opened new avenues for early disease detection and prevention. This research presents a novel approach to the early detection of dental caries. Building upon earlier work, we employ a Convolutional Neural Networks model coupled with image processing techniques for real-time analysis of dental images captured using various sources. The system generates an output specifying the stages of tooth decay, which may serve as valuable tools for dental professionals in the future. This innovative approach not only empowers individuals to take charge of their oral health but also represents a significant step towards enhancing the efficiency and effectiveness of dental care. Through this research, we showcase the potential of technology to transform the landscape of oral health monitoring and contribute to the overall well-being of individuals.**

Keywords—Convolutional Neural Networks, Dataset Organization, Model Training, Image processing, Annotations.

I. INTRODUCTION

Dental health is a fundamental aspect of overall well-being, often overlooked until discomfort or pain becomes undeniable. Yet, the consequences of neglecting oral health can be far-reaching, extending beyond the confines of the mouth to impact one's quality of life. Dental caries, commonly known as tooth decay, stands as a prevailing oral health concern that can lead to discomfort, pain, and more severe complications if left unaddressed.

The need for the early detection of dental caries cannot be overstated. Beyond the discomfort it causes, untreated dental caries can progress to more severe stages, potentially requiring invasive and costly interventions. Furthermore, oral health is intimately linked to broader health outcomes. Poor oral health has been associated with systemic diseases [1] such as diabetes, cardiovascular disease, and even adverse pregnancy outcomes. Neglecting dental health not only affects an individual's physical health but can also impact their self-esteem, social interactions, and overall quality of life [2]. To address the pressing need for early detection and prevention of dental caries, there is a clear imperative for technological advancements. The utilization of web-based technology, combined with state-of-the-art image processing techniques, offers a promising avenue to revolutionize the way we approach oral health monitoring. This research project is driven by a primary objective—to empower individuals with a preventive approach to oral health rather than reactive care. The core focus of this introduction is to introduce a web-based platform tailored to harness the capabilities of standard web cameras and advanced image analysis. Users can effortlessly upload dental images, and with the application of the fast-R CNN model [3] and image processing techniques, receive real-time oral health classifications into three distinct sections. This system is meticulously designed to stress the importance of prevention in oral healthcare, offering timely insights into oral health status. In the pages that follow, we delve into the development and implementation of this innovative solution, highlighting its potential to transform the landscape of oral health monitoring and contribute to the overall well-being of individuals. Our work stands as a testament to the power of technology in advancing preventive healthcare, ensuring that dental health is taken seriously from the outset, and minimizing the potential harms that can arise from its neglect.

A. Motivations and Objectives

Our research is driven by the need to address dental caries, a persistent challenge that often goes undetected until advanced stages, causing pain and financial strain. Oral health is integral to overall well-being, impacting daily life. Utilizing web technology and image processing, our goal is to empower individuals through a user-friendly website for early dental caries detection. This cost-effective tool enhances proactive oral health management and complements dental professionals' work, improving oral health and quality of life.

The main objectives of the proposed work are:

- To proactively deliver preventive dental care through the early-stage detection of dental caries.
- To facilitate the identification of caries and tooth decay issues by enabling patients to submit images as diagnostic inputs.
- To proactively deliver preventive dental care through the early-stage detection of dental caries.
- To optimize healthcare costs by mitigating the necessity for more expensive treatments that may arise from untreated conditions.

- To conduct a comprehensive analysis of patient-uploaded images and offer tailored dental solutions.
- To impart patient education concerning the significance of maintaining optimal oral hygiene practices and recognizing the precursory indicators of dental caries.

The paper is structured as follows: Section II covers the related work, Section III delves into the methodology, Section IV provides implementation details, Section V demonstrates the implementation of various application modules, and, lastly, Section VI offers the paper's conclusion.

II. Related Work

The various work and research initiatives related to early detection of dental caries through advanced image processing techniques.

Massimo Salvi, U. Rajendra Acharya [4] explored that machine learning methods typically incorporate pre- and post-processing stages to simplify classification, detection, or segmentation tasks. The fusion of these techniques within deep learning frameworks has gained widespread attention, becoming the standard approach for image analysis across various research domains, notably in digital pathology.

Elina Väyrynen, Sanna Hakola [5] introduced a mobile-based oral health monitoring application that utilizes image processing techniques. While their primary focus is on monitoring, their work provides insights into the integration of mobile technology for dental care, aligning with the research objectives.

Ruchika Chandel, Gaurav Gupta [6] investigated that image filtering techniques, with a primary focus on non-linear filtering algorithms like median filtering, was conducted. Various algorithms and methods for image smoothing and filtering were explored, aiming to identify the most effective approach. These techniques were particularly valuable for addressing challenges such as random intensity variations, illumination discrepancies, and poor contrast that often arise in early stages of vision processing.

Man Hung, Maren Wright Voss, Megan N. Rosales [7] explored the application of machine learning algorithms in the early detection of dental caries. While this approach differs in the use of mobile images, this research underscores the efficacy of machine learning in dental diagnostics, complementing their own efforts in this area.

Jae-Hong Lee. [8] conducted a study on the potential of deep learning models in dental image analysis. They explored the use of convolutional neural networks (CNNs) to detect dental caries from dental radiographs with impressive accuracy. This research showcases the applicability of deep learning techniques, which aligns with utilization of image analysis, albeit with a different approach.

Abdulhadi Warreth [9] found it essential to adopt a strategy and framework that prioritizes community education initiatives, with patient-centered care as a central component of our dental duties. It's important to explore methods like non-invasive, microinvasive, and minimally-invasive approaches, particularly in cases where cavities are not yet fully formed.

B Sarvesan, K Bhanu Sundar [10] explored the integration of chatbots in healthcare for providing personalized health recommendations. Their study emphasized the importance of tailoring chatbot responses based on user data and preferences. This aligns with their objective of implementing an NLP-powered chatbot to provide tailored health guidance and support.

Geethapriya. S, N. Duraimurugan, [11] investigated that YOLO analyzes the entire image when predicting boundaries, resulting in fewer false positives in background areas. This algorithm is straightforward to construct and can be directly trained on the complete image. In contrast, region proposal strategies constrain the classifier to a specific area.

Yang Jie, Yuchen Xie [12] developed an automated and streamlined dental image analysis approach that integrated dental image diagnosis knowledge. It supported the automated identification of the apical region, which saved a considerable amount of manual effort in data preparation. Their approach enabled the use of CNNs for diagnosis classification, even when working with small datasets.

Prior research highlights the importance of image processing in dental care, aligning with our project's objectives. Web-based and mobile applications have shown promise in oral health monitoring. Additionally, image filtering techniques offer insights into dental caries detection. In the future, improvements in image processing, innovative mobile solutions, and enhanced image filtering algorithms are avenues to enhance early dental caries detection, contributing to preventive oral healthcare and overall well-being.

III. Methodology

The proposed work focuses on the comprehensive study and implementation of various practices related to caries identification, classification, and access. The research project involves a multifaceted approach to the early detection of dental caries and the enhancement of oral health through the development of an integrated web application. The methodology comprises the following key components:

A. Dataset

1) Dataset Collection Phase

Early detection of dental caries necessitates a specialized dataset that encompasses various stages of dental health, including cases with mild to moderate levels of dental caries. This specific dataset was not readily available in existing online repositories, aligning with the primary objective of this research, which focuses on early detection. A significant portion of the dataset was procured through manual image collection, facilitated by dental experts' guidance followed by collecting images from online sources.

A substantial corpus of approximately 6,000 dental images, encompassing diverse oral health scenarios, was amassed from various sources. These images represented a broad spectrum of dental conditions, ranging from the presence of lesions to affected teeth and cavities. There are 1133 training images, 283 testing images and in total 1416.

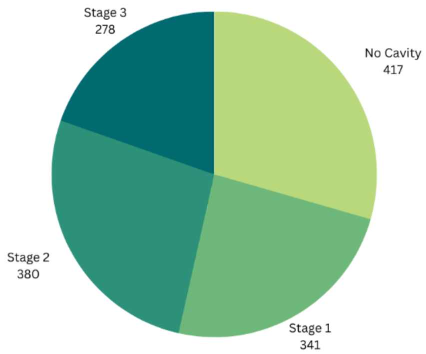


Fig.1. Dataset Class-wise Proportions

2) Data Curation and Refinement: Subsequent to the data collection phase, a critical curation and refinement process was executed. The aim was to eliminate redundancy, irrelevant images, and ensure dataset representativeness. The stringent curation process meticulously sorted through the amassed images, ultimately retaining a focused subset of 1,400 images that best encapsulated the diversity of dental conditions.

B. Annotation

1) Manual Annotation through Dentist Consultation: To imbue our dataset with precise and clinically relevant labels, we engaged dental professionals who played an instrumental role in the manual annotation process. Each of the 1,400 selected images underwent comprehensive assessment and tagging under the guidance of dentists specializing in oral health. The expertise and consultation of these dental professionals ensured the accuracy and clinical relevance of the annotations.

2) Utilization of CVAT for Annotation: For the systematic annotation of dental images, we employed an open-source image tagging tool known as Computer Vision Annotation Tool (CVAT) [13]. This versatile tool allowed for the precise annotation of dental conditions within the images, facilitating detailed categorization [14].

3) Three Distinct Tags: The images were tagged based on three distinct categories, each serving as a crucial element in early dental caries detection:

- Type1 - White Lesion on Tooth: This category encompasses images depicting the presence of white lesions on teeth [15]. White lesions are indicative of enamel demineralization, often considered a preliminary stage of dental caries.
- Type2 - Yellow Lesion: Images categorized under this category denote the presence of yellow lesions on dental surfaces. Yellow lesions represent an intermediate stage in the progression of dental caries, signifying the deterioration of enamel integrity.
- Type3 - Affected Tooth or Cavity: The Type3 category includes images portraying teeth in an affected state, potentially exhibiting cavities or advanced carious lesions. These images encapsulate the severe end of the dental caries spectrum [16].

Fig.2. Classification of Teeth as per Stages

4) Integration with Image Processing Model: The meticulous manual annotation process culminated in the creation of annotation files. These annotation files were seamlessly integrated with the image processing model, serving as invaluable ground truth data for training and evaluation. The model included 8 layers.

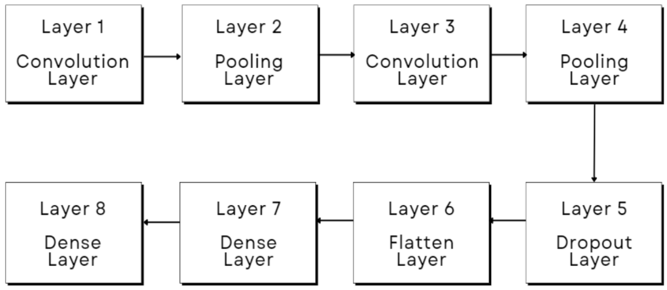


Fig.3. Layers in Fast-R CNN Model

IV. IMPLEMENTATION

A. Dataset Collection and Annotation

Data preparation plays a critical role in training the Fast R-CNN model, a specialized variant of the Convolutional Neural Network (CNN) tailored for object detection tasks. Raw images and annotations were loaded, typically in JPEG or PNG format.

Images are associated with precise annotations specifying object classes and bounding box coordinates. Structured formats (e.g., XML, JSON) ensure data consistency. Augmentation techniques (e.g., cropping, scaling, rotation) enhance dataset diversity. It also improved model generalization for object variations. We also did Bounding Box Augmentation where in Randomized Box Position i.e. perturbing the positions of object bounding boxes within images to mimic variations in object placement was performed.

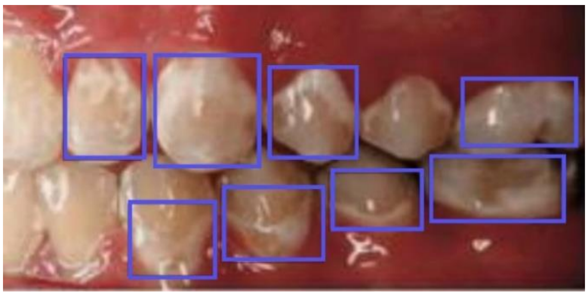


Fig.4. Example of Bounding Box Augmentation

B. *Creation of CSV file of annotations*

The images imported from CVAT were converted into HTML format for structured presentation, and subsequently transformed into '.xls' (Microsoft Excel) format for data extraction and formatting. Within Excel, pertinent annotation details, including image file paths, bounding box coordinates (x, y, width, height) for each annotated object, and class labels, were meticulously organized. This process culminated in the creation of a structured CSV (Comma-Separated Values) file, complete with appropriate column headers, encapsulating the essential annotations for the Fast R-CNN model's training.

C. *Fast R-CNN Model creation*

Various Python libraries were employed. Specifically, layers were imported for constructing the neural network architecture. We achieved customization of the model's training process by integrating the RMSprop optimizer [17], which effectively reduces oscillations in the vertical direction. Consequently, this allowed us to elevate our learning rate and enable our algorithm to take larger steps in the horizontal direction, leading to quicker convergence.

In the model's architecture, Rectified Linear Unit (ReLU) activation functions [18], defined as max (0, x), were integrated.

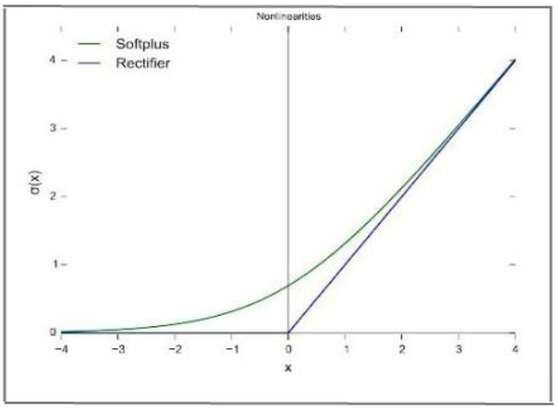


Fig.5. Graphical representation of ReLU Function

Furthermore, the Softmax activation function [19] was included, serving as a critical component for multi-class classification tasks. This function transformed the model's output into probability distributions across multiple classes, enabling efficient classification.

$$\boxed{\mathrm{softmax}(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \text{ for } j = 1,\dots,K}$$

Fig.6. Formula for Softmax Function

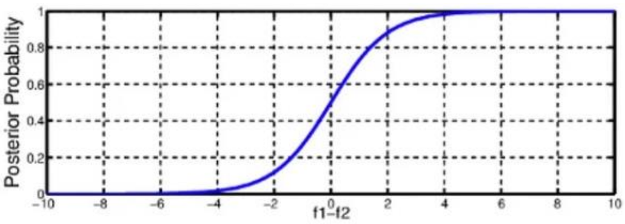


Fig.7. Graphical Representation for Softmax Function

D. *Model Training and Configuration*

In the Model Training phase, images were imported into the pre-trained model. An '.h5' file extension served as a container to save and deploy the trained model as needed, ensuring its accessibility for future applications. The model underwent 50 epochs of training to achieve peak accuracy.

E. *Image Classification and Dataset Organization*

The trained Fast R-CNN model categorized dental images into four classes: 'Healthy,' 'Type 1,' 'Type 2,' and 'Type 3.' These classifications facilitated precise assessments of oral health conditions, aiding in the early detection and management of dental caries. It's worth noting that the validation and training datasets were organized such that each class shared the same name as its corresponding classification, ensuring seamless integration of the data into the model training and validation processes.

V. RESULTS AND DISCUSSION

This attempt involved the training and evaluation of two models, CNN (Convolutional Neural Network) and Fast R-CNN (Region-based Convolutional Neural Network), for dental caries detection. Upon analysis, the CNN model demonstrated an accuracy of 77.3%, while the Fast R-CNN model achieved an accuracy of 92.6%. Based on these results and other relevant considerations, we selected the Fast R-CNN model for further development and implementation. The choice of 50 epochs for model training yielded minimal information loss, as supported by an accompanying graph illustrating the relationship between accuracy and epochs.

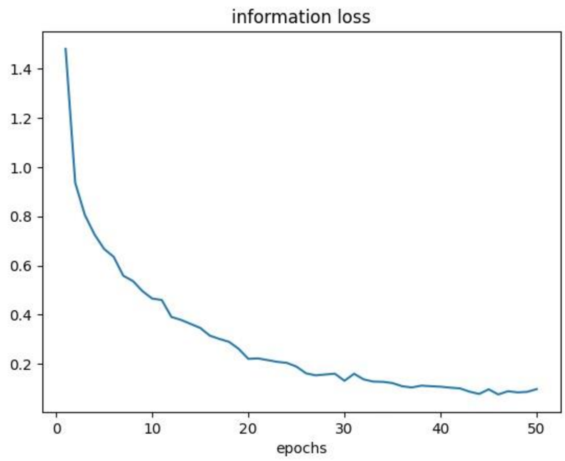
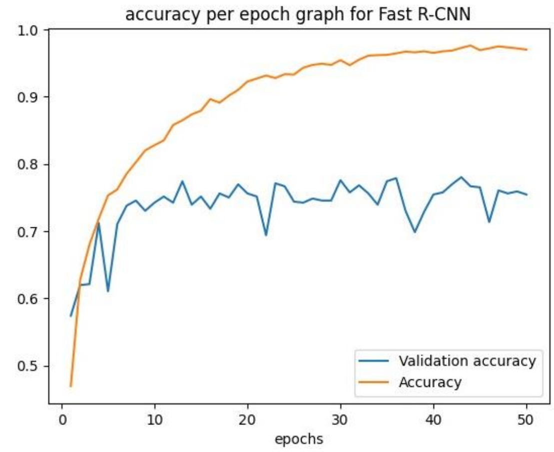


Fig.8. Graphical Representation of Information Loss

During the Fast R-CNN model training phase, we monitored accuracy across various epochs. The model's performance steadily improved, peaking at 92.6% within the 50-52 epoch range. Beyond this range, a decline in accuracy was observed, underscoring the importance of selecting the optimal epoch value. This trend, captured in the accuracy per epoch versus epoch graph, emphasizes the need for careful epoch selection to balance training time and model accuracy.



VI. Conclusion And Future Scope

Leveraging the Fast R-CNN model, this research illustrates the transformative potential of advanced machine learning in early dental caries detection. With its user-friendly interface and high accuracy, this technology equips individuals of all ages to proactively manage their oral health. By minimizing the consequences of untreated dental caries, including pain and financial burden, our work highlights the broader impact of technology on preventive healthcare, ultimately contributing to a healthier future for all.

A. Future Scope

- The development of an Android application for enhanced accessibility to dental caries detection.
- Expansion of the dataset to further improve model accuracy.
- Exploration of predictive analytics for early identification of individuals at a high risk of developing dental caries, utilizing dental images and comprehensive health data.
- Integration of an inbuilt chatbot within the application to provide real-time assistance and information.

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