Deep Learning-Based Teeth Disease Detection Using Dental X-ray Images

By

Name:Jubair Rahman Jim
ID:213-15-4536

Name:MD Shorowar Islam Shajib
ID:213-15-4552

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by
Name: Ms. Nusrat Khan
Designation: Lecturer
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by
Name: Dr. Md. Taimur Ahad
Designation: Associate Professor
Department of Computer Science and EngineeringDaffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

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APPROVAL

This Project titled **"Deep Learning Based Teeth Disease Detection using Dental X-ray Images"**, submitted by Jubair Rahman Jim ID No: **213-15-4536** and Md Shorowar Islam Shajib ID No: **213-15-4552** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **16 September, 2025.**

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Ms.Nusrat Khan, Lecturer,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by: 16.09.25

Ms. Nusrat Khan
Designation: Lecturer
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by:

Dr. Md. Taimur Ahad
Designation: Associate Professor
Department of Computer Science and EngineeringDaffodil International University

Submitted by:

Jubair Rahman Jim
Student ID:213-15-4536
Department of Computer Science and EngineeringDaffodil International University

MD Shorowar Islam Shajib
Student ID:213-15-4552
Department of Computer Science and EngineeringDaffodil University

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ABSTRACT

Oral health is vital for overall well-being. However, dental problems like cavities, gum disease, and infections are still very common around the world. Early diagnosis is crucial to avoid serious issues. Traditional detection methods depend largely on the expertise of clinicians, visual checks, and manual reading of dental X-rays. These methods can be subjective and time-consuming, leading to inconsistent results. Recent advances in artificial intelligence have introduced machine learning techniques as useful tools for improving medical image analysis and providing automated support for healthcare professionals. This study explores how machine learning can be used to detect dental diseases through dental X-rays. The research included systematic preprocessing of image data, with steps like normalizing images and enhancing features. Researchers then applied feature extraction methods to find important dental structures and disease indicators. Various algorithms, including decision trees, support vector machines, and convolutional neural networks, were trained and tested to classify healthy teeth against diseased ones. Among these, CNN-based deep learning models showed better results because they can automatically learn important features from the image data. The most acceptabble accuracy via MobileNetV2 ia 85.88%. The experimental results showed high accuracy, precision, and recall. This confirms that machine learning models can help with reliable and efficient dental disease detection. Additionally, the findings suggest that these systems can reduce the diagnostic workload, improve early intervention, and better patient outcomes. This research adds to the evidence that supports the use of artificial intelligence in dentistry. It provides a framework for incorporating machine learning into dental diagnostics. Ultimately, this approach highlights how technology can transform modern healthcare, making oral care more accurate, accessible, and preventive.

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Chapter 1

Introduction

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1.1 Introduction

Dental diseases tooth discoloration and caries are still very common around the world. They can seriously affect oral and overall health if not detected and treated quickly. These conditions sometimes develop quietly in their early stages so catching them early is vital to prevent complications such as pain, infection and tooth loss. Unfortunately, traditional diagnostic methods mainly depend on the subjective skill and experience of dental professionals. This can lead to inconsistencies and mistakes, particularly in the subtle or early signs of disease. The problem is worse in underserved and remote communities where access to specialized dental care is limited. Many people in these areas cannot get the treatment they need on time. This situation creates a significant gap in oral healthcare outcomes among different socioeconomic groups, which raises public health concerns.

To address these issues, this study looks into the potential of artificial intelligence, especially deep learning and Convolutional Neural Networks (CNNs), to automate and improve the classification and detection of dental diseases using clinical images. We will implement and evaluate three top CNN architectures: DenseNet201, VGG19, and ResNet50V2, MobileNetV2 on a carefully curated labeled dataset that includes three common dental conditions—calculus, tooth discoloration, and caries. Our goal is to find the most accurate and reliable model for use in clinical settings.

The main aim of this research is to create a strong diagnostic tool that helps dental practitioners by providing quick, objective, and scalable analysis. This tool could lessen the diagnostic burden and reduce human error. It has the potential to make quality dental diagnostics more accessible, especially in areas with insufficient professional care.

This project is based on extensive teamwork with a wide range of stakeholders, including experienced dentists and female dental professionals. Their clinical insights and practical knowledge have played an important role in shaping the design and validation of the system. This collaborative approach ensures that the technology tackles real-life challenges and meets professional standards, building trust and usability within the dental community.

By combining advanced technological methods with clinical expertise and addressing social barriers, this work aims to make a significant impact on improving oral health outcomes worldwide. If successful, this automated dental disease detection system could change preventive care practices, making early diagnosis more accessible, accurate, and fair for everyone.

1.2 Motivation

Now a days teeth disease became a global problem and increase the hardness day by day. Most of the people who doesn't care about their activities which they are taking through mouth and increase the risk to have various type of teeth related problem. For all this type of problem teeth disease detection is a solution for a betterment. From several types of research, we have gathered our knowledge that how to solve all this type of limitation. If we solve this type of problem, people will get rid from various type of pain like infection, fracture in teeth and many types of impacted teeth and also get a proper knowledge about healthy teeth and how they can be taking care of their own teeth.

So, making better and more reliable methods to find teeth problems early is very important. It can help people all over the world keep their mouths healthy and avoid serious issues in the future.

1.3 Objectives

The main goal of this project is to use machine learning techniques to create an intelligent, automated system that can precisely identify and categories common dental diseases, particularly calculus, tooth discoloration, and caries. The goal is to lessen reliance on manual diagnostic processes, which are frequently laborious, arbitrary, and highly dependent on dental professionals' knowledge. This system aims to improve the precision, speed, and consistency of dental diagnoses by utilizing the power of deep learning, specifically Convolutional Neural Networks (CNNs). This is especially important in places where access to specialized care is limited.

In order achieved this, the project aims to create an extensive collection of expertly annotated dental images that will be used as the basis for model training and validation. To ensure quality the images will be preprocessed and enhanced, which will improve the models' ability to generalize under various conditions. Following that, the project will apply and optimize three cutting-edge CNN architectures, each of which is well-known for its prowess in image classification tasks: VGG19, DenseNet201,MobileNetV2 and ResNet50V2. Through the use of transfer learning techniques, the models will be trained to be highly accurate in detecting dental diseases.

Last but not least, the project will attempt to incorporate the top-performing model into a straightforward, approachable prototype application that can take a dental image and produce a disease prediction. In removed and underprivileged areas, this tool might help dentists make initial diagnoses and provide a useful remedy. By achieving these goals, the project supports the continuous endeavor to improve oral healthcare via intelligent, AI-powered technology.

1.4 Methodology

he dataset used in this study consists of almost 1075 JPG images of teeth, each labeled with one of three dental conditions: Calculus, Tooth Discoloration, or Caries. These images were carefully annotated by dental professionals to ensure high-quality labels that accurately reflect the observed conditions. To enhance generalization and reduce overfitting, data augmentation techniques such as random rotations, horizontal and vertical flips, zooming, and contrast adjustments were applied.

For the classification task, three pre-trained convolutional neural network (CNN) models were selected: VGG19, DenseNet201 and ResNet50,MobileNetV2, VGG19 models are known for their deep architecture and ability to capture spatial hierarchies, while ResNet50 introduces residual connections to effectively train deeper networks by overcoming vanishing gradient issues and. All models were initialized with ImageNet weights and fine-tuned by freezing the initial layers and retraining the deeper layers to adapt to dental disease classification.
To ensure reliable evaluation, 5-fold cross-validation was employed. The dataset was split into five equal parts, with each fold using a different subset as the test set while the remaining served for training. This process was repeated five times, and the results were averaged to obtain a robust estimate of each model's performance. This method maximized the use of limited data and ensured that the models generalized well to unseen images.

1.5 Project Outcome

Systematic method are used to identify teeth classes according to specific disease. But using desktop version for analysis gives more efficient and accurate result for the desire topic which we have input as the data in our paper. In the teeth disease detection system it will work as a web based machine learning method where many types off tool will provide instant , more accurate , more efficient result . Here is the specification of every step of our project:

1.Utilization of great accuracy specification of various type of disease in dental sector where exist 6 different types of class among the country. To prevent the irrelevant activities it will provide a enough perfect method to execute.

2. Building a easy to use ,simple, practical web application to show the implementation of the classes which we have input here to execute. This application will provide use friendly experiences to the user to get a expected accuracy and accurate outcome which they have searching for

3.It will gives a visual explanation in the form of heatmap over the images.

4. Will able to accure the exact road map to detect the teeth disease detection and will find the common disease for human in this country which they are suffering for in regular days.

5. People will get a proper knowledge about their problem which they suffering for. Can determine the exact problem and will get a proper treatment for their betterment.

6. The model can be improved by training on larger and more diverse datasets, making it suitable for real-world applications and integration into dental healthcare systems.

1.6 Organization of the Report

i. Chapter 1: Introduction. This chapter presents the background, motivation, objectives, scope, and expected outcomes of the teeth disease detection system.

ii. Chapter 2: Background. This chapter reviews existing dental disease detection methods, deep learning applications, and identifies research gaps.

iii. Chapter 3: Methodology. This chapter explains dataset collection, preprocessing, augmentation, model architectures (VGG16, DenseNet201, ResNet50V2, MobileNetV2) and evaluation methods.

iv. Chapter 4: Implementation and Results. This chapter covers model training, testing, performance metrics, visualizations, and comparative analysis of models.

v. Chapter 5: Engineering Standards and Challenges. This chapter discusses compliance with standards, ethical considerations, sustainability, and project challenges.

vi. Chapter 6: Conclusion. This chapter summarizes project achievements, limitations, and recommendations for future improvements.

Chapter 2

Background

Dental diagnosis done by hand is time-consuming and prone to human error. Recent developments in CNNs have demonstrated significant promise for automating the analysis of medical images. These methods can improve the speed and accuracy of detection in dental imaging, particularly in underserved areas.

2.1 Introduction

Teeth disease defines various type of problem that can be revolutionized by the higher sector of artificial intelligence separately as machine learning and deep learning. This will handle the efficiency of the detection of exact problem and all this will execute by merging all the data have inputted which will resize the images and deal with better quality of images and give the perfect outcome. First of all we discover the Convolutional neural network(CNN) which is perfect for image classificational work and next we allow some of effective and simple model to train all the data for get expected better outcome. Last of all we analyze and find the relatable output which has transform normal data to heat map and require all the activities which have given to this system then finally we explore all the data and give the real time example of web based application and get the perfect output.

2.2 Literature Review

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Mino,S et al.	2024	Automated Teeth Disease Classification using Deep Learning Models	Qualitative Anal-ysis	Classification using deep learning
Kim, Changgyun, et al	2022	Tooth-Related Disease Detection System Based on Panoramic Images	Web-based	Detection based on Panoramic Images.
Alam, M. K. et al	2022	Human Teeth Disease Detection Using Refractive	Quantitative Analysis	Refractive index-based surface

		Index Based Surface Plasmon Resonance Biosensor		
Y. Zhang et al	2023	Children’s Dental Panoramic Radiographs Dataset for Caries Segmentation and Dental Disease Detection	quantitative dataset-driven research	Panoramic Radiographs Dataset
Chen, H et al	2021	Dental Disease Detection on Periapical Radiographs Based on Deep Convolutional Neural Networks	quantitative dataset-driven research	Deep CNN based
Ayşe Betül Oktay	2017	Tooth Detection with Convolutional Neural Networks	Web-based	Based on CNN
Endres, M et al	2020	Development of a Deep Learning Algorithm for Periapical Disease Detection in Dental Radiographs	quantitative dataset-driven research	Deep learning approach for Periapical Disease
Lin, Nung-Hsiang, et al	2018	Teeth Detection Algorithm and Teeth Condition Classification Based on Convolutional Neural Networks for Dental Panoramic Radiographs	Quantitative Analysis	Classification based on CNN
Li, Kuo-Chen, et al	2024	Detection of Tooth Position by YOLOv4 and Various Dental Problems Based on CNN With	Quantitative Analysis	Various Dental Problems Based on CNN

		Bitewing Radiograph		
Hussein, Abdelaziz, et al	2025	Deep Learning-based Tooth Multi-Disease Detection in Dental Diagnostics	Quantitative Analysis	Tooth Multi-Disease Detection based on Deep Learning.
Park, Saron, et al	2023	Periodontal Disease Classification with Color Teeth Images Using Convolutional Neural Networks	Quantitative Analysis	Color teeth with CNN
Wang, Hongliang, et al	2024	An Automatic Tooth Position and Dental Disease Detection Algorithm Based on YOLOv8	quantitative dataset-driven research	Tooth position based on YOLOv8
Yoon, Kyubaek, et al	2024	AI-based dental caries and tooth number detection in intraoral photos: Model development and performance evaluation	Web-based	AI Based Dental caries
Mohammed, M. S et al	2023	Teeth Disease Recognition Based on X-ray Images	quantitative dataset-driven research	Disease Recognition based on x-ray images
Rawashdeh, M et al	2024	Enhancing Dental Diagnosis through Automated Detection of Teeth Diseases in Panoramic Radiographs	Quantitative Analysis	Enhancing through automated detection

2.3 Gap Analysis

After reviewing many research papers, several key gaps have been identified that, if addressed, could significantly improve data processing systems, especially in image analysis. Many studies depend on raw datasets but do not fully explore systematic data augmentation techniques, which are crucial for improving model robustness and generalization. Effective augmentation exposes models to different variations, ultimately increasing accuracy.

Another important area that is often neglected is image cropping and preprocessing. Properly cropping images to focus on relevant regions can greatly enhance the precision of the analysis by removing noise and irrelevant information. Similarly, sorting and organizing the input data before training is rarely prioritized, even though it can reduce training time and improve overall efficiency.

Time complexity is a persistent challenge. Many highly accurate models require significant processing time, making them unsuitable for real-time applications like medical diagnosis. Future work should aim to optimize algorithms and preprocessing pipelines to create a better balance between accuracy and speed.

Moreover, user interface design is frequently overlooked. A well-designed, user-friendly interface with clear visualization tools would make these systems more accessible and easier to operate, improving the overall user experience.

Finally, most research validates their methods on limited or domain-specific datasets, which restricts the generalizability of their results. There is a need for broader testing on large-scale and diverse datasets to ensure that the proposed methods are robust and scalable across different scenarios.

In summary, addressing these gaps, including improved data augmentation, standardized preprocessing and cropping, better data management, reduced time complexity, enhanced user interfaces, and thorough validation, will lead to more accurate, efficient, and user-friendly systems. This will ultimately benefit real-world applications where speed and precision are crucial.

2.4 Summary

A well-prepared dataset is very important for AI to detect dental problems accurately and quickly. By properly editing the images like cropping, improving quality, and adding more data. The system works faster and gives more reliable results, helping patients get quick and easy feedback. This teeth disease detection system can find dental issues more precisely than many current methods. It also has a simple, user-friendly interface, making it easy for dentists, technicians, and patients to use.

By combining good image preparation and an easy to use system and it provides a strong and reliable solution that improves disease detection, speeds up diagnosis, and helps provide better dental care.

Chapter 3

Research Methodology

3.1 Methodology

The method for detecting dental diseases using deep learning had several stages. First, researchers collected a dataset of 1,075 dental images and sorted them into six disease categories. They preprocessed the images by resizing, normalizing, and augmenting them to improve model strength. They used three CNN architectures: VGG19, DenseNet201, MobileV2 and ResNet50V2, applying transfer learning with pretrained ImageNet weights. Training occurred with optimized hyperparameters, using the Adam optimizer and early stopping techniques. They evaluated model performance based on accuracy, precision, and the confusion matrix. Finally, they integrated the best-performing model into a web-based prototype for disease prediction.

3.1.1 Overview

This chapter overviews machine learning for detect common and known problem in dental sector which has possible by analyzing a healthy amount of raw data as image. Those image help the system to identify all the gap which we have found. Various type of image have trained through this system and lots of model mechanism approved to appropriate the system properly. Our aim is to develop the system way more better then past activities and help the use to get a better option to find there necessaries. The system will merge all the image and find the detected point through hit map image form and get the detected area to short out the problem. It will crop images as augmentation method and give the data a proper size that will help the system to identify the main point of the data and multiple deep learning model have trained here which (VGG19,DenseNet201 ,MobileNetV2,ResNet50V2) analyzes the data to fine the possibilities detected point and a custom build Convolutional neural network(CNN). To increase the acceptability, we have suppose to design a visualization model with a simple website which will work as web application. By building this all sector of people like doctor, patient and normal user will get a proper knowledge how it works and how can It be good option to find a better accuracy for dental sector. They simply upload their affected teeth and our system will process the data and find the almost perfect result for their betterment.

3.1.2 Proposed Methodology

The proposed system aims to identify various types of dental diseases while ensuring it can be easily reproduced, scaled, and used in clinical settings for dental image analysis. This system addresses the technical needs of deep learning as well as the practical usage for real-world dental diagnostics. The key parts of the methodology are:

i. Data Collection

A dataset of dental images is collected from clinics and public repositories. This dataset includes different dental conditions such as Infection, , impacted teeth, healthy teeth, fractured teeth, caries, BDC-BDR. Because the images come from real clinical settings, they show practical differences in quality, exposure, and angle, making the model better suited for real-life situations.

ii. Data Preprocessing

Raw images go through a systematic preprocessing stage. To improve accuracy, cropping techniques focus on the region of interest, such as the tooth. Data augmentation increases diversity and reduces overfitting by using rotation, shifting, zooming, flipping, and adjusting brightness.

iii. Model Development and Training

Multiple deep learning architectures are used, including ResNet50, VGG19, DenseNet201, MobileNetV2, and a Custom CNN. Each model uses the Adam optimizer and categorical cross-entropy loss. The dataset is split into training (80%), validation (10%), and testing (10%) sets to ensure fair evaluation. Early stopping and learning rate scheduling are applied during training to improve performance.

iv. Data augmentation

To improve the model and prevent overfitting, the images are slightly altered in various ways. Some images are rotated, shifted, scaled, or flipped for variety. Brightness and contrast are adjusted, and a bit of noise is added so the model can handle different image qualities. Small shape changes are applied without losing important features of the image. To address the issue of some classes having fewer images, methods like balanced sampling, mixup, and focal loss are used. This ensures the model learns from all classes fairly.

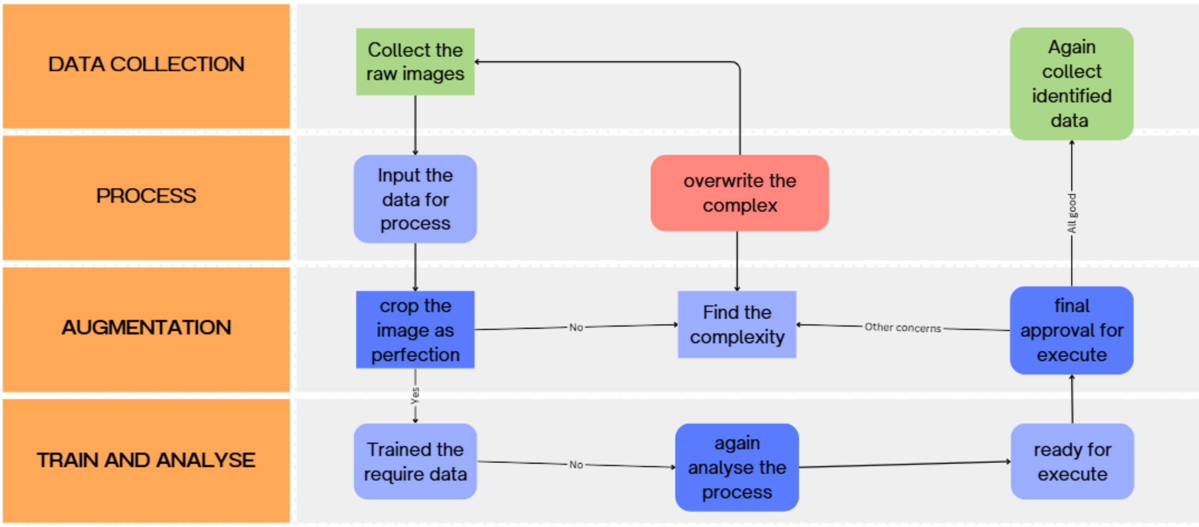


Figure 3.1.1: Methodology diagram

This methology diagram which is on "fig-3.1.1 Methodology diagram" shows a summary system of this research paper. There are some step of declaration has been given through in methodology diagram where data collection on the top and it refers the process as it is granted to the necxt level and then it goes for augmentetion for a better rotation view to detect exact process but if there is any issure in the augmentation sector it will overwrite the problem and it will fix to input as a required data. After this those data will be trained by custom CNN and some suitable model which are VGG19, ResNet50V2, MobileNetV2, DenseNet201 and analyse the dataset for betterment then it will execute for the final approval and we will witness of a better deep learning based Research paper.

3.1.3 Functional and Nonfunctional Requirements

Functional Requirement:

a. This system will allow you to use the interface of this mode
b. You can upload the require images which is the main point of your disease you have affected.
c. You can remove the uploaded images as well.
d. This system will display the accuracy of your desire problem.
e. This system will provide you a proper knowledge of Realtime activities of your tooth.
f. This system will gives you actual segmentation data which will help you to get acknowledgment about that disease.

Non-functional Requirement:

a. This System will analyses the data and provide realtime output in 5-10 second.
b. No barrier for usage to acknowledge any time of information which is related about this system because of its user friendly activities.
c. This system has capability to maintain lots of data through given model.
d. Marinating this system according to given data is easy to use all the time.
e. From all type of user anyone can have access from any type of search engine.

3.1.4 Data Flow Diagram

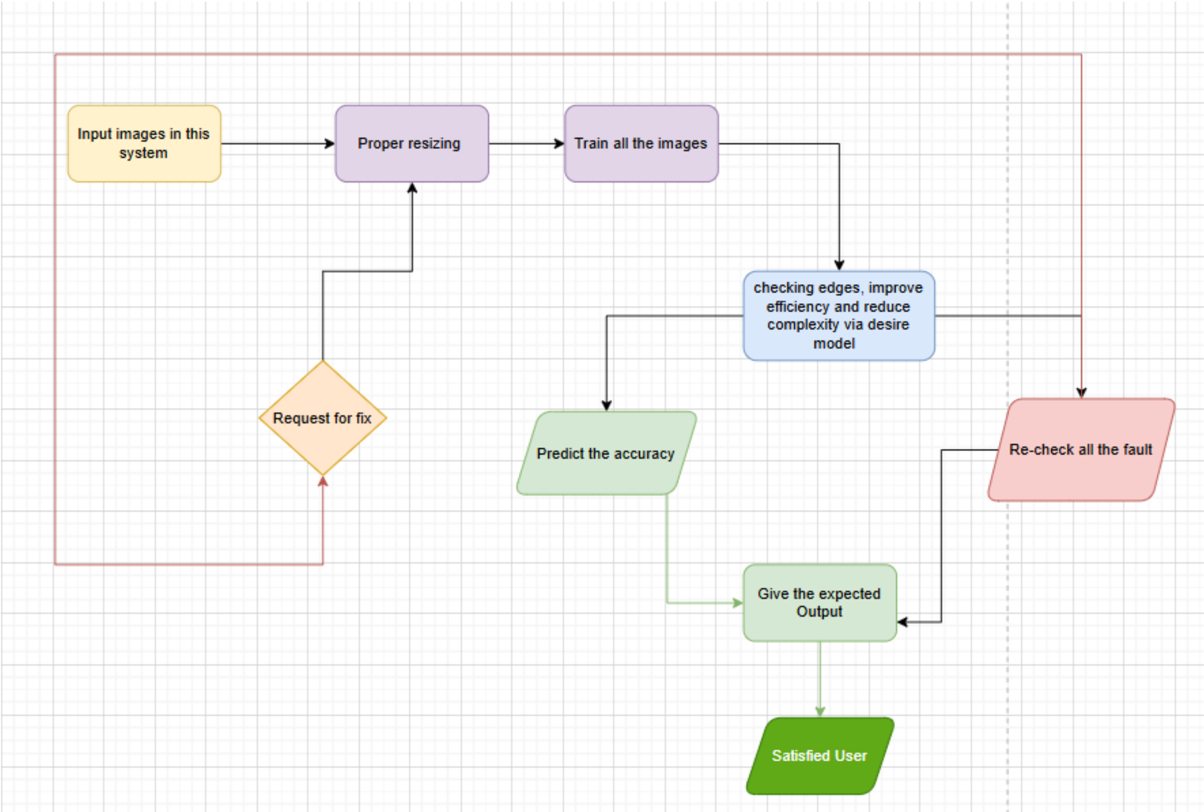


Figure 3.2.2: Data Flow Diagram

The Data Flow Diagram in Figure 3.2.2 shows the overall workflow of the proposed system. The process starts with inputting images into the system. These images are resized to ensure uniformity and meet the model's requirements. After resizing, the images are used to train the deep learning model. During training, the system checks edges, improves efficiency, and reduces complexity to boost performance. After training, the system predicts the model's accuracy. If the prediction meets the expected level, the system produces the output and delivers it to the user for satisfaction. However, if the results are unsatisfactory or if errors are found, the system reviews the dataset and processes the images again to fix any issues. This repeated approach improves the model's reliability and efficiency, ensuring users receive accurate and helpful results.

3.1.5 UI Design

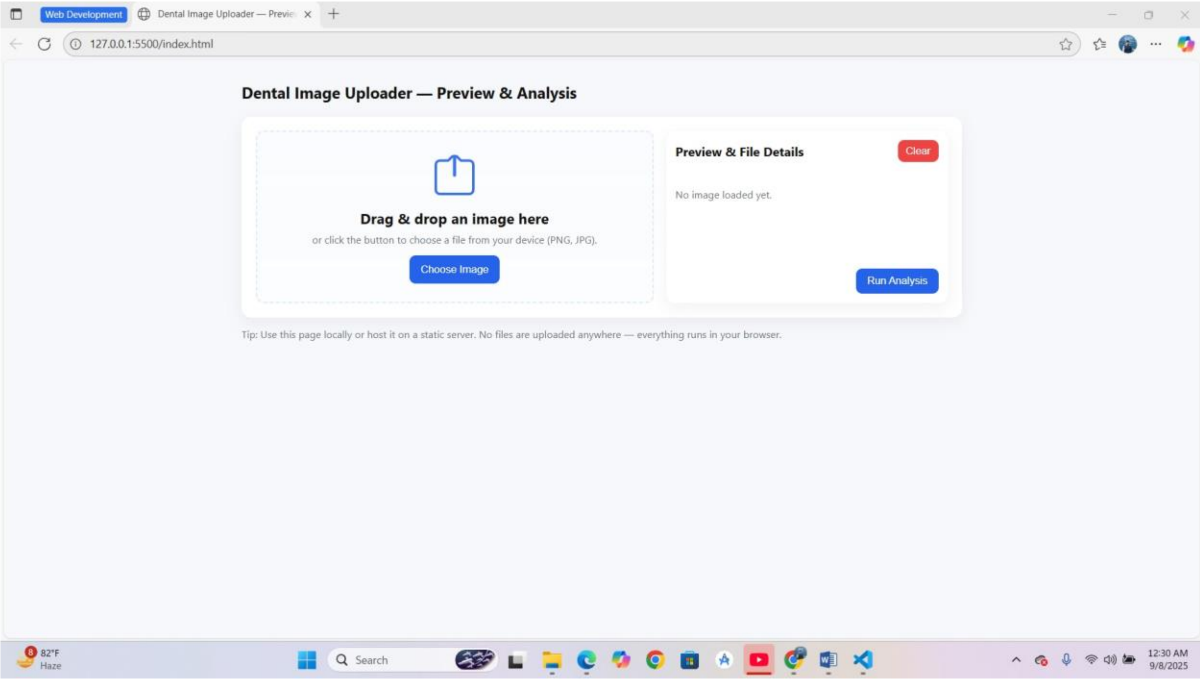


Figure 3.1.3: UI Design

UI design in figure 3.1.3 shows the proper visualization of this research paper . As we can see its help us to introducce with this project peoperly. It refers all the system flow how to upload and analyse the required data. Its the path that we can manage all the data in a single design and process them based on our need. It is a nacessary way to show a project via website and the flows refers that you can choose the photo what you need and click it for the run analys then it will analyse the data to detect the accurate problem acording to the desire model.

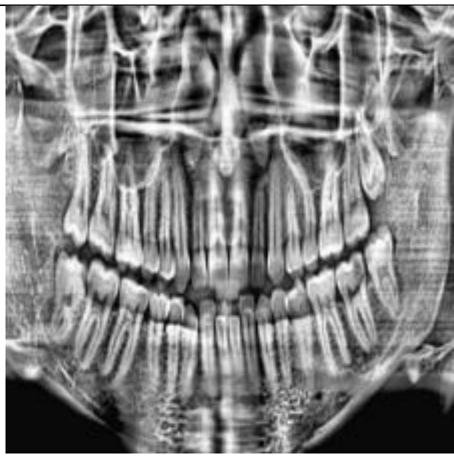
3.2 Detailed Methodology and Design

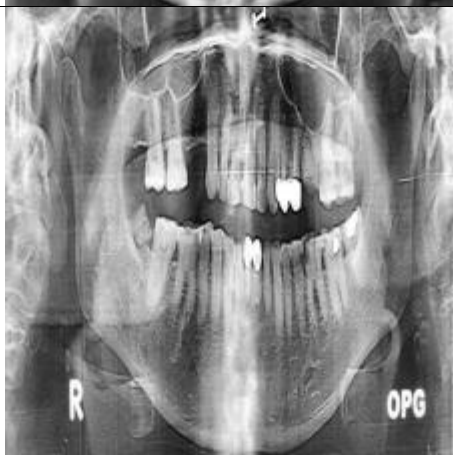
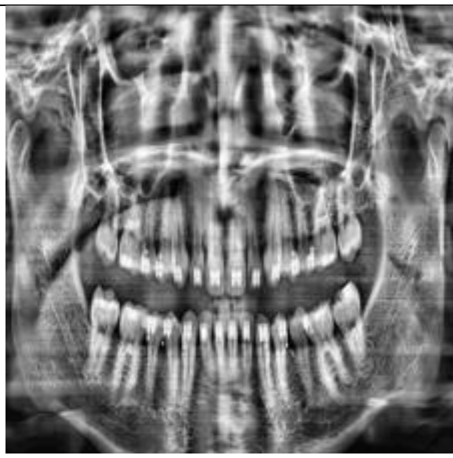
All the step which has implemented through design and augmentation that approach the machine learning and provide the user friendly interface. That is how a system works properly and all the process describe as proper step by step method which will enable to take data and process for a accurate output with proper visualization to the user.

3.2.1 Data Collection and Preparation

For this study, we made a dataset with 6 categories of common dental diseases. We collected 1,075 dental images to represent these conditions. The images came from dental clinics and publicly available repositories. They were taken in real clinical settings to ensure authenticity. We organized the dataset into a folder structure. Each disease type has its own subdirectory. The images were then standardized and labeled correctly within their respective folders.

Table 3.2: Showing the sample of data

No	Class	Number of images	Sample
01	Infection	223	
02	Healthy Teeth	223	
03	BDC-BDR	200	

04	Impacted Teeth	187	
05	Fractured Teeth	123	
06	Caries	119	

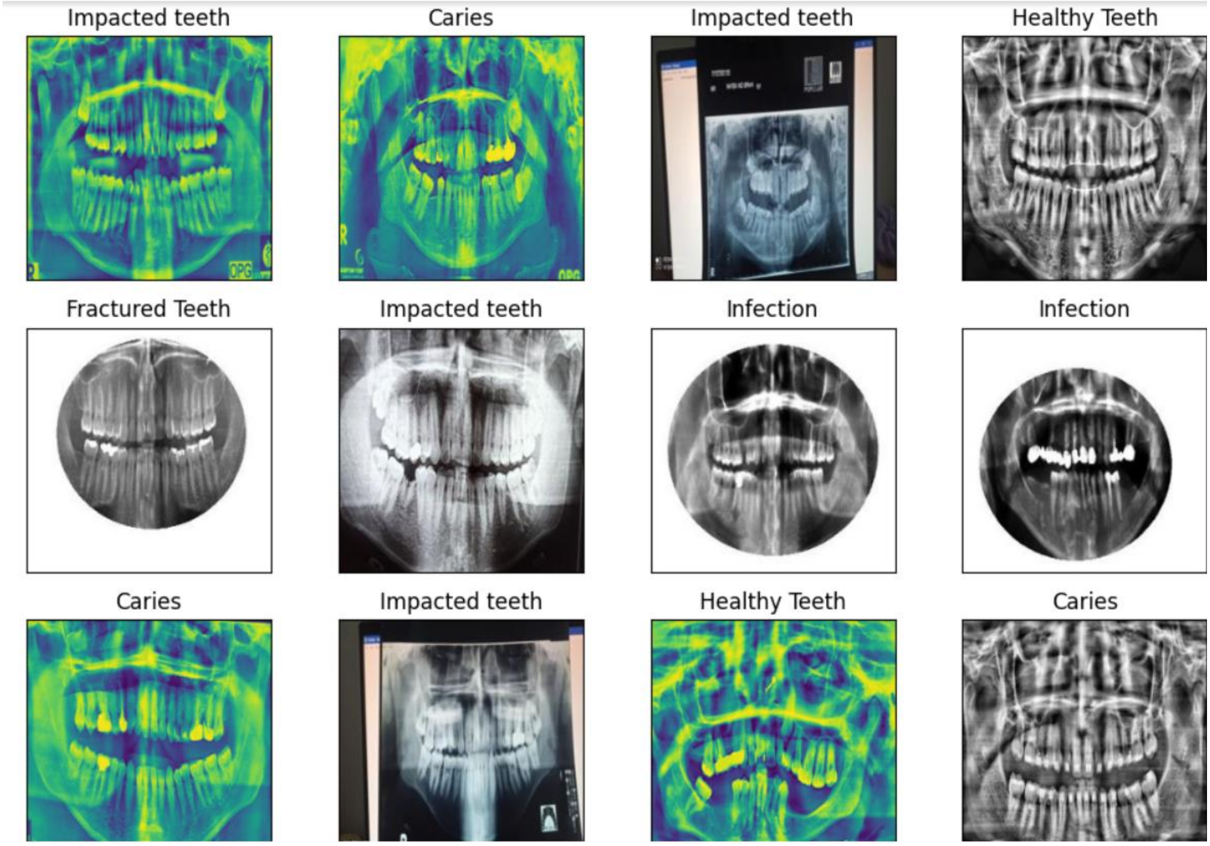


Figure 3.2.1: Display some pictures of the dataset with their labels

3.3 Project Plan

The tooth disease detection is a well planned system and it takes a good number of time to execute and if we distribute it part by part through our own planning that would be like this which we have given below:

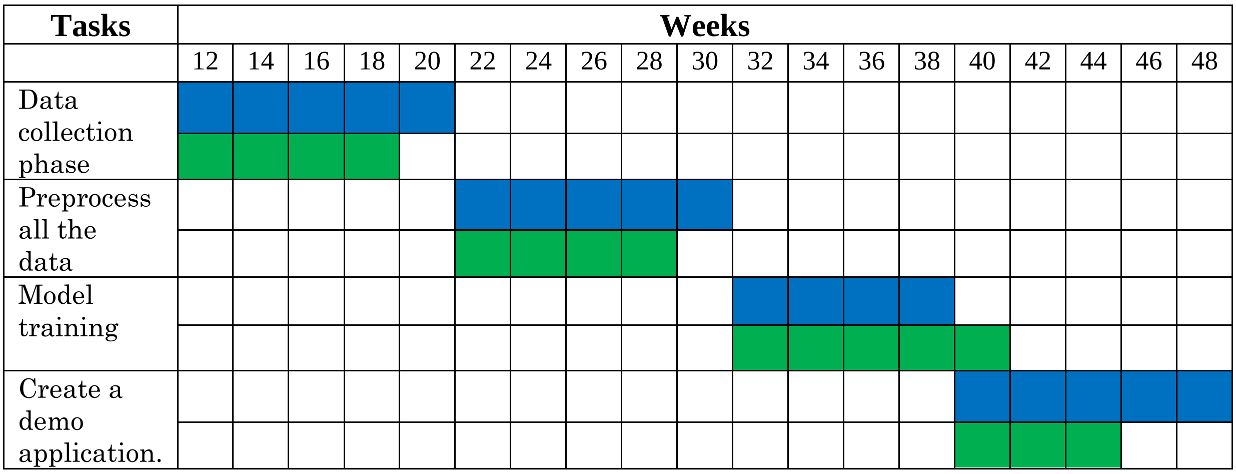
Table 3.3: Showing the project plan

Part	Activates	Duration
Part-1(Data collection)	Gathers data from various types of dentist and expertise	Week12-Week22
Part-2(Resize and augmentation)	Modify all the required images and resize all the image in actual form	Week23- Week 25
Part-3(Train data through Model and execute)	Process the remaining data and train all the images as per model through architecture.	Week26-Week32
Part-4(Collecting and determining)	Collects all the successful outcome which this system have	Week33-Week40

	predict and ensure the details of prediction	
Part	**Activates**	**Duration**
Part-5(Developing website))	Developing a user friendly website to upload and review how can it be effective for our dental sector and will get a proper visualization	Werek41-Week47

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.



3.5 Summary

The proposed teeth disease detection system aims to spot dental problems more accurately and efficiently using machine learning. The process begins by gathering raw dental images from experts. Next, these images are resized, cropped, and enhanced to improve quality. They areused to train deep learning models like VGG19, DenseNet201, MobileNetV2, ResNet50V2, and a custom CNN to identify disease areas with high precision. The system collects and checks prediction results to ensure reliability.So, web application is created for dentists and patients, allowing them to upload dental images and receive clear diagnostic results. This approach improves accuracy and offers a practical solution for better dental healthcare.

Chapter 4

Implementation and Results

This chapter describes how we implemented the proposed method and the results we got. We used Python libraries like TensorFlow, Keras, NumPy, Matplotlib, Seaborn, scikit-learn, and Pandas for the implementation. Each step was done in an organized manner to ensure effective model training, seamless deployment, and precise results.

4.1 Environment Setup

The proposed teeth disease detection system was implemented using Python. Several deep learning and image processing libraries were used. TensorFlow and Keras built and trained the deep learning models. NumPy handled image preprocessing, visualization, and numerical computations. Pandas managed datasets, handled labels, and organized patient image records in a structured format, improving the workflow. The experiments took place both locally and on Google Collab cloud. The local device had a 12th gen Intel Core i3-1215U, 8 GB RAM, and Intel(R) UHD graphics with 128 MB of dedicated memory. GPU acceleration sped up model training and optimization, particularly for convolutional operations in deep learning architectures. The operating system was Windows 11. This setup provided enough computational power for preprocessing tasks like resizing, normalization, and augmentation. It also supported training deep neural networks with large dental image datasets.

4.2 Testing and Evaluation

The proposed deep learning-based teeth disease detection system was evaluated using a carefully divided dataset of 1,075 dental X-ray images. These images were classified into six categories: BDC-BDR (Bone Loss and Bone Density Reduction), Caries, Fractured Teeth, Healthy Teeth, Impacted Teeth, and Infection. This classification covered common dental conditions, allowing the model to generalize across various diagnostic cases. To ensure fair training and evaluation, the dataset was divided into three subsets using stratified sampling. This method maintained the same class distribution across all splits, which is crucial in medical imaging because class imbalance can greatly impact model performance. The dataset was split as follows: 80% for training, 10% for validation, and 10% for testing. The training set taught the model to recognize patterns linked to each disease class. The validation set helped fine-tune the model's parameters and monitor performance during training to prevent overfitting. The test set, which was not used during training or validation, served as an independent benchmark to evaluate the model's performance. This final evaluation provided an unbiased measure of the model's ability to generalize to new, unseen data. The structured split ensured a robust and fair assessment of the teeth disease detection system.

Table 4.2: Showing the classes

Classes	Precision	Recall	F1-score
BDC-BDR	0.83	0.91	0.87
Caries	0.84	0.89	0.86
Fractured Teeth	0.73	0.57	0.64
Healthy Teeth	1.00	1.00	1.00
Impacted Teeth	1.00	0.95	0.98
Infection	0.79	0.92	0.85

Figure 4.2 shows the normalized confusion matrix for the ResNet50V2 model used in dental disease classification. The matrix displays how cases are accurately and inaccurately classified across six categories: BDC-BDR, Caries, Fractured Teeth, Healthy Teeth, Impacted Teeth, and Infection. The diagonal values represent true positives, where the model has correctly identified the actual disease class. For example, the values are 0.84 for Caries, 0.73 for Fractured Teeth, and 0.79 for Infection. These figures show relatively strong recognition in those categories. In contrast, the off-diagonal values indicate misclassifications, which can be seen as false positives or false negatives. For instance, a false negative occurs when actual Caries cases are incorrectly classified as Healthy Teeth . A false positive happens when BDC-BDR cases are wrongly predicted as Caries . True negatives are not shown in the confusion matrix but can be calculated as the correctly rejected cases outside the class of interest. Overall, the matrix demonstrates that ResNet50V2 works well for some disease categories, especially Fractured Teeth and Infection. However, it struggles with others like BDC-BDR and Impacted Teeth, which have lower classification accuracy. This analysis highlights both the strengths and weaknesses of the model, offering insight into areas that need further improvement.

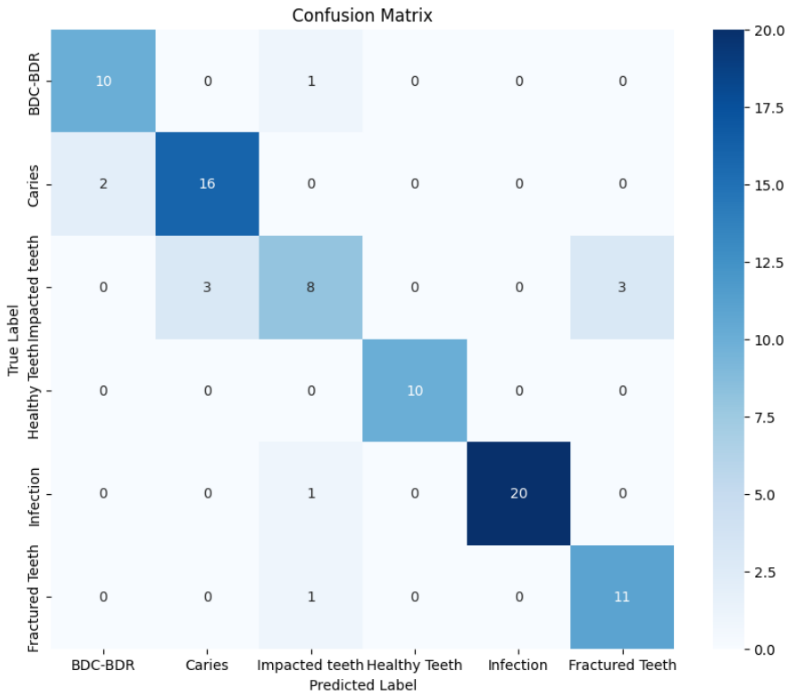


Fig 4.1: MobileNetV2 Confusion Matrix

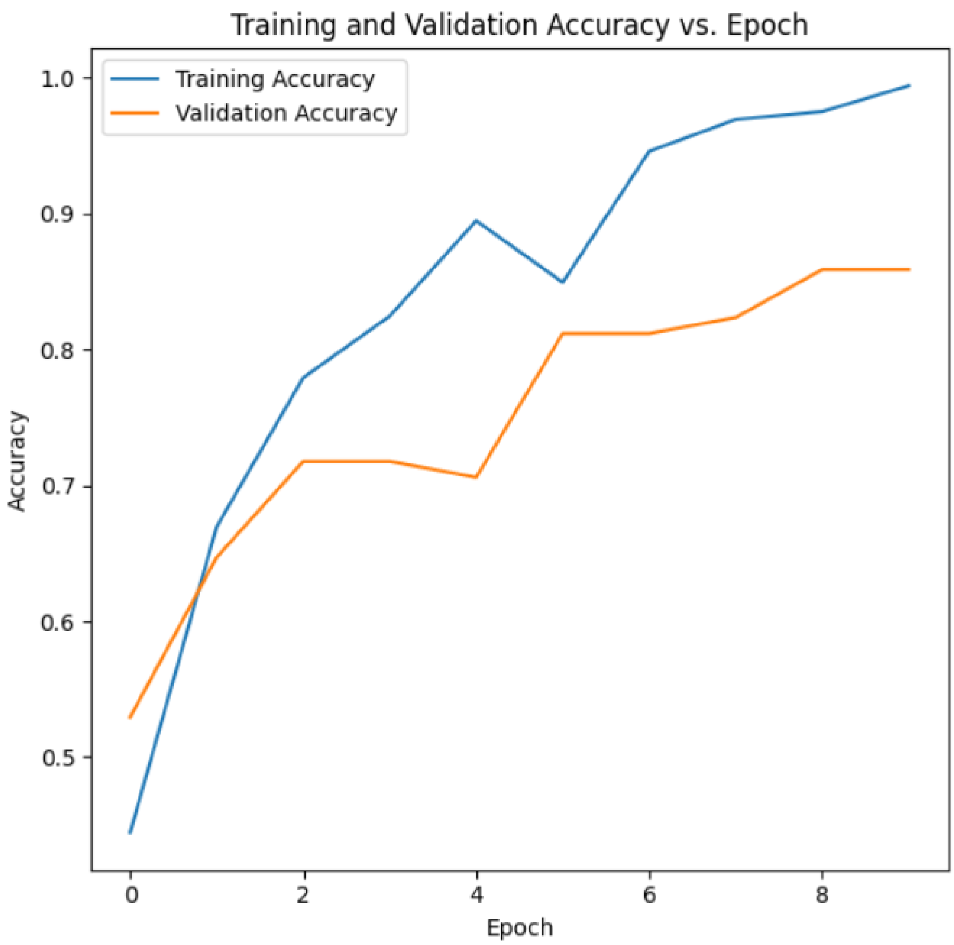


Fig4.2: Training Accuracy

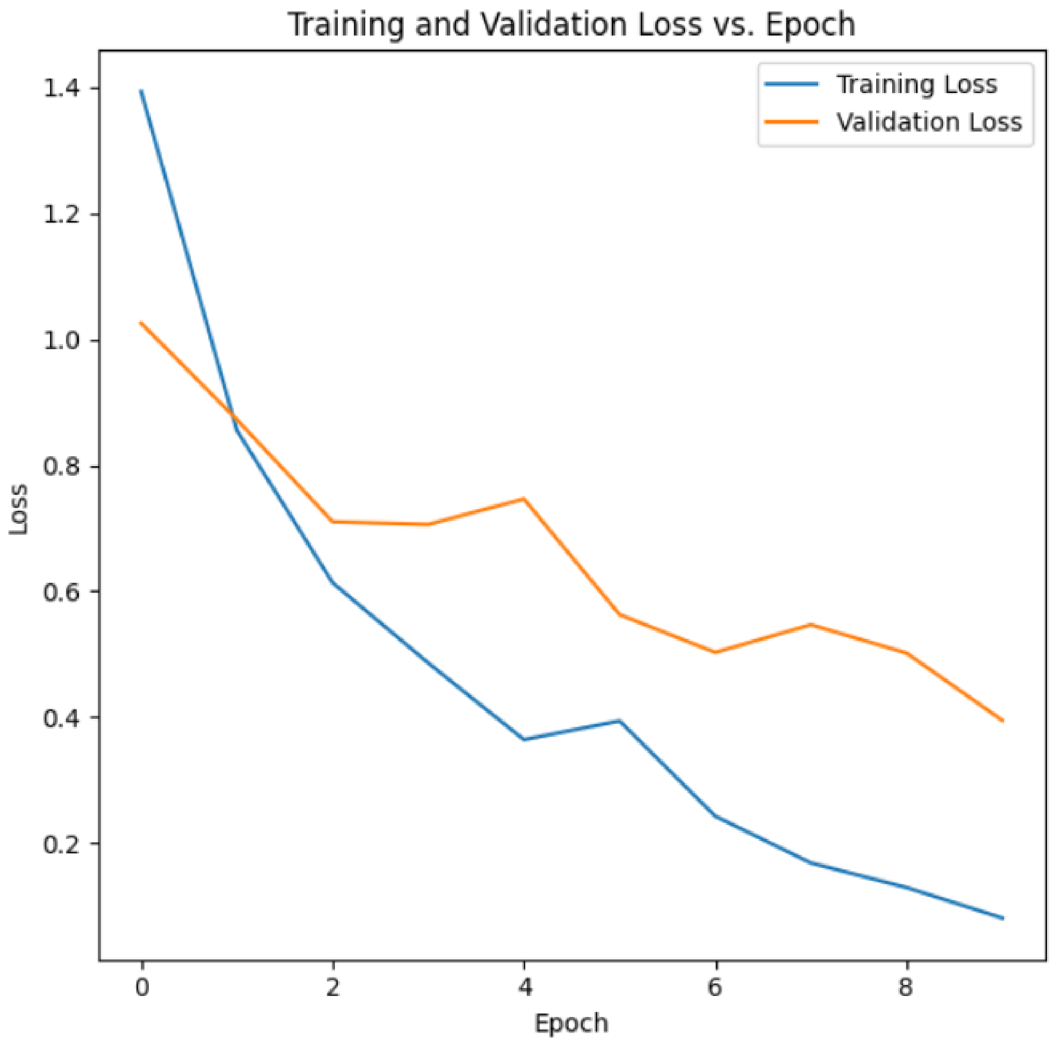


Fig4.3: Training Loss

On the test set as fig4.2 shows MobileNetV2 model reached an overall accuracy of 85.88%. It recorded a precision of 87%, recall of 87%, and F1-score of 87%. The performance varied across classes, showing recall for Infection (0.95) and Caries (0.89), while BDC-BDR (0.91) and Healthy Teeth (1.00). These results showcase both strengths and limitations of the model, suggesting that while it performs well in some disease categories, others need more data and model improvements. Figure 4.3 shows the training and validation loss curves for the MobileNetV2 model. The blue line represents the training loss, and the orange line represents the validation loss. At the start of training, both losses are relatively high. This indicates that the model is still learning the patterns in the dataset. As the number of epochs increases, both training and validation losses steadily decrease. This shows that the model is improving its ability to reduce classification errors. The close match between the two curves suggests that the model generalizes well to new data and does not experience significant overfitting. The losses stabilize at a consistent value. This demonstrates that the model has learned from the data and reached an optimal training state.

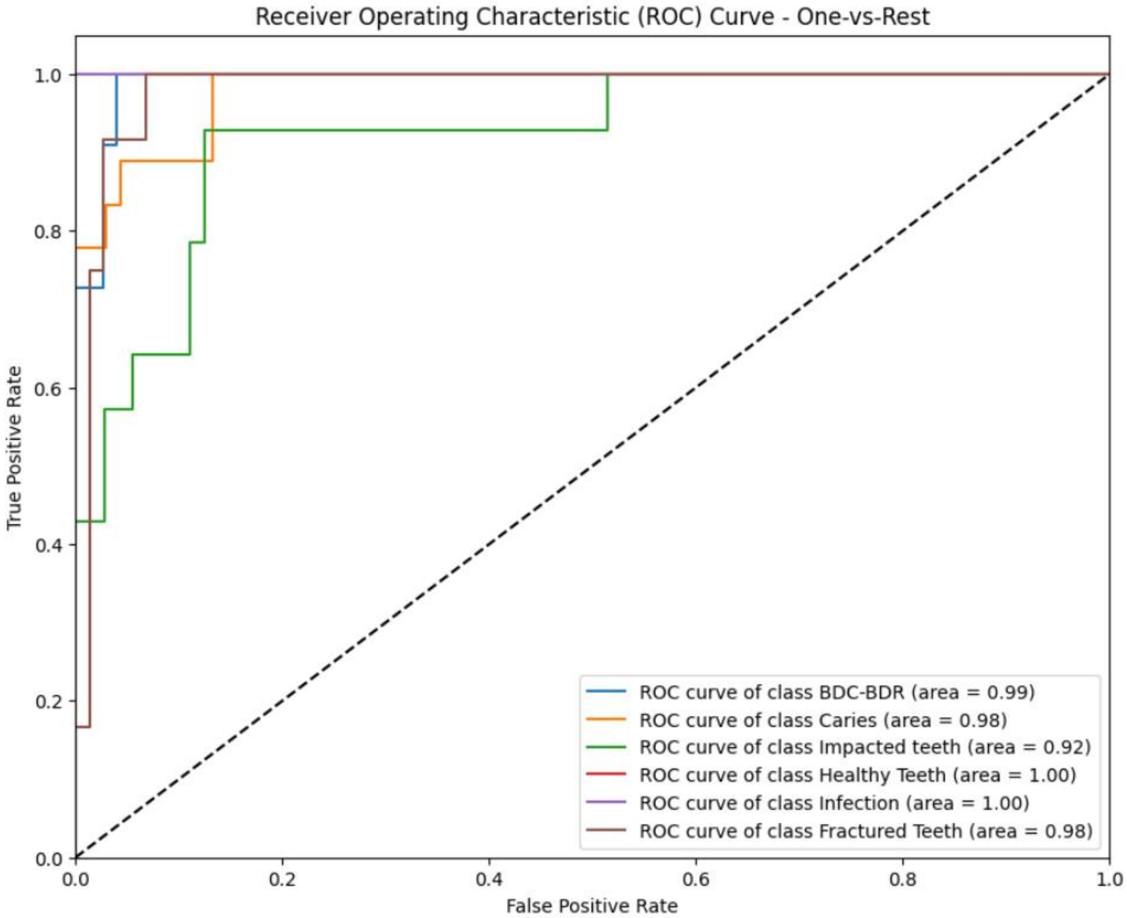


Fig4.4: ROC Curve

4.3 Results and Discussion

After a detailed observation it clearly demonstrate a output as a good accuracy. It confirms the Image to capture exact result as we have inputted. Extracting all the images and augmenting all the images its become a good featural model and while working on the dataset this would chooses 6 classes as well and give the desire result according to the dataset.

Table 4.3: Showing results

Model	Accuracy
MobileNetV2	85.88%
DenseNet201	72.47%
ResNet50V2	64.78%
VGG19	50.05%

4.4 Summary

The proposed teeth disease detection system aims to provide a reliable method for identifying dental problems using deep learning techniques. The process starts with collecting dental images. These images are then prepared through preprocessing steps like resizing, cropping, normalization, and data augmentation. These steps ensure that the dataset is balanced, diverse, and suitable for effective training, which reduces errors and improves model performance.

Once the dataset is ready, several deep learning architectures are used, including VGG16, DenseNet201, ResNet50V2,MobileNetV2 and a custom CNN. Each model has its strengths. VGG19 is simple and stable. DenseNet201 improves feature reuse and training efficiency. ResNet50V2 effectively manages deeper structures with residual connections. The models are trained and validated systematically, with testing done to measure performance and accuracy.

The results show that the system can successfully detect and classify various dental diseases with high precision. While performance varies slightly among the models, all show strong potential for practical use in dental diagnostics.

Chapter 5

Engineering Standards and Design Challenges

In this chapter, we explain how the teeth disease detection system was created. We discuss the engineering methods, standards, and practices that were used, along with the challenges faced during the process. The chapter also examines how the project followed to software and hardware guidelines, communication rules, and project management practices. Additionally, it looks at the social, environmental, and ethical effects of the system. Finally, we evaluate the system to show how well it addresses complex engineering problems and how it brings together knowledge from various technical fields.

5.1 Compliance with the Standards

The system was built using established rules for software, hardware, communication, and ethics. This approach made the project reliable, easy to maintain, and ethically responsible. It also allowed for future expansion and use.

5.1.1 Software Standards

The classification system was built in Python with TensorFlow and Keras, along with helpful libraries like NumPy, pandas, pathlib, scikit-learn, Matplotlib, and Seaborn. The code is organized clearly for easier reading, maintenance, and reuse. Data loading and preprocessing are kept separate from model definitions and training scripts. Utility functions for tasks like image loading, resizing and normalization are reused. Model checkpoints and training history are saved for later analysis. The final model is saved in a standard Keras format for easy loading and reuse.

The preprocessing steps include error handling to skip unreadable or corrupted images without stopping the program. This is important because images collected from markets can vary in quality. Data is split using stratified sampling to maintain class balance. Labels are converted to one-hot encoding before training. Training progress is tracked by saving loss and accuracy history. This makes it easy to reproduce and analyze results.

Best practices in the project include:

Keeping different code parts separate: preprocessing, augmentation, model, and evaluation.

Saving models and checkpoints in standard formats for easy reuse and deployment.
Using version control and cloud storage to support teamwork and reproducibility.

5.1.2 Hardware Standards

During testing, the system was improved to work on both regular local computers and cloud-based GPU platforms. On a typical mid-range Laptop with an Intel i3 CPU, 8 GB RAM the application ran smoothly. For quicker training and fine-tuning, Google Collab with NVIDIA T4 GPUs was used.

The final model, DenseNet201, was selected because it is lightweight with about 3.4 million parameters but still accurate, making it suitable for devices with limited resources. In the future, methods like pruning, quantization, or model extraction could be used to make it even faster and more efficient for deployment on embedded or edge devices.

5.1.3 Communication Standards

Clear communication was kept throughout the project. We organized tasks using Google Sheets and GitHub. This setup made it easy to track progress and assign responsibilities. Using consistent names for datasets, checkpoints, and scripts helped prevent confusion.

We held weekly meetings to review goals, address issues, and record results. Collaborative tools ensured smooth development, even as experiments grew more complex. These practices improved transparency and accountability, making the system easier to maintain over time.

5.2 Impact on Society, Environment and Sustainability

The teeth disease detection system created in this project is important for society and healthcare. Below, we summarize the expected impacts and the ethical factors that influenced our engineering choices.

5.2.1 Impact on Life

This teeth disease detection system provides practical benefits for dentists, dental clinics, and patients. It helps reduce diagnostic errors, supports accurate treatment planning, and assists practitioners who may have limited experience with certain dental conditions. In educational settings, it can act as a digital tool for dental students and researchers studying oral health and disease identification. The lightweight web prototype shows how easy it is to use the system for quick, on the spot diagnosis.

Integrated Grad-CAM visualizations improve understanding by highlighting the areas of the dental images, such as cavities, impacted teeth, healthy teeth, infection, that the model considers when making predictions. This clarity increases trust and confidence in the system's results, which is important for its use in real-world clinical applications.

5.2.2 Impact on Society & Environment

From a healthcare perspective, the system cuts down on the need for traditional, time-consuming diagnostic methods and reduces unnecessary clinical procedures. By allowing for precise detection of dental diseases, it enhances patient care and helps prevent misdiagnosis.

Using lightweight models like DenseNet201 also lowers energy use during predictions, making the system more efficient than heavier, resource-hungry models. Implementing the system through cloud infrastructure can further increase efficiency by using optimized, energy-saving data centers.

5.2.3 Ethical Aspects

Ethical principles guided the entire development process. Dental images were collected from clinics and publicly available datasets. Patient privacy was ensured by omitting any personal identifiers. Only non-sensitive images were used to maintain confidentiality.

To address bias, a balanced number of images for each type of dental condition was included, ensuring fair representation. However, the system recognizes that visually similar conditions may sometimes result in misclassifications. This highlights the need for future dataset expansion.

The project also strengthen transparency. All preprocessing steps, training settings, and evaluation results, such as confusion matrices, classification reports, and ROC curves, were thoroughly documented to support open and reproducible research.

5.2.4 Sustainability Plan

Sustainability is like a path where the project cover all the detailed vision. Heres the key tactics given below:

a. Keep collecting new dental images to improve the system. Ensure the data is balanced and that patient information remains secure.

b. Regularly update the system with new data so it stays correct. Check its performance often and make improvements when necessary.

c. Make the system run efficiently to use less power. Use local processing when you can to lower cloud usage.

d. Plan affordable ways for clinics to use the system, such as subscriptions. This approach will help ensure its long-term operation.

e. Build the system so it can be improved easily and remain user-friendly.

5.3 Project Management and Financial Analysis

Table 5.3.1: Financial Analysis

Components	Estimated cost
Visiting	5000-6000 BDT
Data collection	0
Documentation	2500 BDT
Hardware	0
Total	7500-8500 BDT

Total of estimated cost approximately 9000BDT taka

5.4 Complex Engineering Problem

Designing an automated teeth disease detection system is a complex engineering challenge. Dental images differ in quality which makes accurate analysis difficult. Differentiating between similar conditions, such as cavities, infections, and impacted teeth requires great machine learning models. Ensuring the system works well with different populations and imaging devices adds more complexity. Also, the model must provide clear results for dentists, fit with existing software, process data efficiently, and protect patient privacy.

5.4.1 Complex Problem Solving

In this section, provide a mapping with problem solving categories. For each mapping add subsections to put rationale (Use Table 5.1). For P1, you need to put another mapping with Knowledge profile and rational thereof.

Table 5.1: Mapping with Complex Engineering Problem.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓		✓	✓	✓

EP1 Dept of Knowledge developed a dental disease detection system using deep learning for accurate, efficient, and secure diagnostic image analysis.

EP2 examines the conflicting needs in tooth disease detection, including accuracy and speed, data quality and quantity, and model complexity and system efficiency. Balancing these factors is crucial for dependable diagnostics, effective processing, and wide use in various clinical settings.

EP3 shows a strong analysis of tooth disease detection using image processing, deep learning models, performance evaluation, including accuracy and ROC, and ongoing improvement based on clinical feedback.

EP4 shows knowledge of tooth disease detection problems. These include variations in image quality, similar symptoms for different conditions, data imbalance, patient diversity, and challenges in integrating with clinical workflows.

EP5 covers relevant codes, including medical imaging standards (DICOM), machine learning frameworks (TensorFlow, PyTorch), data privacy regulations (HIPAA/GDPR compliance), and software development best practices for dependable dental disease detection.

EP6 highlights extensive involvement from various stakeholders, including dentists, radiologists, data scientists, software developers, and patients. This ensures that the tooth disease detection system meets clinical needs and usability standards.

EP7 looks at how system parts depend on each other. These include data quality, model accuracy, hardware efficiency, and user interface. They all work together to provide effective and reliable tooth disease detection.

Mapping with Knowledge Profile

This section is designed to map the overall problem and EP1 ***(multiple between K3, K4, K5, K6, K8 for attaining EP1)*** to the Knowledge Profile.

Table 5.2: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
✓	✓	✓	✓		✓	✓	✓

K1 shows how natural science applies to detecting tooth diseases. It involves understanding dental anatomy, pathology, and radiographic principles. This knowledge helps in interpreting and classifying dental conditions with AI models.

K2 uses mathematics for algorithms, image analysis, and performance metrics in tooth disease detection systems.

K3 shows engineering basics through the design and development of the detection system. This includes model architecture, optimization methods, hardware-software integration, and ensuring reliability, scalability, and usability in actual dental diagnostic settings.

K4 requires expert knowledge in dental imaging, deep learning, and diagnostic systems designed for effective tooth disease detection.

K5 focuses on engineering design. It creates an efficient, user-friendly, and scalable tooth disease detection system. This system combines hardware, software, and clinical needs smoothly.

K6 involves engineering work through repeated development, testing, and validation of the tooth disease detection system. It includes using good coding practices, fixing bugs, improving performance, and working with dental experts to ensure the system meets clinical and technical standards.

K7 demonstrates its understanding of dental disease complexities. It interprets diagnostic images, evaluates model results, and combines clinical knowledge with technical solutions for effective tooth disease detection.

K8 uses research literature to keep up with the latest advances in dental imaging, machine learning techniques, and best practices for improving the accuracy and efficiency of tooth disease detection.

5.4.2 Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping add subsections to put rationale (Use Table 5.3).

Mapping with Complex Engineering Activities

This section is designed to map the overall problem and EA's ***(multiple).***

Table 5.3: Mapping with Complex Engineering Activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

EA1 involves using a wide range of resources, including dental image datasets, related journals, machine learning libraries, dental care and expert dentist for tooth disease detection.

EA2 shows strong interaction among dental professionals and end-users to develop and improve the tooth disease detection system effectively.

EA3 showcases innovation by combining advanced deep learning algorithms with cloud computing. This improves the accuracy of tooth disease detection, cuts down diagnosis time, and offers scalable, accessible solutions for various clinical settings.

EA4 shows positive effects on society and the environment. It improves dental health results, cuts down on unnecessary treatments, lowers energy use with efficient models, and encourages sustainable and accessible healthcare technologies.

EA5 understands the challenges of detecting dental diseases. These challenges include data variability, ethical issues, model limitations, and the need for easy-to-use diagnostic tools that fit into clinical practice.

5.5 Summary

The automated dental disease detection system provides several advantages in healthcare, environmental, ethical, and technical areas. It decreases the reliance on traditional diagnostic methods, saving time and improving patient care by increasing diagnostic accuracy. By using lightweight models like DenseNet201, the system uses less energy, and its cloud-based deployment boosts efficiency with optimized data centers.

Ethically, the project prioritized patient privacy by only using non-sensitive dental images and removing personal identifiers. A balanced dataset helped reduce bias, although similar-looking conditions can still lead to misclassifications, which emphasizes the need for future dataset expansion. Transparency was maintained by documenting all processes, including preprocessing, training, and evaluation measures.

The sustainability plan focuses on gathering more balanced data, regularly updating the system, using energy-efficient processing, providing affordable access to clinics, and ensuring ease of use along with future upgrades.

From an engineering perspective, the system needs to manage varying image quality and distinguish between similar conditions. It also has to work with different devices and populations, protect privacy, and integrate seamlessly into clinical settings.

Chapter 6
Conclusion

This chapter will present the overall outcome of teeth disease detection and classification according to those required class. It will merge the whole system in some topic or pera which we can have good view of this system. All the activities during this research will provide as a summary. This is a machine learning approach research which has the proper deep and machine learning acknowledgment with output of a healthy predicted of data with good accuracy.

6.1 Summary

This thesis proposed a complete method for the automated detection and classification of common teeth diseases using deep learning. A dataset of 1,075 self-collected dental X-ray images was gathered from local dental clinics to ensure authenticity. The research method followed a structured process that included data collection, preprocessing, augmentation, model training, evaluation, and deployment. Images were resized to 224x224 pixels, normalized, and augmented to enrich the dataset and reduce the risk of overfitting. The dataset was split into 70% for training, 15% for validation, and 15% for testing. Several models were evaluated, including DenseNet201, ResNet50, VGG19, and a Custom CNN. The performance of these models was measured using accuracy, precision, recall, F1-score, confusion matrices, and ROC-AUC. Among them, the models surpassed both ResNet50 and VGG19 in accuracy and efficiency and significantly outperformed the custom CNN and MobileNetV2 lightweight and efficient deep learning model designed primarily for computer vision tasks on mobile and embedded devices. Its main purpose is to provide accurate results while minimizing computational cost, memory usage, and power consumption. This makes it ideal for real-time applications where resources are limited, such as smartphones, IoT devices, and other edge computing environments.

Finally, the trained model was successfully incorporated into a web-based application. This allows users to upload an X-ray image and receive the predicted disease type and its corresponding confidence score, along with real-time visualizations. This ensures the system is useful not only for research but also for practical application in dentistry, diagnostics, and educational settings.

6.2 Limitation

This research have gain a lot of acceptability but still there are some limitations given below:

a. With a good amount of data(1075) which have implemented here are raw and authentic but if we compare to other related works in a big scale, it will be remain slightly small because of not collecting as much data as we need like any type of dentist.
b. The visualization of this system is too simple for any type of user with poor security in the website sector.
c. It will only available in website and not available in any type of mobile app or iOS system or IOT sector.
d. Being upgrade the research paper the main issue is now accuracy.

6.3 Future Work

Establishing the a good system with proper use of model will witness for future development in dental segment. Describe all in below:
This research showed that using deep learning for detecting teeth diseases can yield great results. However, there is still more to be done to improve the system. In the future, we can enhance it by gathering more dental images from various clinics and hospitals. This will make the model stronger and more dependable for all types of patients. We can also test new models to boost accuracy in identifying different issues, such as cavities, infections, fractures, and impacted teeth. In the future, using 3D dental scans will help the system spot hidden problems in roots and bone structure more clearly. Another key step is to make this system available on mobile phones and small devices. This will allow people in rural and remote areas to receive quick dental checkups without always needing to go to a clinic. Finally, the system should be more user-friendly, with clear results and easy-to-read reports. This will help both dentists and patients trust the technology and use it in practice for better dental care. In conclusion, this research shows that using deep learning to detect teeth disease can significantly improve dental diagnosis by identifying conditions like cavities, infections, fractures, and impacted teeth. The system shows promising results, but there are ways to make it even better. Future improvements include gathering more diverse dental images from various clinics to improve model reliability, testing advanced deep learning architectures for greater accuracy, and including 3D dental scans to find hidden root and bone issues. Making the system available on mobile devices will help people in rural and remote areas get timely dental check-ups. Integration with tele-dentistry platforms can also provide remote guidance from dentists. Additionally, designing user-friendly interfaces with clear, easy-to-read results will boost trust and usability. Overall, with these enhancements, the system could transform dental care by making diagnosis faster, more accessible, and more accurate for both patients and dental professionals.

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*% detected as AI

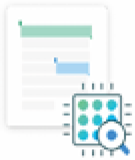
AI detection includes the possibility of false positives. Although some text in this submission is likely AI generated, scores below the 20% threshold are not surfaced because they have a higher likelihood of false positives.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.



False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.