Vivekanand Education Society's Institute of Technology,

(An Autonomous Institute Approved by AICTE and Affiliated to the University of Mumbai)

ToothBuddy : Remote Dental Diagnostic and Consultation System

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN COMPUTER ENGINEERING

By

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CERTIFICATE

This is to certify that the Major Project entitled **“ToothBuddy : Remote Dental Diagnostic and Consultation System”** is a bonafide work of **Mahendra Girase (D17B/14),Mohit Patil (D17B/39), Pranav Rane (D17B/43), Amisha Chandwani (D17A/02)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **“Bachelor of Engineering”** in **“Computer Engineering” .**

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Examiners

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Date: 22/10/2024
Place: Mumbai

7. Conclusions

8. References

9. Appendix

Abstract

Oral health is a vital yet often overlooked aspect of overall well-being. Many oral diseases, such as cavities, gingivitis, and oral cancer, can be detected early through routine check-ups, but barriers like limited access to dental care often prevent timely intervention. This paper presents **ToothBuddy**, an intelligent system that leverages machine learning to assist in the early detection of common dental diseases using smartphone-captured images. By allowing users to upload images of their teeth and gums, the system analyzes the visuals to identify potential issues like cavities, gingivitis, hypodontia, ulcers, and calculus. Additionally, it integrates the user's medical history to improve diagnostic accuracy. If diseases are detected, the system provides recommendations for local dentists and generates reports for further consultation. In the absence of disease, users receive personalized dental hygiene tips. This solution empowers individuals, particularly those in underserved regions, to manage their oral health proactively and reduces the burden of untreated dental issues. The proposed system could play a significant role in improving global oral health outcomes by offering timely, accessible, and personalized care.

Chapter 1 : Introduction

In this chapter, we present the methodology of a system designed to detect oral health issues using smartphone-captured images. Users upload images of their teeth and mouth, which are analyzed by machine learning models trained on a dataset of dental images. The system checks for potential diseases and, if detected, provides recommendations for local dentists and sends reports for further consultation. If no disease is found, it offers dental hygiene tips. The user's medical history is incorporated into the analysis to enhance diagnosis accuracy, ensuring personalized care and early intervention for optimal oral health management.

1.1 Introduction

Oral health is a critical component of overall well-being, yet it is often neglected until severe problems arise. Many individuals do not realize the significance of timely detection and intervention, which could prevent a wide range of oral diseases from advancing into more serious, painful, and costly conditions. Gum disease, tooth decay, and oral cancer are just a few examples of issues that can be caught early with proper care, but the lack of access to regular dental check-ups remains a barrier for many.

In response to this widespread challenge, we are developing an innovative application that leverages machine learning to detect externally visible oral diseases from images. The core of our solution is a sophisticated diagnostic system designed to classify and identify common oral health issues, including conditions such as cavities, gingivitis, hypodontia, ulcer and calculus using visual input. By analyzing photographs of a person’s teeth, gums, and oral cavity, the system will provide real-time feedback on potential issues, flagging early signs of disease before they escalate.

This tool is particularly valuable in regions with limited access to dental care, where regular check-ups may not be feasible due to economic, geographical, or logistical constraints. It empowers users to take control of their oral health by offering early detection and personalized recommendations for intervention. By facilitating proactive health management, this system could significantly reduce the burden of untreated oral diseases and improve overall quality of life, particularly in underserved communities.

1.2 Motivation

1. Oral Health Detection Using Machine Learning

- **Preventive Care:** Early detection of oral health issues can prevent severe conditions.
- **Access to Care:** Provides dental care in underserved areas with limited access to professionals.
- **Cost-Effectiveness:** Reduces the financial burden of late-stage treatments.
- **Empowerment:** Enables users to monitor their oral health conveniently with AI technology.

- **Global Impact:** Promotes better oral health worldwide, especially in low-resource regions.

2. ML-Based System for Detecting Dental Problems and Providing Treatment Plans

- **Timely Interventions:** Helps users detect issues before they worsen.
- **Education:** Raises awareness of early dental problem signs.
- **Personalized Care:** Offers tailored treatment suggestions for common issues.
- **Relieves Healthcare Systems:** Reduces unnecessary dental appointments.
- **Convenience:** Provides a remote, accessible way to assess and manage oral health.

1.3 Problem Definition

Untreated oral diseases can result in serious health complications and reduced quality of life. However, many individuals face geographic, financial, or awareness barriers that limit their access to regular dental care. Current detection methods often require in-person exams by dental professionals, which are not feasible for everyone. To bridge this gap, this project proposes the development of an AI-powered application capable of detecting visible oral diseases using images. This app will empower users to self-assess their oral health, facilitating early diagnosis and timely treatment. By making dental assessments more accessible, the app aims to improve overall oral health outcomes.

1.4 Relevance of the Project

Improving Diagnostic Accuracy: Machine learning models, trained on large datasets of dental images, have the potential to detect subtle signs of oral health issues with high accuracy. This can lead to earlier and more reliable diagnoses compared to manual visual inspections.
Scalable and Automated Solutions: ML-based systems can analyze thousands of images quickly and efficiently, making the solution highly scalable. This is especially important for handling a large volume of cases in regions with limited dental professionals.
Enhanced Accuracy with Deep Learning: Image-based disease classification using deep learning models (e.g., CNNs) can significantly improve diagnostic accuracy by learning to recognize even subtle visual patterns of dental diseases that may be missed by the human eye.
Building a Comprehensive Dataset for Oral Health: As the system is trained on diverse dental images, it can evolve to recognize a wide variety of oral health issues, creating a valuable dataset that could be shared for further research and improvement of other AI-driven healthcare applications.

1.5 Methodology used

Capture Image through Smartphone: The user captures an image, likely of their teeth or mouth, using a smartphone.

Analyze Image: The system analyzes the captured image to detect any dental problems, likely using machine learning algorithms trained for image recognition.

Model Training: The model is initially trained on a dataset of dental images to learn patterns related to various conditions.

Model Testing: After the training phase, the model is tested to ensure its accuracy and reliability in identifying dental issues.

Display Result: Once the image is analyzed, the system displays the results of the analysis to the user.

Take Medical History at the Time of Login: When the user logs in, the system takes their medical history, which is used in the diagnosis or report generation.

Generate Report: The system generates a report based on the image analysis and the user's medical history.

Is Disease Detected?: The system checks if any dental disease is detected in the analyzed image.

- **Yes**: If a disease is detected, it shows a list of related dentists that can treat the condition. The user can then consult the dentist.
    - After consulting, the report is automatically sent to the dentist.
- **No**: If no disease is detected, the system suggests health tips to maintain good dental hygiene.

This system aims to assist users in detecting dental issues early, providing professional connections for further consultation when necessary.

Chapter 2. Literature Survey

In this chapter, we reference research papers that provide a foundation for our project and discuss our interactions with a senior dentist, whose expertise significantly influenced our approach. The dentist's insights into early detection, patient management, and the importance of identifying key visual indicators of dental diseases helped shape our machine learning system. Their practical experience highlighted the need for accessible, accurate diagnosis tools. We also review existing systems in the field of oral health detection, analyzing their limitations and identifying opportunities for improvement. This informed the development of a more efficient, accessible, and reliable solution.

2.1 Research Papers referred

1) H. Yi, B. Liu, B. Zhao and E. Liu, "Small Object Detection Algorithm Based on Improved YOLOv8 for Remote Sensing," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 1734-1747, 2024, doi: 10.1109/JSTARS.2023.3339235.

Abstract:

Small object detection in remote sensing images is challenging due to issues like background noise and incomplete information. This paper introduces LAR-YOLOv8, an enhanced version of YOLOv8, aimed at improving detection accuracy. Key improvements include a dual-branch architecture attention mechanism for better feature extraction, a vision transformer block for enhanced feature representation, and an attention-guided bidirectional feature pyramid network for discriminative information. Additionally, the proposed RIOU loss function focuses on shape consistency between predicted and ground-truth boxes. Experiments on datasets such as NWPU VHR-10 and RSOD demonstrate the effectiveness of these enhancements.

Inference:

LAR-YOLOv8 significantly enhances the detection of small objects in remote sensing images by incorporating advanced attention mechanisms, a vision transformer block, and an improved loss function. These modifications lead to better feature extraction and shape consistency, improving accuracy across varying object sizes. The algorithm's performance on multiple datasets, combined with its efficiency in real-time applications, demonstrates its robustness and versatility for detecting objects at different scales.

2) Chen, H., Zhang, K., Lyu, P., Li, H., Zhang, L., Wu, J., & Lee, C. H. (2019). A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films. Scientific reports, 9(1), 3840.

Abstract:

This study proposes a method for detecting and numbering teeth in dental periapical films using Faster R-CNN within the TensorFlow framework. To enhance detection accuracy, three post-processing techniques are introduced, including a filtering method to eliminate overlapping detection boxes, a neural network model to identify absent teeth, and a rule-based module for consistent labeling of detected teeth. The intersection-over-union (IoU) between detected and ground truth boxes averaged 91%, with precision and recall exceeding 90%. The results were validated against manual annotations from three independent dentists, indicating that the machine's performance is comparable to that of a junior dentist.

Inference:

The primary objective of this research was to automate the detection and numbering of teeth in dental periapical films, thereby enhancing diagnostic efficiency and alleviating the workload of dental professionals. Utilizing a dataset of 1,250 dental X-ray films, the study trained a Faster R-CNN to detect teeth while employing a deep neural network (DNN) to predict missing teeth. High precision and recall rates were achieved, showcasing the effectiveness of deep learning in accurately detecting and classifying teeth, particularly in complex scenarios that challenge human experts. The study also acknowledged challenges such as detecting partially truncated or overlapping teeth, emphasizing the contributions of deep learning to dental diagnostics. Ethical guidelines were followed, with the privacy of patient data ensured through anonymization.

3) S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios and E. J. Calilung, "Common Garbage Classification Using MobileNet," 2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM), Baguio City, Philippines, 2018, pp. 1-4, doi: 10.1109/HNICEM.2018.8666300.

Abstract:

This study presents a model for garbage classification, categorizing common waste into six types: glass, paper, cardboard, plastic, metal, and other trash, using MobileNet. A dataset of 2,527 garbage images in .jpg format was utilized for training, leveraging transfer learning from the ImageNet dataset. After retraining the model over 500 steps, the final test accuracy reached 87.2%. The optimized model showed a confidence level of 89.34% for plastic detection and 99.61% for cardboard. The model was successfully implemented in an Android app on a Samsung Galaxy S6 Edge+, demonstrating accurate recognition of waste materials. Further training steps are recommended to enhance the performance of the quantized model, which is better suited for mobile devices.

Inference:
The study aims to enhance waste management by classifying common garbage types using a MobileNet model, which categorizes waste into six classes: glass, paper, cardboard, plastic, metal, and other trash. Training was conducted on a dataset of 2,527 .jpg images, applying transfer learning from ImageNet and optimizing the final classification layer over 500 steps. The model achieved a test accuracy of 87.2%, with the optimized model attaining a confidence level of 89.34% for plastic and 99.61% for cardboard. An Android app was developed and successfully installed on a Samsung Galaxy S6 Edge+, accurately recognizing waste types. The study underscores the importance of effective garbage classification for promoting recycling and reducing community pollution, recommending additional training to further improve the quantized model's performance for mobile use.

4) J. Yang, Y. Xie, L. Liu, B. Xia, Z. Cao and C. Guo, "Automated Dental Image Analysis by Deep Learning on Small Dataset," 2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC), Tokyo, Japan, 2018, pp. 492-497, doi: 10.1109/COMPSAC.2018.00076.

Abstract:
This study investigates automated clinical quality evaluation in dental treatments through the analysis of periapical dental X-ray images. A dataset of 196 pairs of pre- and post-treatment radiographs was created, where dental specialists classified the images as "getting worse," "getting better," or "having no explicit change." The proposed method utilizes a convolutional neural network (CNN) to analyze cropped regions of interest (ROIs) from the images, specifically the apical areas. The model achieved an F1 score of 0.749, demonstrating performance comparable to skilled radiologists and dentists, thereby providing a tool pipeline to assist in clinical decision-making.

Inference:
The research aims to automate the clinical quality evaluation of dental treatments, particularly root canal therapy, by analyzing periapical dental radiographs. A dataset of 196 pairs of pre- and post-treatment images was classified into three categories—'getting better,' 'no change,' and 'getting worse'—by experienced dentists. The methodology involved cropping regions of interest (ROIs) from the apical areas, aligning images using SIFT and SURF algorithms, and training a modified GoogLeNet CNN to classify clinical outcomes. The model achieved an F1 score of 0.749, matching the proficiency of expert dentists. Comparative studies indicated that the CNN outperformed traditional classifiers in identifying improving conditions, though challenges remained in diagnosing cases classified as 'getting worse,' which were difficult for both the model and human experts.

2.2.Books/ Journals/ Articles referred :

1. H. Yi, B. Liu, B. Zhao, and E. Liu, "**Small Object Detection Algorithm Based on Improved YOLOv8 for Remote Sensing**" *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 1734-1747, 2024, doi: 10.1109/JSTARS.2023.3339235.
2. H. Chen, K. Zhang, P. Lyu, H. Li, L. Zhang, J. Wu, and C. H. Lee, "**A Deep Learning Approach to Automatic Teeth Detection and Numbering Based on Object Detection in Dental Periapical Films**" *Scientific Reports*, vol. 9, no. 1, pp. 3840, 2019.
3. S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios, and E. J. Calilung, "**Common Garbage Classification Using MobileNet**" *2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, Baguio City, Philippines, 2018, pp. 1-4, doi: 10.1109/HNICEM.2018.8666300.
4. J. Yang, Y. Xie, L. Liu, B. Xia, Z. Cao, and C. Guo, "**Automated Dental Image Analysis by Deep Learning on Small Dataset**" *2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC)*, Tokyo, Japan, 2018, pp. 492-497, doi: 10.1109/COMPSAC.2018.00076.

2.3 Interactions with domain experts

We had the privilege of consulting with a highly experienced dentist holding a senior position in the field, whose guidance proved invaluable for our project. Their extensive knowledge and expertise not only provided us with crucial insights into the various aspects of oral health but also helped us understand the complexities involved in diagnosing common dental issues.

During our discussions, the dentist shared their professional experiences, highlighting the importance of early detection and intervention in preventing more serious oral health problems. This conversation allowed us to gain a deeper understanding of the clinical significance of our project and the specific visual indicators that are crucial for accurate diagnosis.

Furthermore, their insights into current practices in dental care and patient management enriched our perspective on the practical applications of our machine learning system. This collaboration has been instrumental in shaping our approach and ensuring that our project aligns with real-world needs and challenges faced in dental healthcare. Overall, the expert guidance we received has significantly enhanced the quality and relevance of our work, ultimately contributing to our goal of improving oral health management through innovative technology.

2.4 Patent search

A patent search was conducted to identify existing technologies in dental diagnostics, machine learning in healthcare, and automated visual detection systems, ensuring our system does not infringe on intellectual property and highlighting innovation opportunities. In dental diagnostics, most patents focus on imaging tools like X-rays for detecting issues, but few incorporate advanced machine learning algorithms, presenting an opportunity for our approach. While many patents exist for machine learning in medical image analysis, there is a niche for applying object detection algorithms specifically to dental imaging. The search revealed gaps in advanced dental imaging analysis for early disease detection, the application of object detection algorithms like YOLO to dental images, and real-time dental diagnostics integrated with cloud-based processing. Overall, this patent search confirmed that our system could offer novel contributions to the field while maintaining legal and ethical compliance.

2.5 Exiting Systems

2.5.1 AICaries App

The purpose of this study is to employ a community-based participatory research approach to refine and evaluate the usability of an AI-powered mobile app, AICaries, designed for parents or caregivers to detect dental caries in their children.

With the AICaries app, parents can utilize their regular smartphones to capture images of their children's teeth, allowing the app to assist in detecting early childhood caries (ECC). This early detection enables parents to seek treatment for their children at an initial and potentially reversible stage of ECC. Additionally, AICaries provides parents with valuable information on how to reduce their children's risk of developing caries. The data gathered from this study will lay the groundwork for a future clinical trial aimed at assessing the real-world effectiveness of this app in detecting and preventing ECC among children from low-income families.

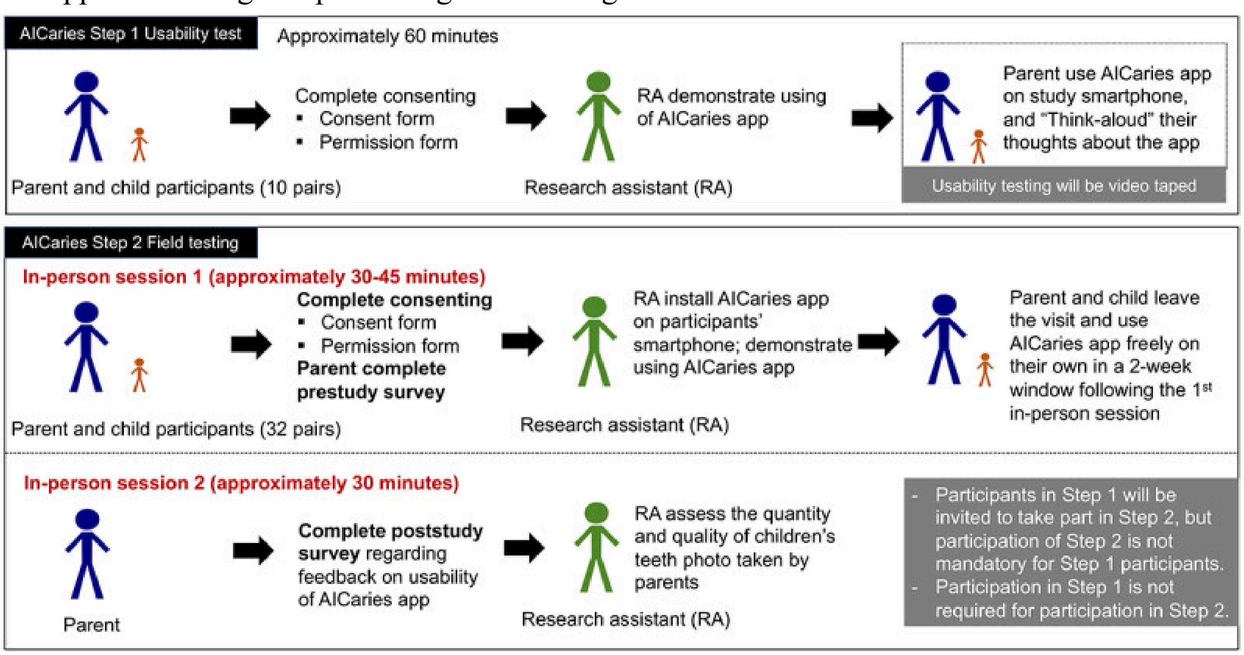

Fig 2.1 : AICaries usability test study flow

2.5.2 iGAM App

This study was motivated by the recognition that oral and periodontal health might deteriorate between routine dental checkups. By utilizing an mHealth app that enables dentists to remotely monitor patients' periodontal status through patient-submitted photos of their oral cavity (referred to as "dental selfies"), it is expected that any decline in oral health between visits can be minimized. Additionally, this system allows for timely clinic visits if deemed necessary by the dentist.

The primary goal of this study was to introduce an mHealth app designed to enhance communication between dentists and patients during the time between dental checkups. The paper outlines the design and development of an mHealth app named iGAM, specifically focused on supporting periodontal health. As part of an integrated research project that combined both quantitative and qualitative methods, iGAM was created to encourage better oral health through expert-guided applications. The app is available for download on both the Apple Store and Google Play.

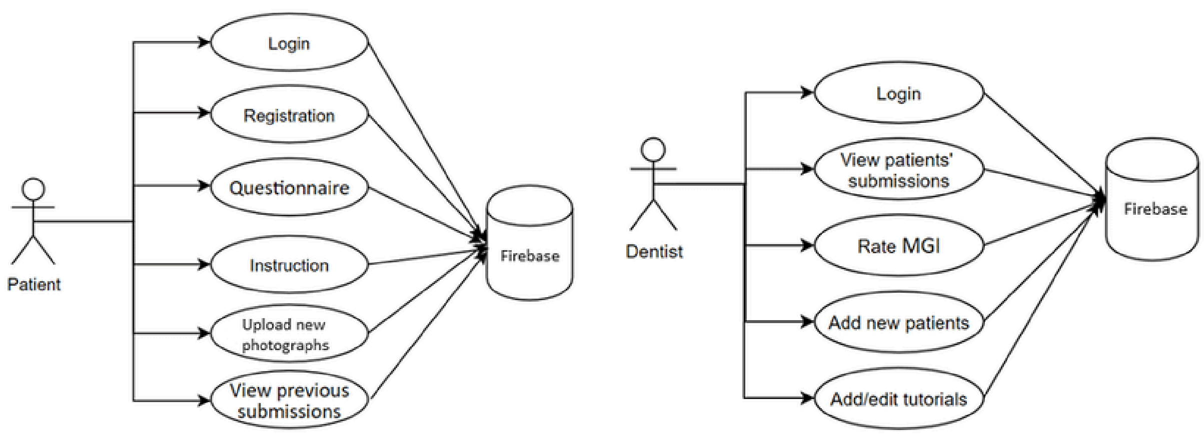

Fig 2.2 : Patient and Dentist use cases

2.5.3 Utilizing Mask R-CNN for Detection and Segmentation of Oral Diseases

In existing systems related to oral disease detection, various methods have been explored to automate diagnosis through image analysis and deep learning. Techniques such as convolutional neural networks (CNNs) have shown success in tasks like medical image segmentation, but most approaches require controlled clinical environments with specialized equipment. A few studies have attempted to adapt these techniques for less controlled settings, such as visible light images captured on smartphones, making them more accessible for preliminary diagnosis. This is particularly useful for common diseases like cold sores and canker sores, which can now be segmented using methods like Mask-RCNN, a neural network that enables both object detection and segmentation. One example is the automated segmentation of inflamed gingiva, as proposed by Rana et al., using fluorescence images from intraoral cameras to detect gingivitis and periodontal diseases.

Mask-RCNN has been successfully applied to the detection and segmentation of oral diseases by extending its utility beyond natural image segmentation to a more specialized domain. Studies such as those by Johnson et al. demonstrate that Mask-RCNN can achieve high accuracy with minimal modifications when adapted for medical applications, such as nucleus segmentation in microscopy images. This system uses region proposal networks to localize objects and applies masks for instance segmentation, offering pixel-wise accuracy. The study shows that even with a small dataset of cold and canker sore images, Mask-RCNN can perform well, provided the images are sufficiently diverse in terms of lighting conditions, shapes, and sizes. This approach has potential for broader application in oral pathology, including the detection of more complex diseases like oral cancer.

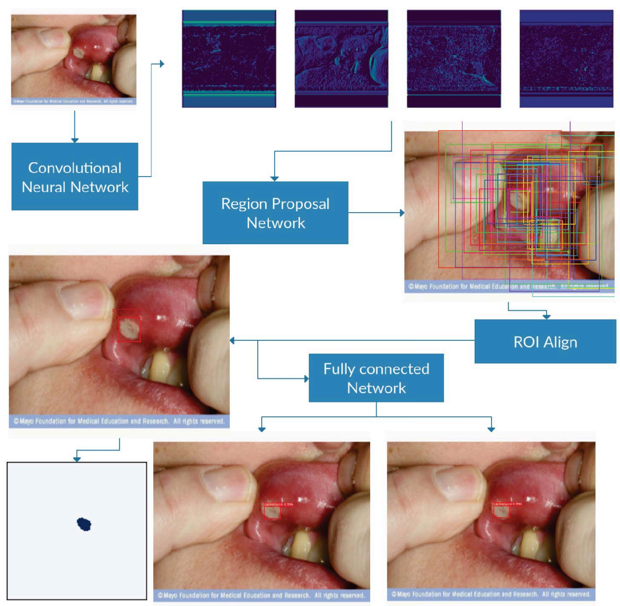

Fig 2.3 : Mask R-CNN Workflow

2.5.4 Use of Patient-Oriented Mobile Apps for Oral Health Management

The use of mobile health (mHealth) applications in oral health has grown significantly, as detailed in several studies. Mobile apps are primarily focused on oral health promotion and behavior management, particularly among children and adolescents. These apps have been effective in promoting oral hygiene practices, such as toothbrushing, and reducing dental plaque, as demonstrated by multiple randomized controlled trials (RCTs). For instance, approximately 39% of the reviewed RCT studies reported a notable reduction in dental plaque and improved gingival health. In addition, mobile apps have been used to manage dental anxiety, familiarize children with dental procedures, and improve patient-dentist communication. Despite their benefits in oral health education, other areas like remote consultations and diagnostic tools remain underexplored, highlighting the need for further research in teledentistry(The_Use_of_Patient-Orie…).

Most of the studies on mobile apps for oral health are from Asia, especially India, reflecting the widespread use of smartphones in this region. The high adoption of mobile apps in oral health has not yet extended to other regions like Africa, possibly due to infrastructural and technological challenges. The COVID-19 pandemic further accelerated the use of mHealth, particularly in remote consultations and teledentistry, offering alternative solutions for rescheduling dental appointments and providing emergency advice. However, the use of mobile apps in diagnostics and remote care remains limited, suggesting significant potential for growth in these areas. The literature shows that while mobile apps play a crucial role in oral health promotion, the future lies in expanding their use to teledentistry and diagnostic services

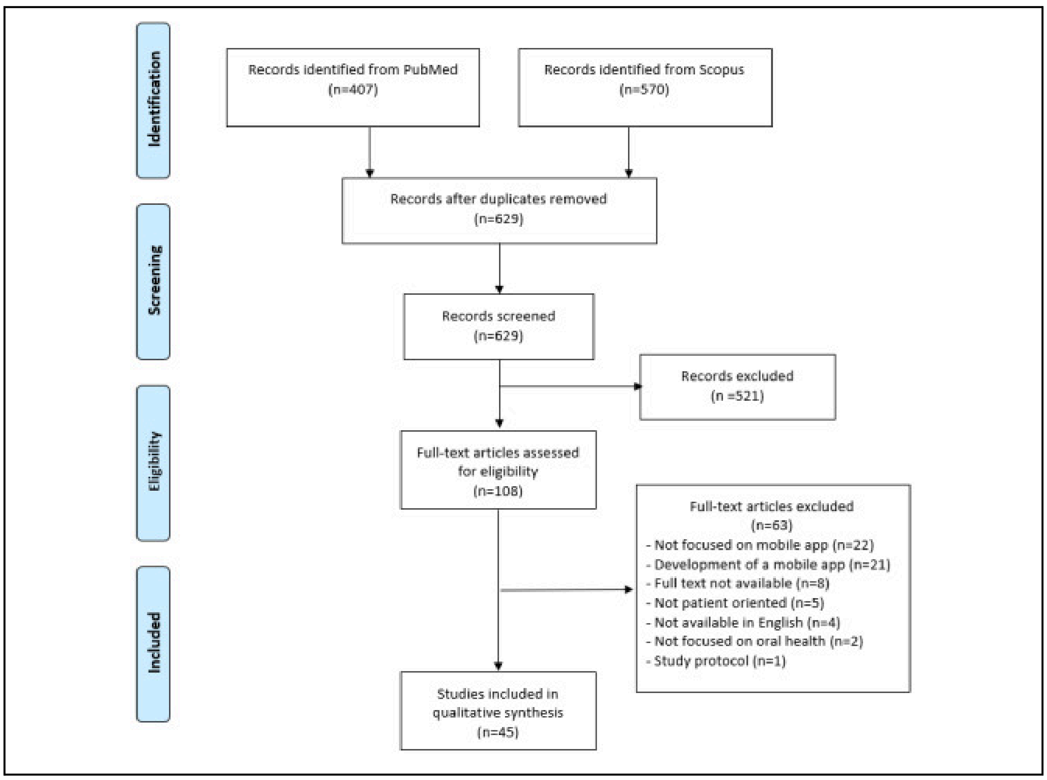

Fig 2.4 : PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart of study selection progress.

2.6. Lacuna in the existing systems

2.6.1 AICaries App:

Small sample sizes and reliance on self-reported data affect the generalizability and accuracy of results, while short-term studies overlook long-term effectiveness and clinical outcomes.

2.6.2 iGAM App:

The app's limited demographic (ages 18-45) and cultural constraints reduce its adaptability, requiring future research for broader applicability.

2.6.3 Mask R-CNN:

Limited dataset size and narrow disease focus hinder model generalization, reducing practical use in diverse real-world settings.

2.6.4 Oral Health Apps:

Lack of diagnostic tools, teledentistry features, and global adaptability limit comprehensive oral health management.

2.7 Comparison of existing systems and proposed area of work

Existing systems for oral health detection often rely on traditional diagnostic methods that require in-person visits and manual examinations by dental professionals. While some AI-driven solutions exist, they tend to focus on specific conditions and may lack accuracy or accessibility in underserved regions. Many systems are also limited in scope, addressing only a narrow range of oral health issues.In contrast, our proposed system utilizes advanced machine learning techniques to analyze images of the oral cavity, providing a more comprehensive and accessible solution. By incorporating a broad dataset of dental images, our system can detect a wider range of conditions, such as cavities, gingivitis, periodontitis, and oral lesions. Additionally, it offers real-time feedback, personalized recommendations, and the ability to connect users with dental professionals for further consultation when needed. This approach addresses the limitations of existing systems by enhancing diagnostic accuracy, accessibility, and scalability, particularly in areas with limited access to dental care.

2.8. Focus Area

The focus of our project is on developing an AI-based system that improves early detection of common oral health issues using image recognition. Our goal is to create a solution that empowers individuals, particularly those in underserved areas, to proactively manage their oral health. By combining machine learning with comprehensive dental image analysis, we aim to provide an accurate, scalable, and user-friendly tool for diagnosing oral diseases. The system focuses on both preventive care and timely intervention, ensuring that users receive the guidance they need to maintain good oral health and seek professional help when necessary.

Chapter 3: Requirements

In this chapter, we describe the machine learning model used to detect common dental diseases like Calculus, Gingivitis, and Mouth Ulcers through smartphone-captured images. The system preprocesses images for optimal quality, then uses advanced models like CNNs, DenseNet, and YOLO, Mobile net for feature extraction and disease detection. Once analyzed, the system generates a detailed report with tailored recommendations for users, including whether professional dental care is needed. If no issues are found, preventive health tips are provided. The system's efficient design enables regular dental health monitoring, empowering users to take proactive steps in maintaining oral health.

3.1 Proposed model

Model Explanation: The proposed system is a machine learning-based solution designed to detect common dental diseases, such as Calculus, Hypodontia, Gingivitis, Caries, and Mouth Ulcers, using smartphone-captured images. After the user captures an image, it undergoes preprocessing techniques like noise reduction and normalization. The preprocessed image is then analyzed by a deep learning model (CNNs, DenseNet, ResNet, YOLO, MobileNet) trained on a large dataset of labeled dental images, enabling it to recognize disease-specific patterns. If dental issues are detected, the system generates a report detailing the disease, its severity, and personalized recommendations. If no issues are found, preventive health tips are provided to maintain optimal dental hygiene.

Working Overview: The system starts with a user capturing an image of their dental area via a smartphone. After image preprocessing to ensure quality, the image is analyzed by the machine learning model, which identifies signs of targeted dental diseases. If abnormalities are found, a report is generated, offering recommendations for professional care or preventive measures. If no issues are detected, the system provides general health tips. The model is designed to empower users to monitor their dental health regularly, potentially reducing the need for frequent dentist visits by catching early signs of issues.

3.2 Functional Requirements

Core Functionality: The proposed system offers several key features designed to assist users in detecting dental issues and receiving recommendations for further action. The core functionalities include:

1. **Image Capture and Upload:** Users can capture images of their teeth or gums using a smartphone camera. The system allows users to upload these images for analysis.
2. **Image Preprocessing:** Before the analysis, the system processes the uploaded images, ensuring they are in the correct format and quality for optimal analysis. This step includes resizing, filtering, and enhancing the image to improve detection accuracy.

3. **Machine Learning Model Analysis:** The system utilizes a pre-trained machine learning model to detect dental issues like Calculus, Hypodontia, Gingivitis, Caries, and Mouth Ulcers. The model analyzes the images and identifies potential problems.
4. **Report Generation:** Once an issue is detected, the system generates a detailed report outlining the identified condition, its severity, and recommended next steps. The report may suggest seeking professional dental care if necessary.
5. **Health Tips and Recommendations:** For cases where no issues are detected, the system provides users with general dental health tips to maintain proper hygiene and prevent future problems.
6. **Data Logging and Storage:** The system securely logs and stores user data, including uploaded images and generated reports, allowing users to track their dental health over time.

Use Cases:

1. **Scenario 1: Dental Issue Detection**
   - **Input:** A user captures and uploads an image of their teeth using their smartphone.
   - **Process:** The system preprocesses the image and runs the machine learning model to analyze it for dental issues.
   - **Output:** The system detects signs of gingivitis and generates a detailed report recommending professional dental care.
2. **Scenario 2: Routine Checkup Without Issues**
   - **Input:** A user uploads an image for a routine dental checkup.
   - **Process:** The image is processed and analyzed by the machine learning model.
   - **Output:** No dental issues are detected, and the system provides personalized health tips to the user for maintaining good dental hygiene.
3. **Scenario 3: User Follows Recommendations**
   - **Input:** After receiving a report indicating the presence of caries, the user follows the recommendations.
   - **Process:** The system tracks the user's progress after they seek professional dental care.
   - **Output:** A follow-up image is uploaded after the user's treatment to confirm that the issue has been resolved.

User Roles and Permissions:

1. **Regular User:**
   - **Permissions:** Can capture and upload images, view analysis reports, receive health tips, and track dental health over time.

    - **Role:** The regular user interacts directly with the system, using it to monitor their dental health. They can view personalized reports, follow recommendations, and upload new images for future analysis.
2. **Admin:**
    - **Permissions:** Can manage the system, update the machine learning model with new training data, oversee user data management, and monitor system performance.
    - **Role:** The admin ensures the system runs smoothly, updates the dataset used for training the model, and manages user information securely. They also have the ability to monitor how the model performs and refine its accuracy.

3.3.Non-Functional Requirements

Performance: The system aims for a response time of under 5 seconds for image processing and disease detection, efficiently handling multiple concurrent users and high volumes of images without delays.

Scalability: Designed for growth, the system will scale horizontally by adding computing resources or nodes, utilizing cloud infrastructure for dynamic resource allocation based on demand.

Security: Data security is prioritized, with AES-256 encryption for sensitive user data and health reports, secure password mechanisms for user authentication, and token-based authentication for session protection.

Reliability: The system targets 99.9% uptime, with regular backups of user data and machine learning models, and fault tolerance mechanisms to minimize downtime during unexpected failures.

Usability: The user interface will be intuitive and accessible for non-technical users, featuring clear instructions, real-time status updates, and easy-to-read reports, optimized for both mobile and desktop platforms.

Compatibility: The system will support all modern browsers and iOS and Android devices for image capture and uploads, ensuring cross-platform access without compatibility issues.

3.4.Hardware & Software Requirements

Hardware Requirements:

- **Processor:** Minimum 2.5 GHz Quad-core processor
- **RAM:** At least 8 GB RAM for development and testing
- **Storage:** Minimum 256 GB SSD for storing application data, images, and development tools
- **Mobile Device:** Smartphones running iOS or Android for testing the app's functionality, as well as access to the camera for image capture and uploading
- **Development Devices:** Laptops or desktops with sufficient processing power for running simulators and emulators during development

Software Requirements:

- **Operating System:** macOS (for iOS development), Windows 10, or Linux
- **Programming Languages:** JavaScript, TypeScript (if needed)
- **React Native:** For building cross-platform mobile apps
- **Database System:** Firebase or AWS DynamoDB for real-time data storage
- **Development Tools:** Android Studio (for Android testing), Xcode (for iOS testing), React Native CLI, Expo for quick testing and deployment
- **Libraries:** React Native Camera, TensorFlow Lite for mobile-compatible machine learning, Axios for API calls
- **Version Control:** Git for source code management
- **Cloud Services:** AWS (for backend services, server-side logic, and scalable storage)

3.5.Technology and Tools utilized

Programming Languages:

- **JavaScript:** Core languages used to develop the React Native mobile application

Frameworks:

- **React Native:** The main framework for building a cross-platform mobile app that runs on both iOS and Android
- **Express (if needed):** To handle backend logic in the case of using Node.js for server-side processing

Libraries and Tools:

- **TensorFlow Lite:** For running machine learning models on mobile devices efficiently
- **React Native Camera:** For enabling users to capture images directly from the app
- **Axios:** To handle HTTP requests for interacting with backend services
- **Expo:** For streamlined development, testing, and deployment of the React Native app
- **Git:** For version control to manage collaboration and track code changes
- **Firebase/AWS DynamoDB:** As a database solution for real-time data synchronization and storage

Databases:

- **Firebase (Firestore) or AWS DynamoDB:** Both can handle real-time data, store user images and health reports, and ensure scalability for growing user bases.

Cloud or Server Infrastructure:

- **AWS Lambda:** For running serverless backend functions and processing image uploads
- **AWS S3:** For securely storing user-uploaded images
- **Firebase Authentication:** For managing user login and data access within the app

3.6.Constraints of working

Technical Limitations: Ensuring the machine learning model maintains high accuracy across varying lighting conditions, image quality, and angles is a primary challenge, alongside potential latency in real-time feedback with larger datasets or limited bandwidth.

Time Constraints: The team faces tight deadlines for developing, refining, and testing the machine learning model's performance and creating a user-friendly front end for non-technical users.

Budget Constraints: Budget limitations may restrict compute power and storage in scalable cloud services like AWS, necessitating initial use of free-tier services that could hinder scalability as demand increases.

External Dependencies: The system relies on third-party libraries and APIs for machine learning, image processing, and cloud infrastructure, with changes in these services or user internet speed and device quality potentially impacting functionality and performance.

Chapter 4: Proposed Design

In this chapter, we present the visual representations and structural breakdown of the proposed system. The block diagram outlines the system's overall architecture, while the modular diagram highlights its components and their interactions. Data Flow Diagrams (DFD) Levels 0, 1, and 2 depict the flow of data through the system, from image capture to disease detection and report generation. The state transition diagram illustrates system behavior based on user actions. An ER diagram maps the database structure, showcasing relationships between entities. We also discuss the algorithms used for disease detection and scheduling the project using a Gantt chart for progress tracking.

4.1 Block Diagram of the proposed system

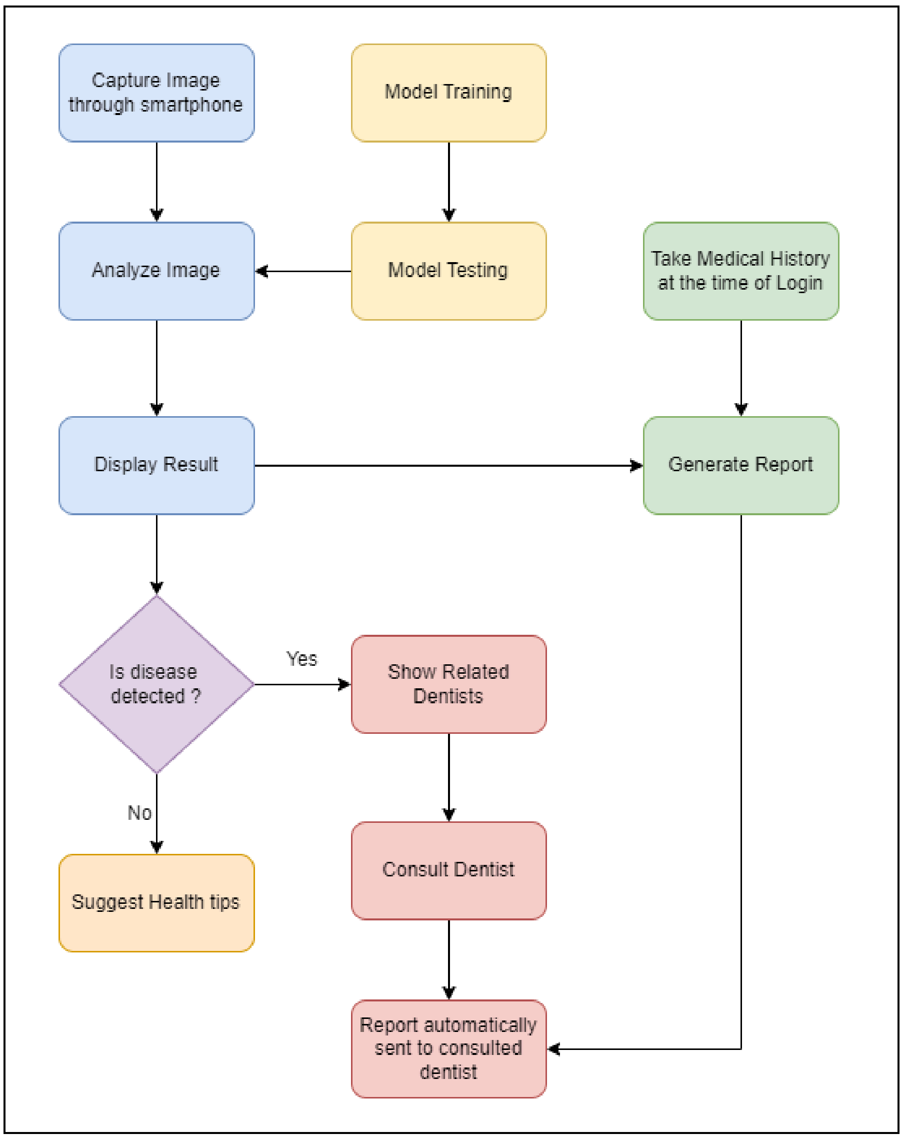

Fig 4.1 : Block diagram of proposed system

The block diagram outlines a system for detecting dental issues using smartphone images and machine learning. Users capture an image of their dental condition, which the system analyzes to identify anomalies through trained machine learning algorithms. Upon logging in, users provide their medical history, enhancing the context for image analysis. The trained model is tested for accuracy before implementation. After analysis, the system displays results indicating whether a disease is detected. If a disease is found, the system suggests related dentists; if not, it offers general dental health tips. Users can consult a selected dentist, and the system automatically sends a report of the findings and medical history to the dentist, facilitating early detection of dental issues and organized information flow.

4.2 Modular diagram

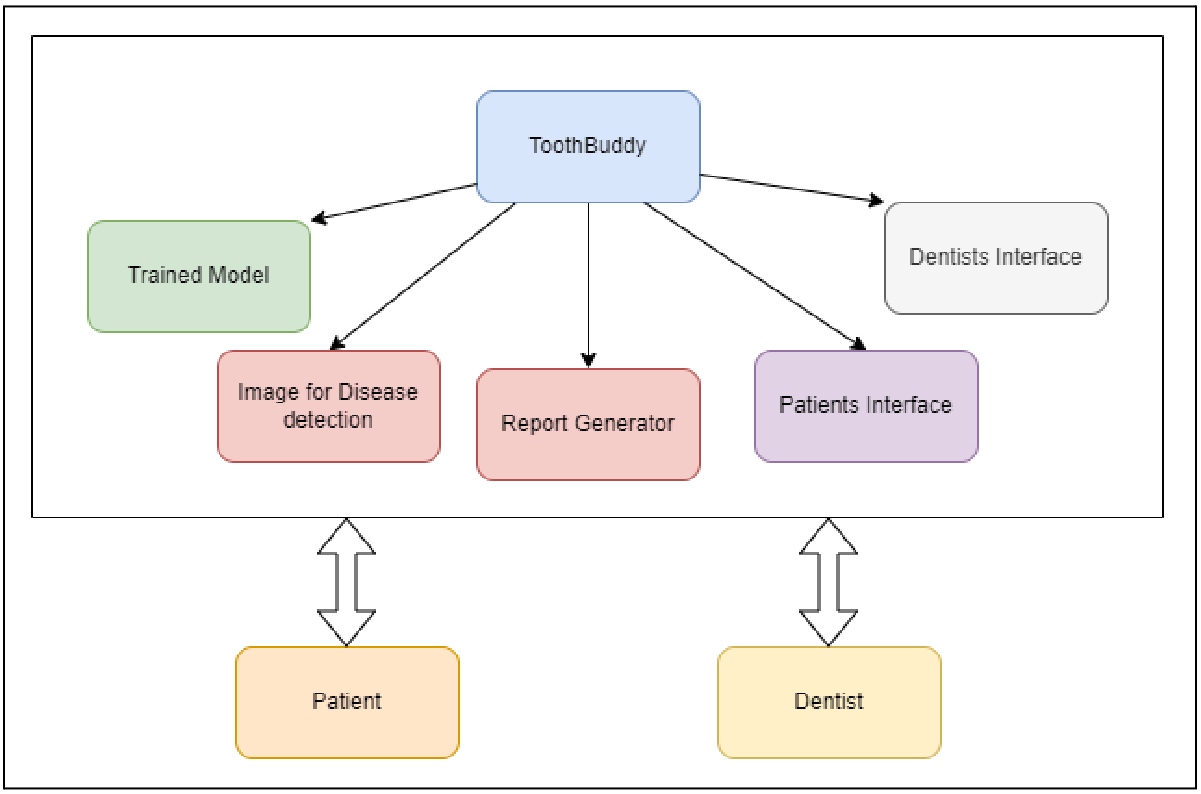

Fig 4.2 : Modular Diagram

ToothBuddy is a system designed to detect dental diseases through image analysis and facilitate communication between patients and dentists. The central module, ToothBuddy, coordinates interactions among various components, including the trained machine learning model, image detection, and report generation. The trained model analyzes dental images to identify diseases, while the Image for Disease Detection module processes images uploaded by patients. The Report Generator then creates a detailed report based on the findings, which is sent to both the Patients Interface for user access and the Dentists Interface for review by dentists. Patients interact with the system to upload images and receive reports, while dentists use their interface to assess cases and provide consultations. Ultimately, ToothBuddy serves as a bridge between patients and dentists, streamlining dental diagnostics and enhancing communication through AI-powered analysis.

4.3.1 DFD Level 0

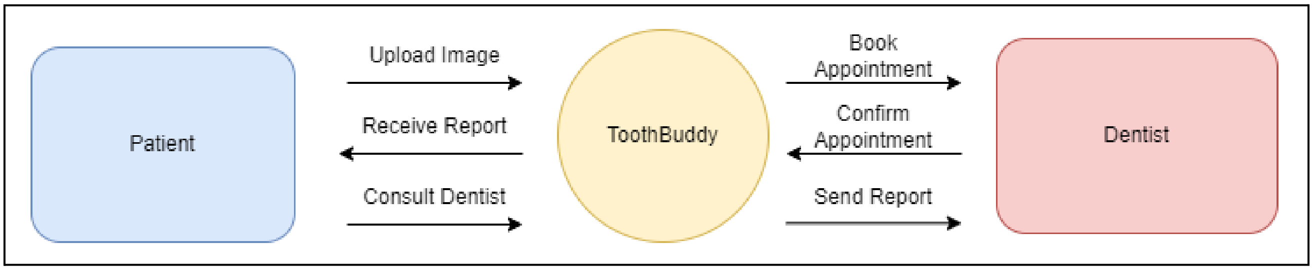

Fig 4.3 : DFD Level 0

The Level 0 Data Flow Diagram (DFD) provides a high-level overview of the ToothBuddy system, showing data flows between the main components: Patient, ToothBuddy, and Dentist. Patients upload images of their dental conditions to ToothBuddy, receive analysis reports, and can consult with dentists through the system. ToothBuddy processes these images and sends the generated reports to dentists, who can then confirm appointments. Serving as an intermediary, ToothBuddy facilitates communication and interaction between patients and dentists, streamlining the dental diagnostic process.

4.3.2 DFD Level 1

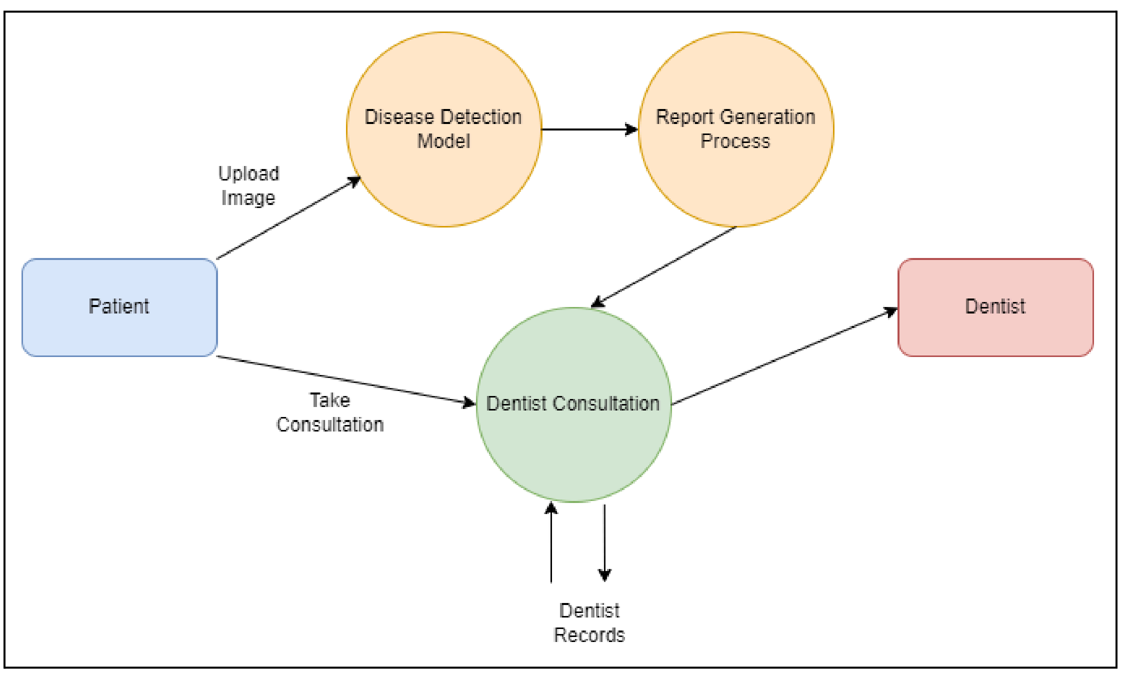

Fig 4.4 : DFD Level 1

The Level 1 Data Flow Diagram (DFD) illustrates the data movement within a dentist consultation system, highlighting interactions among the Patient, Disease Detection Model, Report Generation Process, Dentist Consultation, and Dentist. Patients upload images for disease detection, which the Disease Detection Model analyzes using AI to identify dental issues. The findings are then sent to the Report Generation Process, which creates a report to assist in the dentist's consultation. During this central consultation process, dentists review the report and patient records to provide insights and treatment recommendations. This DFD emphasizes the seamless flow of data and processes aimed at enhancing dental care through automated disease detection and effective dentist consultations.

4.3.3 DFD Level 2

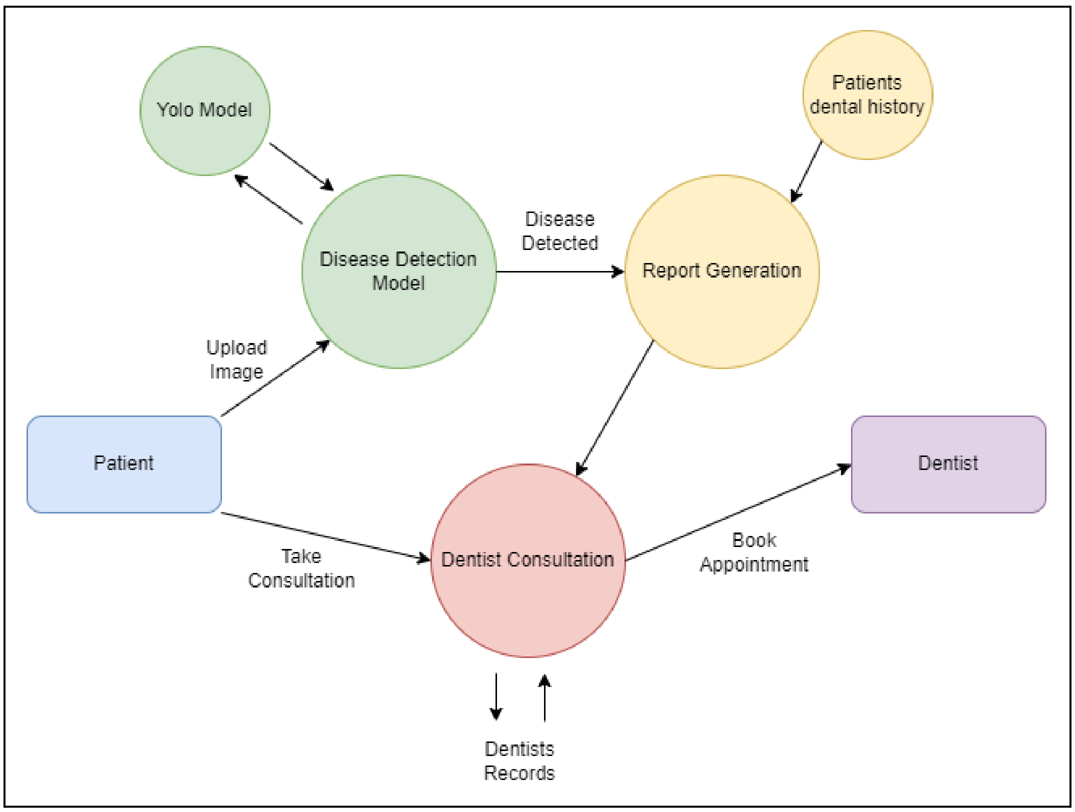

Fig 4.5 : DFD Level 2

The Level 2 Data Flow Diagram (DFD) offers a detailed perspective on the dentist consultation system, highlighting components like the Patient, YOLO Model, Disease Detection Model, Report Generation, Patients Dental History, Dentist Consultation, and Dentist. Patients upload images of their dental conditions, which are processed by the YOLO Model for real-time object detection before being analyzed by the Disease Detection Model to identify any dental issues. The findings inform the Report Generation process, which creates a comprehensive report incorporating the patient's dental history. This report is then sent to the Dentist and used during the Dentist Consultation, where the dentist reviews all relevant information to provide accurate advice and schedule appointments. The dentist's feedback and updates are then integrated back into the system. This DFD Level 2 elaborates on how the YOLO model enhances disease detection and the crucial role of historical data in informing consultations and treatment plans.

4.3.4 State transition diagram

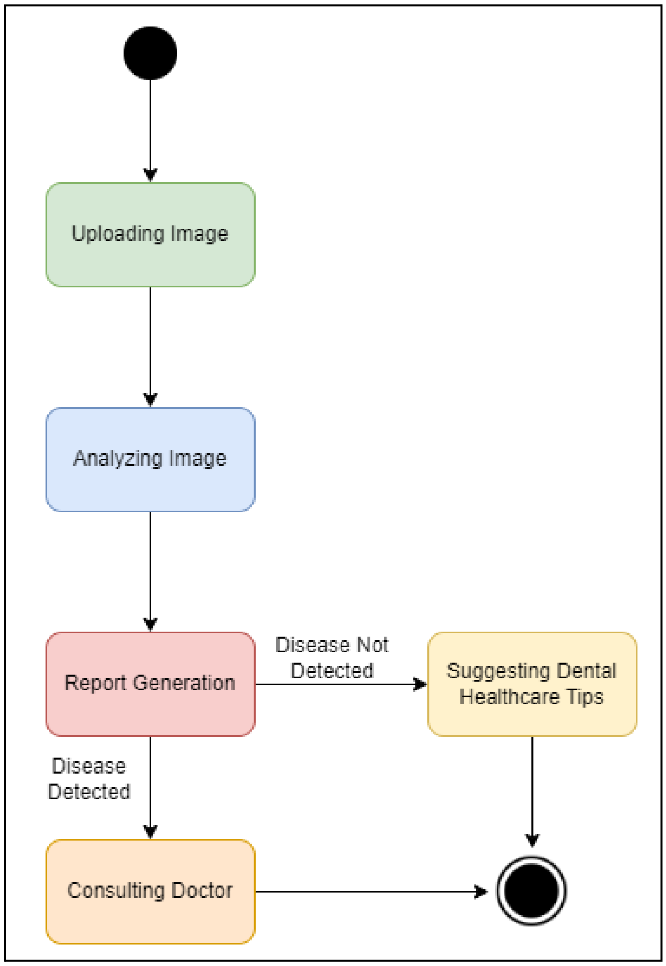

Fig 4.6 : State Transition Diagram

The State Transition Diagram outlines the flow of a dental disease detection system, starting with the patient uploading an image of their dental condition. Following the upload, the system analyzes the image using a disease detection model, leading to report generation that summarizes whether a dental issue was found. If a disease is detected, the process directs the patient to consult with a dentist for further treatment. Conversely, if no issues are identified, the system suggests dental healthcare tips to promote good oral hygiene and prevent future problems. Overall, this diagram illustrates a clear process for efficiently detecting dental diseases and guiding patients toward appropriate next steps, whether that involves seeking professional help or receiving preventive advice.

4.3.5 ER Diagram

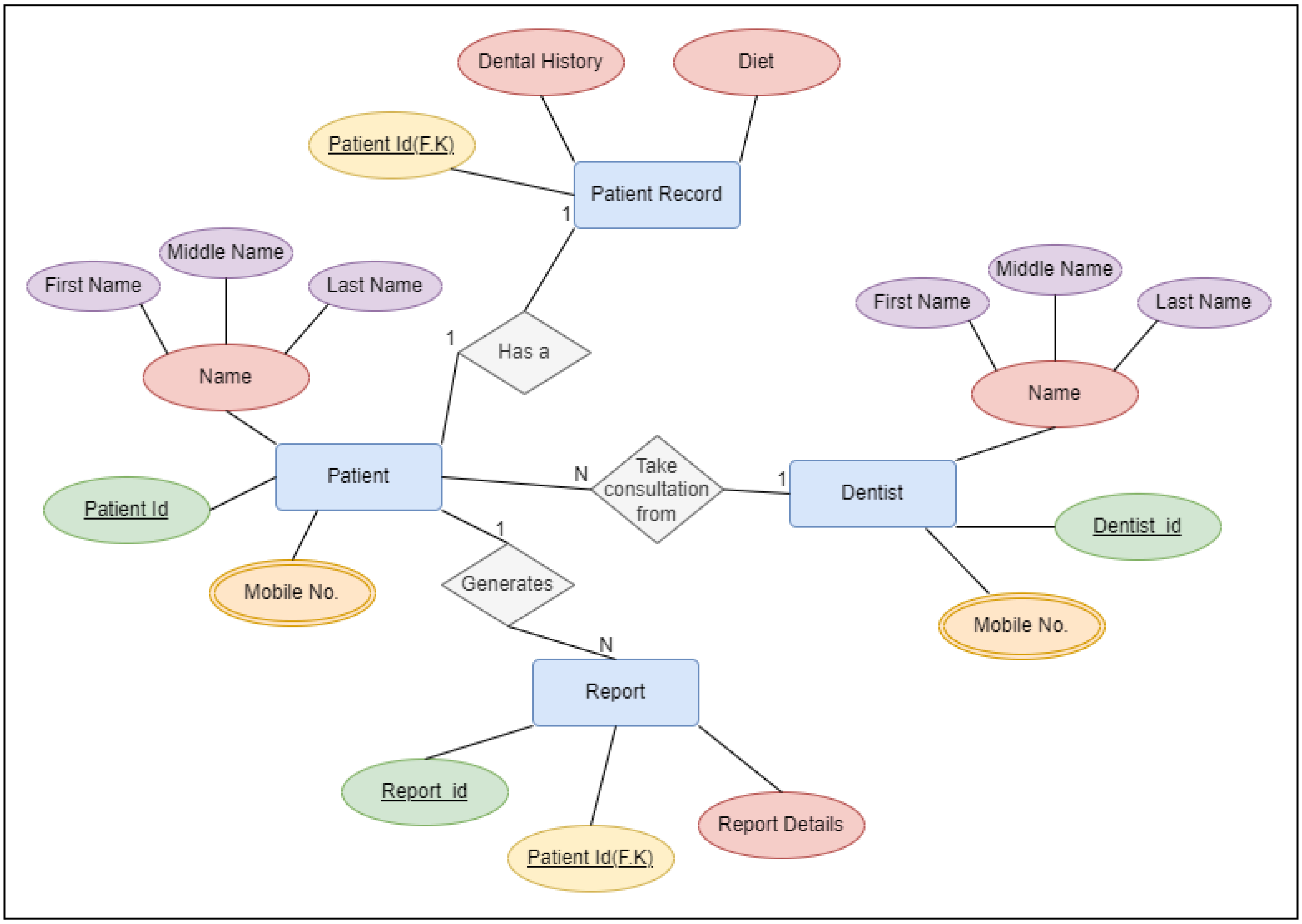

Fig 4.7 : ER Diagram

The Entity-Relationship (ER) model for a dental clinic management system illustrates the relationships between key entities such as Patient, Patient Record, Dentist, and Report. The Patient entity includes attributes like Patient Id, names, and mobile number, establishing a one-to-one relationship with the Patient Record that contains dental history and dietary information. Each patient can consult multiple Dentists, while each dentist can treat numerous patients. The Report entity, linked to the Patient through a foreign key, captures detailed information about the patient's consultations, with each patient capable of generating multiple reports.

This model effectively captures the structure of a dental clinic's patient management system, highlighting how patients interact with records, consultations, and reports. It ensures that critical details about patient history, treatment consultations, and generated reports are well-organized and accessible, facilitating improved patient care and record-keeping.

4.4. Proposed algorithms

- **YOLO (You Only Look Once)**: YOLO is a real-time object detection system known for its speed and accuracy, framing detection as a single regression problem from image pixels to bounding box coordinates and class probabilities. It uses a convolutional neural network (CNN) to divide an image into a grid, where each cell predicts bounding boxes and class probabilities in one forward pass, achieving up to 45 frames per second. YOLO has evolved through several versions, including YOLOv1, YOLOv2 (YOLO9000), YOLOv3, YOLOv4, and YOLOv5, each improving upon speed and accuracy.
- **MobileNet**: MobileNet is a family of neural networks designed for efficient execution on mobile devices, utilizing depthwise separable convolutions to reduce parameters and computations without sacrificing accuracy. This approach separates convolution into depthwise and pointwise operations, making the architecture lightweight. MobileNet is ideal for mobile applications like face detection and object recognition. Variants include MobileNetV1, V2 (introducing inverted residual blocks), and V3 (combining neural architecture search and squeeze-and-excitation blocks) for further optimization.
- **DenseNet (Densely Connected Convolutional Networks)**: DenseNet enhances information flow and gradient propagation by connecting each layer to every other layer in a feed-forward manner, promoting feature reuse and mitigating the vanishing gradient problem. Each layer in a DenseNet receives input from all preceding layers, improving efficiency and accuracy while using fewer parameters compared to traditional CNNs. Variants like DenseNet-121, DenseNet-169, and others differ in depth, making DenseNet suitable for tasks like image classification and segmentation.

Comparisons: YOLO excels in real-time object detection for tasks needing quick localization, while MobileNet is optimized for resource-constrained environments. DenseNet focuses on high-quality feature extraction, making it effective for tasks requiring accuracy with fewer parameters, such as medical imaging.

4.5 Project Scheduling & Tracking using Time line / Gantt Chart

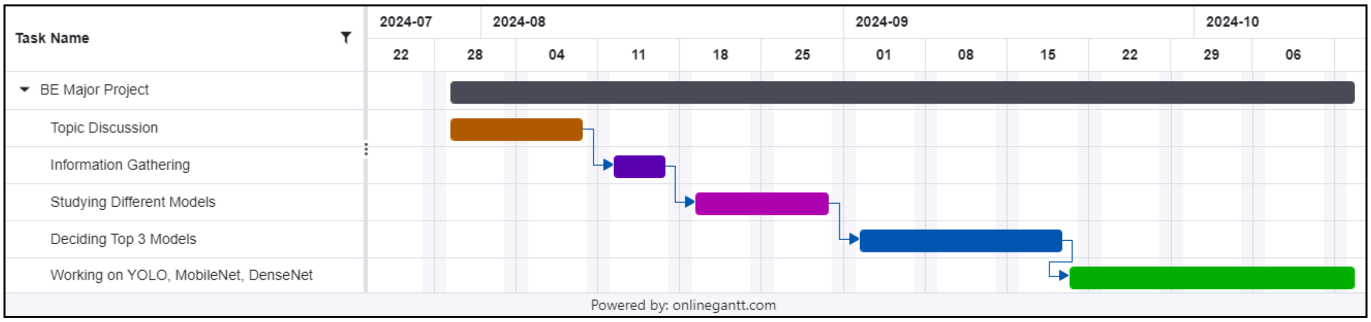

Fig 4.8 : Gantt Chart

The Gantt chart provided outlines the timeline for the **BE Major Project**. Let's break down the tasks and activities based on the chart:

1. **BE Major Project (July 22,2024 - October 15, 2024)**:
   - This is the overall timeline for the major project, spanning from late July to mid-October. All other tasks fall within this timeline.
2. **Task 2: Topic Discussion (October 15, 2024 - August 3, 2024)**:
   - This task took place in the initial phase of the project, where the project topic and scope were discussed and finalized. It lasted about two weeks.
3. **Task 3: Information Gathering (August 3 - August 15, 2024)**:
   - After deciding on the topic, the next step was gathering relevant information, including research, literature, and data, to inform the project. This task lasted around 12 days.
4. **Task 4: Studying Different Models (August 16,2024 - September 1, 2024)**:
   - In this phase, different machine learning models were studied in detail. It included understanding algorithms and their applications for the project. The task lasted roughly two weeks.
5. **Task 6: Deciding Top 3 Models (September 1 , 2024- September 16, 2024)**:
   - After studying various models, the top three models (likely the ones best suited for the project) were selected for further work. This took about two weeks.
6. **Task 7: Working on YOLO, MobileNet, DenseNet (September 17 ,2024 - October 10, 2024)**:
   - This task focuses on the practical implementation and experimentation with the three selected models: YOLO, MobileNet, and DenseNet. It spans almost a month, indicating the key development and testing phase of the project.

Overall, the chart shows a well-organized progression of activities, starting with topic discussion, followed by research, model analysis, and then implementation of selected machine learning models.

Chapter 5: Results and Discussions

5.1: Mobile Net

Using the MobileNet model, we plan to extend our work by integrating it into the mobile app for real-time dental disease prediction. MobileNet has shown its effectiveness in classifying various dental conditions, including calculus, gingivitis, hypodontia, and ulcers, with high accuracy and low latency. In the next phase, patients will be able to upload their dental images through the app, and MobileNet will automatically predict the presence of these conditions. The app will display the predicted disease along with relevant confidence scores, allowing patients to receive instant feedback on their oral health.

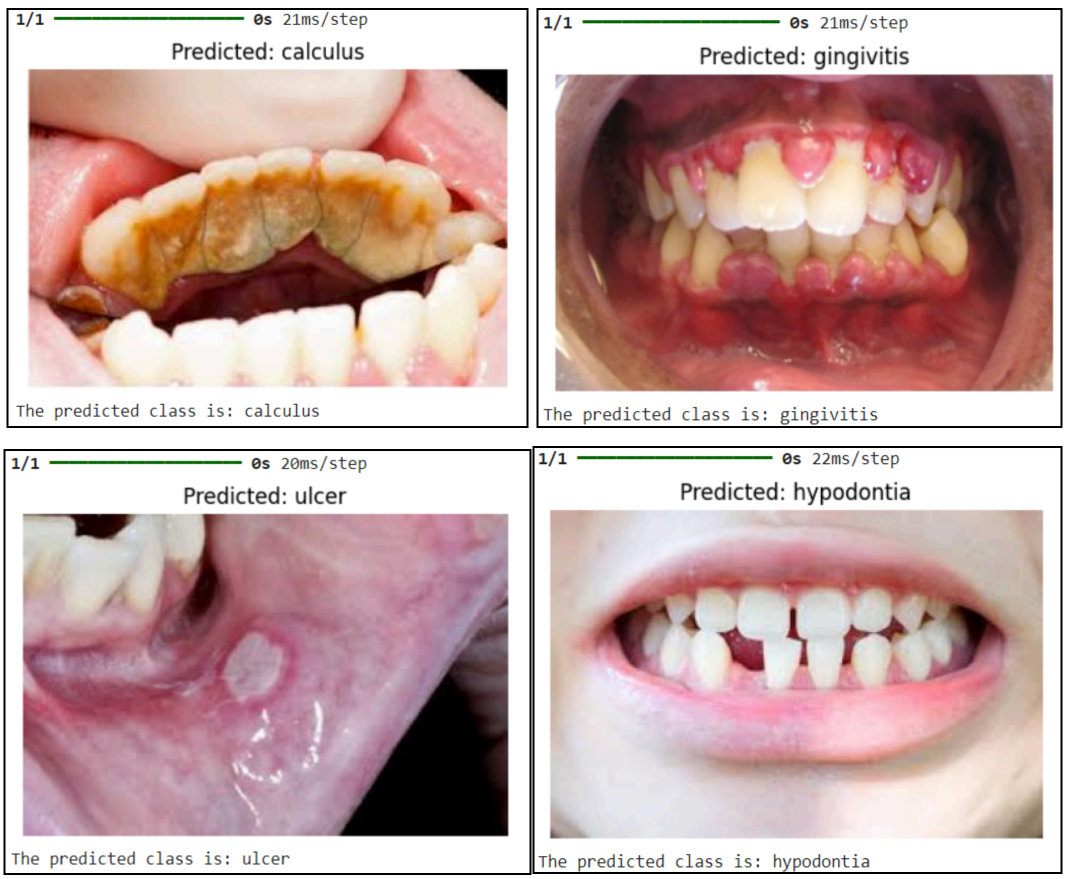

Fig 5.1 Results of MobileNet Model

5.2: Dense Net

The **DenseNet** model was also utilized for dental condition classification, specifically for detecting ulcers in oral images. DenseNet successfully identified the presence of ulcers with a processing time of 20 ms per step, similar to MobileNet. DenseNet's architecture, known for its dense connections and feature reuse, contributed to its effectiveness in handling complex visual patterns. This makes DenseNet a valuable model for dental diagnostics, complementing MobileNet in building robust, high-performance mobile healthcare applications.

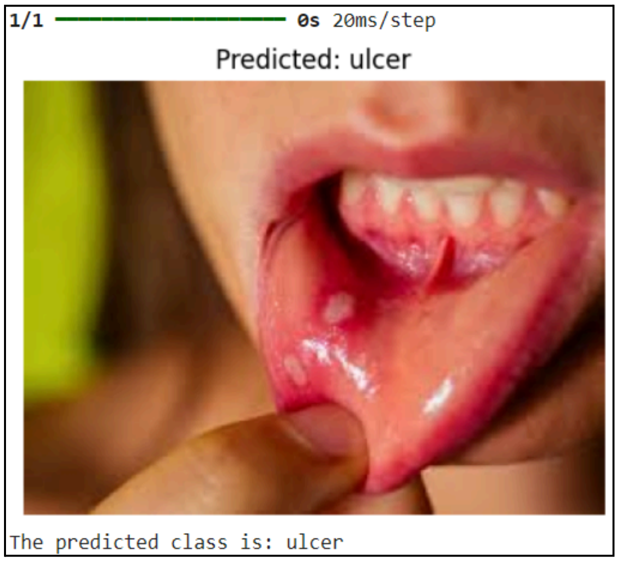

Fig 5.2 Results of DenseNet Model

5.3: YOLO

The **YOLO (You Only Look Once)** model was utilized to detect and classify multiple dental conditions simultaneously in real-time from images. The model accurately identified various conditions, such as ulcers, gingivitis, dental caries, and tooth discoloration, with confidence scores ranging from 0.3 to 0.9. YOLO's object detection capabilities allowed for the precise localization of these conditions, marking each issue with bounding boxes and confidence levels. For instance, an ulcer was detected with a 0.9 confidence score, and multiple instances of dental caries were marked with varying confidence scores around 0.7. YOLO's speed and accuracy in identifying multiple dental conditions in a single image highlight its effectiveness for dental diagnostic tools, making it suitable for applications requiring fast, real-time detection and analysis in clinical or mobile environments.

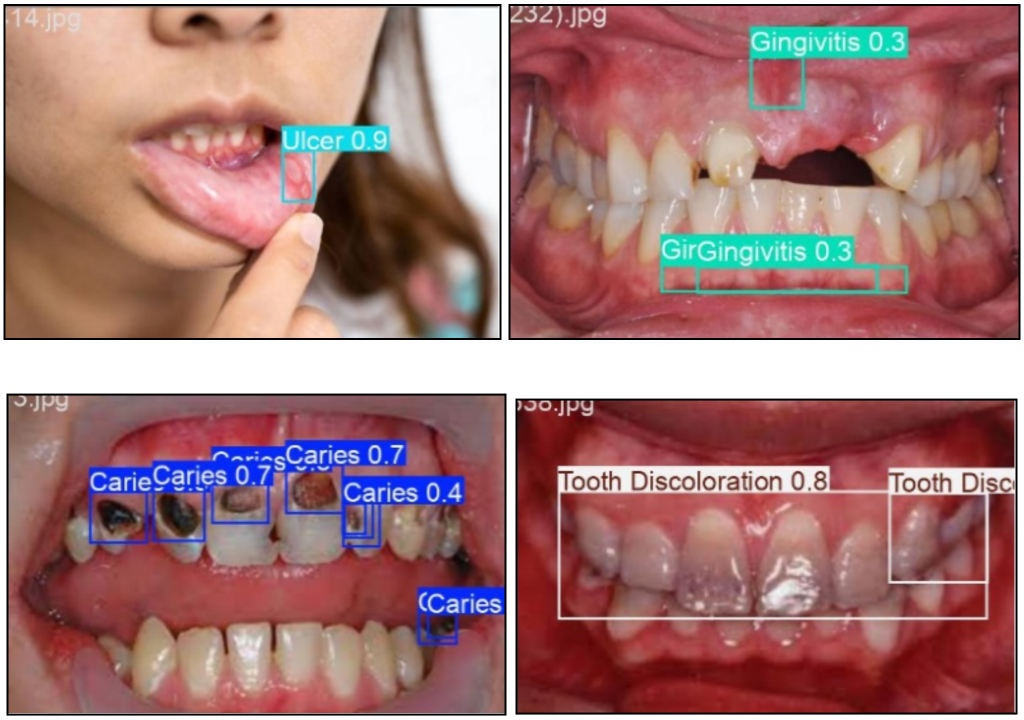

Fig 5.3 Results of YOLOModel

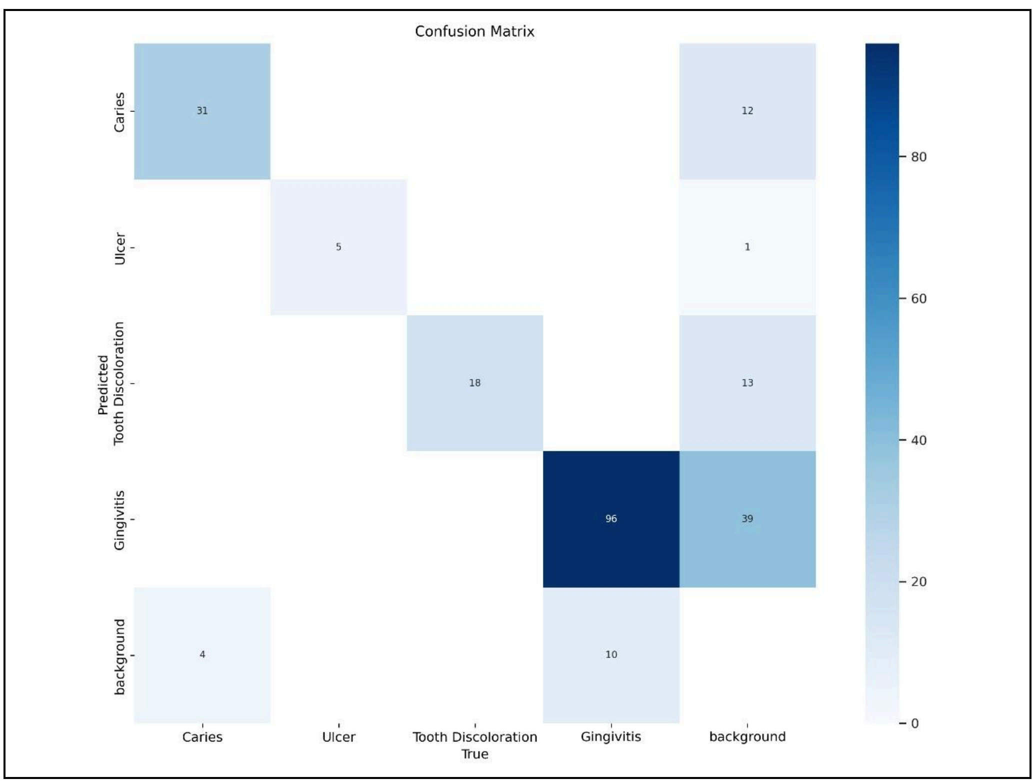

Fig 5.4 Confusion Matrix of YOLO Model

5.4 Table comparing different models

	YOLO	Mobile Net	Dense Net
Caries	Predicted	Not Predicted	Not Predicted
Gingivitis	Predicted	Predicted	Not Predicted
Hypodontia	Not Predicted	Predicted	Not Predicted
Ulcer	Predicted	Predicted	Predicted
Calculus	Not Predicted	Predicted	Not Predicted
Tooth Discoloration	Predicted	Not Predicted	Not Predicted

Table 5.1 : Table comparing different models

Chapter 6: Plan of action for the next semester

In the upcoming semester, our primary focus will be on developing a fully functional mobile application that integrates different user roles, including patients, administrators, and doctors. This app will enable patients to upload dental images for automated analysis using the models we have developed, such as MobileNet, DenseNet, and YOLO. Doctors will be able to review these analyses, provide diagnoses, and communicate directly with patients through the app. Administrators will have access to manage user accounts, track system performance, and ensure that the platform complies with healthcare data regulations.

The mobile app will be designed to create a seamless experience for all users. Patients will have the ability to schedule appointments, receive notifications, and access their diagnosis history. Doctors will have tools to manage patient records and provide personalized care. The integration of these roles will not only improve the efficiency of dental diagnostics but also offer an enhanced patient-doctor interaction. By the end of the next semester, we aim to complete the mobile app's core functionalities, ensuring it is ready for testing and feedback.

Chapter 7: Conclusion

In conclusion, this project presents an innovative approach to addressing the critical issue of oral health management through the development of a machine learning-based system that utilizes smartphone technology. By enabling users to capture and upload images of their teeth and gums, the system democratizes access to dental diagnostics, particularly for those in underserved regions with limited access to professional care.

Through extensive research and expert consultations, we have laid a strong foundation for the system's design and functionality. Our collaboration with a senior dentist has provided invaluable insights into the complexities of diagnosing dental diseases, ensuring that our solution is grounded in real-world practices and needs. The identification of key visual indicators of common conditions such as Calculus, Gingivitis, and Mouth Ulcers allows our model to provide accurate assessments and actionable recommendations.

The proposed design, illustrated through detailed diagrams and models, effectively outlines the system architecture and data flow, demonstrating how the various components interact to deliver a seamless user experience. By incorporating advanced algorithms for image analysis and reporting, the system not only detects dental issues but also provides personalized health tips and referrals to local dentists, fostering a proactive approach to oral health.

Moreover, the system is designed with performance, scalability, security, and usability in mind, ensuring that it can handle a growing user base while maintaining high standards of data protection and user accessibility. The Gantt chart for project scheduling emphasizes our commitment to effective project management, allowing for timely development and deployment.

Ultimately, this project aims to empower individuals to take charge of their oral health by providing them with the tools they need to monitor and manage potential issues proactively. By bridging the gap between advanced technology and dental care, we aspire to contribute to better oral health outcomes and enhance overall well-being in communities worldwide. As we move forward, further testing, refinement, and potential partnerships with dental professionals will be essential to realizing the full potential of this innovative solution.

Chapter 8: References

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Chapter 9: Appendix

a. List of Figures

b. List of Tables