Automated Dental Cavity Detection Using Machine Learning

Ms. Swarali Suryawanshi(Student), Ms. Rajeshwari Patil(Student), Ms. Sakshi Andhare(Student), Ms. Srushti Raut(Student)Professor Sonali Potadar(Corresponding Author)

> Department Of Information Technology Marathwada MitraMandal's College of Engineering Pune, Maharashtra

Abstract-This review paper delves into the realm of automated dental cavity detection, specifically focusing on the machine learning (ML) techniques and their application, within an Android environment. With oral health playing a pivotal role in overall well-being, the fusion of ML algorithms and mobile technology presents a promising avenue for enhancing the accuracy and accessibility of dental cavity diagnosis. The review systematically examines recent advancements in ML-based approaches, spanning traditional algorithms to deep learning models, and assesses their integration into an Android application framework. Key components such as image-based diagnostic tools, data pre-processing techniques, and model architectures are analysed for their efficacy in real-time dental health monitoring. By providing a comprehensive synthesis of existing literature, this review serves as a valuable resource for dental practitioners. researchers, and developers interested in the current landscape of automated dental cavity detection using machine learning, especially when integrated into Android healthcare applications. The insights gained from this review are poised to guide future research directions, fostering advancements at the intersection of dentistry, artificial intelligence, and mobile technology for improved oral healthcare outcomes.

Index Terms—Machine learning, Deep learning, Dental imaging, Android application, Image-based diagnostics, Dental care, Artificial intelligence in dentistry

I. INTRODUCTION

Early cavity diagnosis and treatment are essential to maintaining good oral health, as dental health is a crucial component of general well-being. In recent years, the capabilities of machine learning has brought about revolutionary change in the field of medical diagnostics. Among these advancements, the development of automated dental cavity detection systems stands as a remarkable milestone in the domain of dentistry. This project aims to shed light on an innovative approach to dental care, where we explore the creation and evaluation of an "Automated Dental Cavity Detection System Using Machine Learning." Dental cavities, also known as dental caries or simply "cavities", are a common dental ailment affecting people of all ages. The conventional method of diagnosing these cavities often relies on the keen observations of skilled dentists and radiologists, coupled with extensive training and experience. However, the advent of machine learning has opened up new possibilities for more precise,

efficient, and consistent cavity detection. The significance of early detection of dental cavities not only helps prevent further decay and complications but also reduces the overall cost and pain associated with treatment. Through this project, we delve into the development process and results of an automated system that uses machine learning techniques to detect dental cavities from radiographic images. In the pages that follow, we will explore the methodology employed, the challenges faced, and the achievements realized throughout the course of this project. We will also discuss the implications of such an automated system in the field of dentistry and how it can potentially reshape the way cavities are diagnosed and managed. Furthermore, we will delve into the ethical and practical aspects of implementing this technology in real-world clinical settings through android application, as well as its potential to enhance preventive dental care and improve patient outcomes. This project is not merely a technological endeavour but a step toward a future where technology empowers healthcare professionals, reduces human error, and enhances the lives of patients. The development of an automated dental cavity detection system represents a promising intersection of technology and medicine, and this review serves as a comprehensive exploration of its capabilities and potential impact.

II. LITERATURE SURVEY

There has been a lot of previous work done to automate the cavity detection using many conventional and modern ways. This paper's methodology tried to overcome few aspects of the literature survey done. We found few of the limitations which we have tried to overcome. The dataset used was diverse. This helped calculate performance metrics without any bias. It also compared various algorithms to find the best suited one. It used specific defined metrics for performance measure.

III. SYSTEM ARCHITECTURE

Architecture diagrams are crucial for planning and communication in software development and system design. Hence the above diagram shows that the automated dental cavity detection system project leverages machine learning, a sophisticated dataset, and a user friendly mobile application to provide dental professionals with an efficient, accurate, and real-time tool for early and precise diagnosis of dental cavities *E*. by guidance of the application.

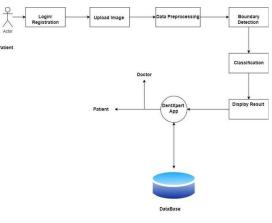


Fig. 1. System Architecture

IV. IMPLEMENTATION

A. Data Collection

Data collection involves gathering the raw data that will be used to train and test a machine learning model. The data can come from various sources, such as databases, sensors, or external datasets. Collecting the right data is crucial to ensure that the model can learn effectively. The radio graphical data was collected from the sponsor.

B. Data preprocessing

Data pre-processing is the process of sanitising and getting obtained data ready for analysis. This include handling missing values, removing duplicates, and handling outliers. Data can also be changed or standardised in order to have it ready formodelling. Here data was cropped and made of equal size. The duplicates were removed and noisiness was removed.

C. Feature Extraction

The process of choosing or generating pertinent features (attributes) from the data that are most instructive for the machine learning model is known as feature extraction. In this step, the dimensionality of the data is decreased and the main factors affecting the target variable are highlighted. Here we used algorithms to detect the edges and segment it.

D. Choose the model

Model selection is the process of choosing the most appropriate machine learning algorithm or model for the task at hand. This depends on the characteristics of the dataset and the type of task (classification, regression, clustering, etc.). Canny edge detection, transfer learning and ResNet9 were implemented to get the desired results.

E. Model Training

A subset of the pre-processed data is used during model training to instruct the chosen machine learning model. With the help of the goal variables and supplied features, the model gains the ability to forecast. To increase the accuracy of the model and fine-tune its parameters, this stage is crucial. The model was trained on certain batch of data

F. Evaluate the model

To make sure the model is effective, its performance must be assessed after training. This is evaluating how effectively the model generalises to new, unobserved occurrences using an alternative set of data (testing data). Among the common evaluation criteria are F1 score, recall, accuracy, and precision. On the other half model was evaluated to check its accuracy.

G. Integrate in an Android Application

App integration refers to the incorporation of the trained machine learning model into an application or system where it can be used to make predictions or provide insights. This step ensures that the model's capabilities are accessible to endusers or other applications.

H. Deployment and testing

The product is either launched into the market or deployed in the client environment after completing both functional and non-functional testing.

V. ALGORITHMS

A. Canny Edge

Canny edge detection is a widely used image processing technique that identifies and highlights edges or boundaries in digital images. It does this by following several steps: smoothing the image to reduce noise, calculating the image gradient to find areas of rapid intensity change, thinning edges to a one-pixel width, and applying high and low thresholds to detect edges accurately. Canny edge detection is particularly useful in computer vision and image analysis for tasks such as object detection and recognition.

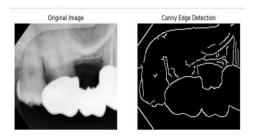


Fig. 2. Output of Canny Edge Detection

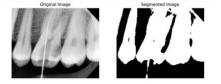


Fig. 3. Output of Canny Edge Detection

B. Transfer Learning

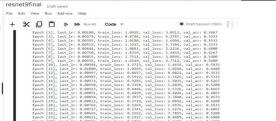
In the context of X-ray image detection, transfer learning can be used to leverage pre-trained models on large datasets, typically from tasks like general image recognition, and then fine tune them for the specific task of detecting abnormalities or diseases in X-ray images. It pre-trains convolutional neural network (CNN) model that has been trained on a large dataset, such as ImageNet, which contains millions of labeled images across thousands of categories. These pre-trained models have already learned to extract meaningful features from images. Utilize the pre-trained CNN as a feature extractor. Removes the last few layers and use the output of the remaining layers as features. These features capture high-level visual representations of the input images. Add new layers to the pre-trained CNN, and train the model on a smaller dataset of X-ray images. This fine-tuning process adapts the model to the specific characteristics of X-ray images. Train the modified model on the X-ray dataset, adjusting the weights of the entire network to minimize the classification error. Evaluate the performance of the fine-tuned model on a separate validation or test dataset of X ray images. Metrics such as accuracy, precision, recall, and F1-score can be used to assess the model's performance in detecting abnormalities.

C. ResNet9

In the context of X-ray image detection, ResNet-9 can be used as a backbone architecture for feature extraction. The lower layers of the ResNet-9 model capture low-level features (such as edges and textures), while the higher layers capture more abstract and complex features (such as shapes and patterns). After using ResNet-9 for feature extraction, additional layers (such as fully connected layers) can be added to the network for classification or detection tasks specific to X-ray images. The entire network can then be fine-tuned on a dataset of X-ray images to adapt it to the particular characteristics of the data and the detection task at hand. It achieves state-of-theart-performance on various image-related tasks such as image classification, object detection, and semantic segmentation.

VI. CONCLUSION

We have examined the amazing possibilities of a machine learning-based automated dental cavity detection system in this project evaluation. This innovative system represents a significant leap forward in the field of dental healthcare, offering a powerful solution to improve the accuracy, efficiency, and accessibility of cavity diagnosis. By automatically identifying cavities in dental X-ray images, it empowers both dental



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Fig. 4. ResNet Accuracy

professionals and individuals to make informed decisions about their oral health.

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