كلية الحاسبات و الذكاء الاصطناعي
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قسم علوم الحاسب

الذكاء الاصطناعي في طب الأسنان

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رسالة مقدمة ضمن متطلبات الحصول على درجة البكالوريوس في الحاسبات والذكاء الاصطناعي، بقسم علوم الحاسب ، كلية الحاسبات والذكاء الاصطناعي، جامعة حلوان

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Abstract

Problem:

Dental diagnostics rely heavily on expert interpretation of panoramic X-ray images, which can be time-consuming, subjective, and prone to human error. Tasks such as identifying dental diseases, estimating age, detecting gender, and counting or numbering teeth require high precision and consistency. The lack of automated, intelligent systems in dentistry limits efficiency, accuracy, and scalability in clinical environments.

Objectives:

The primary goal of this project was to develop a comprehensive, AI-driven solution for automating key diagnostic tasks in dentistry using panoramic X-ray images. Specifically, the system aims to:

1. Detect patient gender based on dental features,
2. Classify age group (child or adult),
3. Automatically detect and number all teeth,
4. Identify regions of dental disease,
5. deliver the results in a user-friendly web application interface.

Methodology:

The system was built as a web application with a React-based frontend and a .NET backend, integrating four deep learning models. For gender and age classification, pre-trained convolutional neural networks (VGG16, DenseNet121, and InceptionV3) were fine-tuned on labeled dental X-ray datasets. Teeth detection and numbering were handled using a customized YOLOv8s object detection model, while dental disease segmentation was performed using a YOLOv8-seg model with both bounding box and mask outputs. Each model was evaluated using standard performance metrics such as accuracy, precision, recall, and mean Average Precision (mAP).

Achievements:

The system successfully meets its objectives, delivering accurate and fast diagnostic insights:

- The gender detection model based on DenseNet121 achieved a 97% accuracy, outperforming all previous methods.
- The age classification task saw VGG16 achieve 94.8% accuracy, indicating strong generalization for pediatric and adult classifications.
- The teeth detection model (YOLOv8s) reached a 96.7% mAP@0.5, precisely detecting and numbering 32 teeth including incisors, canines, premolars, and molars.
- The disease detection model achieved 90.6% precision and 91.1% recall, enabling real-time and robust detection and segmentation of affected regions in dental X-rays.

Keywords

Age Prediction, Artificial Intelligence (AI), Computer-Aided Diagnosis (CAD), Convolutional Neural Networks (CNNs), Deep Learning, Dental Image Analysis, Dental Radiography, Gender Classification, Medical Image Processing, Object Detection, Semantic Segmentation, Teeth Disease Detection, Tooth Numbering, X-ray Image Classification, YOLOv8, YOLOv8_Seg, VGG16, DenseNet121, InceptionV3

Acknowledgement

No one can achieve their goals alone; we all rely on the support and guidance of others to succeed. This moment is one of the most valuable and significant in our journey, and we would like to express our heartfelt gratitude to those who made it possible.

First and foremost, we extend our deepest appreciation to **Dr. Amal**, whose unwavering support, guidance, and encouragement have been instrumental in the completion of this project. Her insightful feedback, patience, and dedication have inspired us to persevere and strive for excellence. It has been an honor to work under her supervision, and we are truly grateful for her invaluable contributions.

Additionally, we are profoundly thankful to our families for their constant support, encouragement, and patience throughout this journey. Their belief in us has been a source of strength. We also extend our gratitude to the staff and faculty at Helwan University for providing exceptional resources and educational opportunities. The nurturing environment they have fostered has played a crucial role in our growth and development

This achievement is a testament to the collective efforts of many, and we are sincerely grateful to all who have supported us along the way

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Glossary

- **X-ray –** A technique that uses radiation to visualize internal structures like bones and teeth.
- **Radiograph –** An image produced using X-ray radiation.
- **Dental X-ray –** An X-ray image specifically used for diagnosing dental and jaw diseases.
- **Caries –** Tooth decay caused by bacterial destruction of tooth structure.
- **Cavity –** A hole or space in the tooth resulting from decay.
- **Enamel –** The hard outer layer of the tooth.
- **Dentin –** The layer beneath the enamel, less hard than enamel**.**
- **Pulp –** The inner part of the tooth containing blood vessels and nerves.
- **Root –** The part of the tooth embedded in the jawbone**.**
- **Crown –** The visible part of the tooth above the gum**.**
- **Gingiva –** The soft tissue surrounding the teeth (gums).
- **Periodontitis –** A severe infection of the gums and supporting structures of the teeth**.**
- **Periapical Lesion –** An infection or inflammation around the tip of the tooth root**.**
- **Impacted Tooth** – A tooth that fails to fully erupt due to an obstruction (e.g., wisdom tooth).
- **Missing Tooth** – The absence of a tooth from its natural position.
- **Wisdom Teeth** – The third molars that typically erupt during adulthood**.**
- **Fracture** – A break or crack in a bone or tooth due to trauma or injury.
- **Root Canal Obturation –** A dental procedure to clean and seal the root canal to prevent infection.
- **Root Piece –** A remaining part of the tooth root left in the jawbone after extraction or fracture.
- **Filling –** A material used to fill cavities caused by decay.
- **Root Canal –** A treatment for infected tooth pulp that involves cleaning and sealing the root canal.
- **Crown –** A prosthetic cap placed over a damaged or decayed tooth to restore its shape
- **Implant** – A dental procedure where an artificial root is inserted into the jawbone to replace a missing tooth.

Chapter 1

[An Introduction and Overview]

Chapter 1 provides an overview of AI's role in dentistry, focusing on automated diagnostics using deep learning. The project develops AI models for gender detection, age classification, disease detection, and tooth identification from dental X-rays. These models, utilizing VGG19, DenseNet121, InceptionV3, and YOLOv8, are integrated into a web application for real-time analysis. The project aims to enhance diagnostic accuracy, reduce human error, and assist dentists in decision-making. A structured AI pipeline is followed, from data collection to model deployment.

1.1Overview

Artificial Intelligence (AI) has transformed various fields, including healthcare, by enhancing diagnostic accuracy and automating processes. In dentistry, AI plays a crucial role in analyzing medical images, aiding in disease detection, and improving patient outcomes.

This project, talk about The Impact of Artificial Intelligence in Dentistry, focuses on utilizing deep learning models to analyze dental X-ray images for four primary tasks: gender detection, age detection, teeth disease detection, and tooth identification & numbering. These models will be integrated into a web application that allows users to upload X-ray images, process them through AI models, and receive diagnostic results. The solution leverages state-of-the-art deep learning architectures such as VGG19, DenseNet121, InceptionV3, and YOLOv8 to enhance accuracy and efficiency

1.2 Motivation

The motivation behind this project stems from the growing need for automated and accurate dental diagnostics. Traditional methods of analyzing dental X-rays rely heavily on human expertise, which can be prone to errors and inconsistencies. Additionally, the increasing workload of dental professionals necessitates tools that can assist in streamlining diagnostic procedures. AI-based dental image analysis can provide quick, consistent, and precise evaluations, helping practitioners make informed decisions and improving patient care. By leveraging deep learning techniques, this project aims to bridge the gap between technology and dentistry, making AI-assisted diagnostics more accessible and reliable

1.3 Problem Statement

Dental diagnostics often rely on manual analysis of X-ray images, which can be time-consuming, prone to human error, and limited in scope. Traditional methods for identifying gender, age, tooth numbering, and diseases from dental X-rays require significant expertise and may not always provide consistent results. Additionally, the increasing volume of dental imaging data necessitates automated solutions to improve efficiency and accuracy

This project addresses the following challenges:

1. Gender Detection: Automatically determining the gender of a patient from dental X-ray images.
2. Age Classification: Classifying patients into age groups (child or adult) based on dental X-ray images.
3. Tooth Identification and Numbering: Accurately identifying and numbering all 32 teeth in a dental X-ray image, including incisors, canines, premolars, and molars.
4. Disease Detection: Detecting and localizing dental diseases such as cavities, infections, or abnormalities in X-ray images.

1.4 Scope and Objectives

Scope:

- The project focuses on dental X-ray images for gender classification, age group classification, disease detection, and tooth identification & numbering.
- It integrates four deep learning models into a web-based system for seamless user interaction.
- The system outputs detailed dental insights, including the presence of diseases and the total number of teeth categorized into incisors, canines, premolars, and molars.

Objectives:

1. Develop AI models for automatic gender and age classification using VGG19, DenseNet121, and InceptionV3.
2. Implement YOLOv8s for tooth identification and numbering.
3. Use YOLOv8-seg for disease detection in X-ray images.
4. Integrate the models into a user-friendly web application for real-time analysis.
5. Enhance diagnostic accuracy to assist dentists in decision-making.

1.5 Work Methodology

The project follows a systematic AI development and deployment process:

1. Research
2. Data Collection
3. Data Preprocessing.
4. Model Selection & Training
5. Model Evaluation
6. Web Application Development
7. Testing & Deployment

Figure 1: Project Deployment process

Chapter 2

[Related Work]

Chapter 2 provides an overview of AI applications in medicine and dentistry, emphasizing its role in diagnosis, treatment, and patient management. In dentistry, AI enhances disease detection, forensic applications, and tooth numbering, improving accuracy and efficiency. The literature survey explores AI models for age estimation from dental X-rays, disease detection using YOLOv8, and automated tooth numbering with YOLOv4. Studies demonstrate AI's superiority over manual methods, achieving high accuracy but facing challenges like dataset limitations. Despite advancements, further research is needed to enhance AI's clinical applicability and interpretability.

2.1Background

2.1.1Artificial Intelligence in Medicine

Artificial Intelligence (AI) has emerged as a transformative force in the field of medicine, revolutionizing how healthcare is delivered, diagnosed, and managed. AI technologies, particularly machine learning (ML) and deep learning (DL), have demonstrated remarkable capabilities in analyzing complex medical data, including imaging, genomics, and electronic health records. These technologies enable the automation of tasks that were traditionally reliant on human expertise, such as disease diagnosis, treatment planning, and patient monitoring.

In medical imaging, AI models, especially Convolutional Neural Networks (CNNs), have achieved state-of-the-art performance in detecting abnormalities, segmenting organs, and classifying diseases. For instance, AI has been successfully applied in radiology to detect cancers, cardiovascular diseases, and neurological disorders from X-rays, MRIs, and CT scans. Beyond imaging, AI is also used in predictive analytics to forecast patient outcomes, personalize treatment plans, and optimize hospital operations.

The integration of AI in medicine has led to improved diagnostic accuracy, reduced healthcare costs, and enhanced patient outcomes. However, challenges such as data privacy, model interpretability, and the need for large annotated datasets remain significant barriers to widespread adoption.

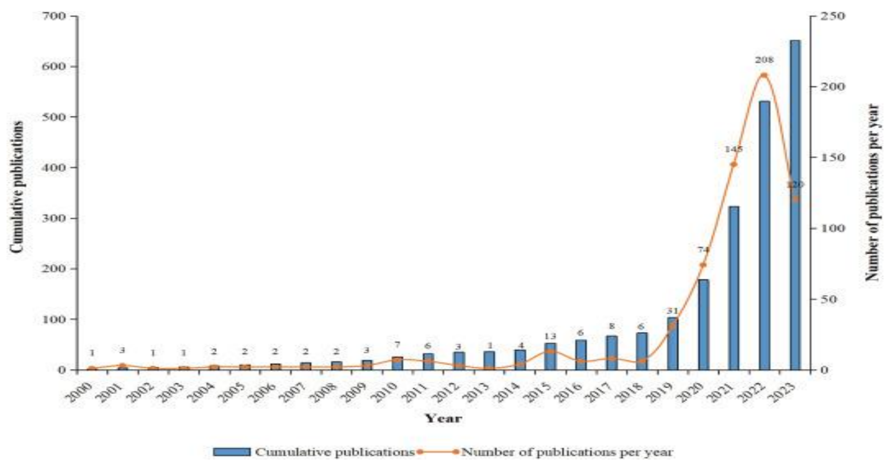

Figure 2: Evolution of AI in Healthcare

2.1.2 Artificial Intelligence in Dentistry

Artificial Intelligence (AI) has significantly transformed the field of dentistry, providing automated, precise, and efficient diagnostic tools. Traditional dental diagnosis relies heavily on manual interpretation of X-ray images, which is time-consuming and prone to human error. AI-driven solutions leverage machine learning (ML) and deep learning (DL) algorithms to assist dental professionals in disease detection, tooth identification, and forensic applications, enhancing accuracy and efficiency.

The integration of AI in dentistry offers multiple benefits, including:

- Automated Diagnosis: AI models can detect dental caries, periodontal diseases, and oral tumors with high accuracy.
- Faster Decision-Making: AI reduces the time required for tooth numbering, gender classification, and

age estimation, streamlining clinical workflows.

- Improved Accuracy: AI models minimize misdiagnosis and interobserver variability, leading to more reliable results.
- Forensic Applications: AI-driven age and gender estimation from dental X-rays assist in forensic investigations.

2.1.3 Role of Deep Learning in Medical Imaging and Dental Applications

Deep Learning (DL) is a subset of Machine Learning (ML) that utilizes artificial neural networks (ANNs) to learn and recognize patterns in images. It has revolutionized medical imaging, including radiology, dermatology, and dental imaging, by providing:

- Feature Extraction: Identifying complex patterns in medical images without manual intervention.
- Object Detection & Segmentation: Pinpointing and classifying anatomical structures in X-rays.
- Enhanced Image Interpretation: Reducing subjectivity in diagnosis by providing quantitative analysis.

In dental applications, DL models have been extensively used in:

- Tooth Detection & Numbering: Identifying and labeling 32 teeth in panoramic radiographs.
- Caries & Disease Detection: Recognizing dental cavities, infections, and anomalies in X-ray images.
- Age & Gender Classification: Estimating biological sex and age using craniofacial and dental structures.

Common deep learning architectures used in dentistry include:

- CNN (Convolutional Neural Networks): Used for image classification and object detection in X-rays.
- YOLO (You Only Look Once): Applied for real-time tooth detection and segmentation.
- VGG, DenseNet121, InceptionV3: Utilized for age and gender estimation from dental images.

These deep learning techniques improve diagnostic accuracy, reduce human errors, and accelerate decision-making in dental radiology.

2.1.4 Significance of Analyzing Teeth X-ray Images

1. Gender Detection from Dental X-rays

Teeth and jaw structures exhibit sex-specific variations, making dental radiographs useful for gender classification. Differences in mandibular size, canine prominence, and tooth morphology allow AI models to predict biological sex with high accuracy. Forensic dentistry frequently employs gender estimation to assist in human identification cases where other biological markers are missing.

2. Age Estimation from Dental X-rays

Dental X-ray images play a crucial role in age assessment, particularly in forensic and pediatric dentistry.

- Children & Adolescents: Tooth development and eruption stages help determine age.

- Adults: Enamel wear, pulp chamber narrowing, and root changes provide age-related clues.
  Deep learning models can classify individuals as children or adults based on dental features, supporting legal and forensic cases.

3. Disease Detection from Dental X-rays

AI models can automatically identify and segment common dental diseases, including:

- Dental Caries (Cavities)
- Periodontal Disease
- Periapical Lesions & Abscesses
- Root Fractures & Cysts
  By highlighting diseased regions, AI enhances early diagnosis, improves treatment planning, and reduces dental complications.

4. Tooth Detection & Numbering in Panoramic X-rays

Tooth numbering is essential in orthodontics, prosthodontics, and dental surgeries. AI-driven tooth detection and numbering models automatically identify and label 32 teeth (incisors, canines, premolars, molars) in X-ray images. This automation:

- Speeds up dental charting.
- Reduces human error in manual numbering.
- Improves treatment accuracy in dental procedures.

2.2 Literature Survey

2.2.1 Age Detection in Dental X-rays

Paper Title: "Age Detection by Deep Learning from Dental Panoramic Radiograph"

1. Research Summary

The research paper titled "Age Detection by Deep Learning from Dental Panoramic Radiographs" by Baydoğan et al. (2022) presents a deep learning-based approach for age classification using dental panoramic X-ray images. The goal of the study is to classify individuals into two age groups:

1. Children (Ages 2-13 years)
2. Adults (Ages 13-21 years)

The motivation behind this study stems from the importance of age estimation in forensic science, anthropology, and clinical dentistry. Traditionally, age estimation is performed using manual methods based on tooth eruption charts, but these methods are time-consuming and subjective. The study proposes a deep learning alternative to automate this process with improved speed and accuracy.

The key contributions of the paper include:

- The development of a deep learning-based framework to estimate age groups from panoramic X-ray images.

- The use of AlexNet for feature extraction and four machine learning classifiers (k-NN, Decision Tree, Naïve Bayes, and Linear Discriminant) for classification.
- An experimental study using 627 dental X-ray images collected from a university hospital.
- An accuracy of 84% achieved using AlexNet + k-NN classifier.

2. Methodologies, Preprocessing, Datasets, and Deep Learning Techniques

Dataset Details

- The dataset consists of 627 dental panoramic X-ray images collected from Elazig Fırat University, Faculty of Dentistry.
- The images were categorized into two age groups based on the eruption of permanent teeth:
  - 325 images: Children aged 2-13 years
  - 302 images: Adults aged 13-21 years
- Dataset Splitting:
  - 70% of the dataset was used for training.
  - 30% of the dataset was used for testing.

Preprocessing Techniques Used

- Image Normalization: Converted images to a standardized pixel range.
- Resizing: All images were resized to match the input dimensions required by the deep learning model.
- Data Augmentation: Not explicitly mentioned in the paper, but augmentation could improve generalization.

Deep Learning Model Architecture

- Feature Extraction: The study used AlexNet, a Convolutional Neural Network (CNN), for extracting features from the X-ray images.
- Classification Models Used: After feature extraction, the features were passed through four machine learning classifiers:
  1. k-Nearest Neighbors (k-NN)
  2. Naïve Bayes Algorithm (NBA)
  3. Decision Tree (DT)
  4. Linear Discriminant (LD)

- Best Performing Model:
    - The AlexNet + k-NN combination achieved the highest accuracy (84%).
    - The F1-score was 85%, and the sensitivity was 76%.

Effectiveness in Distinguishing Between Child and Adult X-ray Images

- The model performed better than traditional manual methods by leveraging deep learning for feature extraction.
- The classification task was effective due to clear differences in tooth eruption patterns between children and adults.
- The results show that AI-based age estimation is feasible but could be improved with larger datasets and advanced architectures.

3.Comparison Table of Previous Studies on Age Detection

Table 1: Comparison of Previous Studies on Age Detection
(Summary of different studies on age detection, including the models used and their reported accuracy.)

Study	Year	Model Used	Accuracy
Kahaki et al.	2020	Deep CNN	81.8%
Wallraff et al.	2021	CNN	82.5%
Banjšak et al.	2021	Deep CNN	73%
Baydoğan et al.	2022	AlexNet + k-NN	84%

Insights from the Table:

- Most studies use CNN-based architectures, but their accuracies range between 73% and 84%.

2.2.2 Diseases Detection in Dental X-rays

Paper Title: " AI-Driven Dental Radiography Analysis: Enhancing Diagnosis and Education Through YOLOv8 and Eigen-CAM "

1. Research Summary

The paper titled "AI-Driven Dental Radiography Analysis: Enhancing Diagnosis and Education Through YOLOv8 and Eigen-CAM" by Ömer Aldanma et al. (2024) presents a deep learning-based approach to detect dental diseases in panoramic X-ray images. The study aims to aid dentists and students by automatically identifying various dental conditions, including:

- Dentin decay
- Root canal treatments

- Implants
- Crowns
- Fillings

The authors emphasize that traditional manual diagnosis of dental diseases from X-ray images is time-consuming and prone to human error. The proposed AI-based approach seeks to improve diagnostic accuracy, efficiency, and consistency.

Key Contributions of the Study:

- Developed an AI-powered disease detection system using YOLOv8 (a deep learning object detection model).
- Utilized Eigen-CAM to provide interpretability in model decisions.
- Integrated the trained model into a web-based application for real-world usability.
- Conducted experiments on a dataset of 2,500 dental X-rays collected via Roboflow.

2. Methodologies, Preprocessing, Dataset, and Deep Learning Techniques

Dataset

- Source: Roboflow platform
- Size: 2,500 panoramic dental X-ray images
- Classes:
    - Dentin decay
    - Root canal treatments
    - Implants
    - Crowns
    - Fillings
- Data Splitting:
    - Training Set: 80%
    - Validation Set: 10%
    - Testing Set: 10%

Preprocessing Techniques Used

- Data Cleaning: Removed duplicate or noisy images.
- Image Normalization: Adjusted contrast and brightness for uniformity.
- Data Augmentation: Applied techniques such as rotation, flipping, and brightness adjustment to

improve model generalization.

Deep Learning Model: YOLOv8

- Object Detection Approach: Used YOLOv8 for multi-class disease detection in X-ray images.
- Explainability: Integrated Eigen-CAM, which highlights the areas of the image influencing the model's decision.
- Web Application Integration: The trained model was embedded into a web-based interface, allowing users to upload X-ray images for real-time analysis.

3.**Comparison Table of Disease Detection Studies**

Table 2: Comparison of Previous Studies on Diseases Detection
(Summary of different studies on diseases detection, including the models used and their reported accuracy.)

Study	Dataset Size	Model Used	Performance Metrics
Roboflow (Aldanma et al.)	2,500 dental X-rays	YOLOv8	86% accuracy, 64% precision, 60% recall
Brahmi and Jdey (2024)	107 Panoramic radiographs	Mask-RCNN	90% mAP, 96% precision, 63% F1 score
George et al. (2023)	1,000 Panoramic radiographs	YOLOv8	82.36% accuracy

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2.2.3 Teeth Detection and Numbering in Dental X-rays

Paper Title: " Automated Permanent Tooth Detection and Numbering on Panoramic Radiographs Using a Deep Learning Approach**"**

1. Research Summary

The study titled "Automated Permanent Tooth Detection and Numbering on Panoramic Radiographs Using a Deep Learning Approach" investigates the use of deep learning models to automate tooth detection and numbering in panoramic radiographs. The motivation behind this study is to reduce manual errors and workload in dental radiology, as manual tooth numbering is time-consuming and prone to human mistakes.

Key Contributions of the Study:

- Developed an AI-based system to detect and number 32 teeth in panoramic radiographs using YOLOv4.
- Validated model performance using accuracy, precision, recall, and F1-score.
- Compared the AI model's efficiency with human specialists, demonstrating a significant reduction in processing time.
- Highlighted the potential for AI-based models to assist dentists in daily clinical practice.

2. Methodologies, Preprocessing, Dataset, and Deep Learning Techniques

Dataset Details

- Dataset Size: 500 panoramic radiographs.
- Source: Collected from patients at the Academic Dental Hospital Universitas Airlangga between 2016 and 2022.
- Dataset Splitting:
    - Training set: 400 images (80%).
    - Testing set: 100 images (20%).
- Annotations:
    - The dataset was labeled manually by certified dental radiologists using LabelImg software.
    - Each image contained bounding boxes for 32 teeth, following the universal numbering system.

Preprocessing Techniques

- Image Standardization: Resized to 416 × 416 pixels for input compatibility with YOLOv4.
- Contrast Enhancement: Adjusted brightness and contrast to improve feature visibility.
- Data Augmentation:
    - Applied rotation, flipping, and brightness adjustments to improve model robustness.
    - Used Mosaic and CutMix augmentation techniques, which YOLOv4 supports, to enhance object detection.

Deep Learning Model: YOLOv4

The study implemented YOLOv4, a one-stage object detection model, which consists of:

- Backbone: CSP-Darknet53 for feature extraction.
- Neck: Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PAN) to improve multi-scale feature fusion.
- Head: Final detection layers using bounding box regression and classification scores.

Training and Testing Configuration:

- Hardware: Google Colab cloud-based GPU processing.
- Batch Size: 64
- Optimizer: Adam Optimizer
- Learning Rate: 0.001 (decayed after 30 epochs)
- Training Duration: 148.78 hours

Effectiveness in Tooth Detection and Numbering

- The model correctly detected all teeth with 100% recall, meaning no missing detections.
- The system successfully classified 32 teeth types, with some misclassification in adjacent teeth.
- Significant time reduction:
    - YOLOv4 average detection time: 20.58 ms per image
    - Human radiologist detection time: 9.93 seconds per image

3.Performance Comparison Table

Table 3: Comparison of Previous Studies on teeth Detection
(Summary of different studies on teeth detection, including the models used and their reported accuracy.)

Approach	Dataset	Model Used	Accuracy
Chen et al. (2019)	1,250 Periapical X-rays	R-CNN	77.4%
Hardani Putra et al. (2023)	500 Panoramic X-rays	YOLOv4	88.5%

2.2.4 Gender Detection in Dental X-rays

Paper 1: Biological Gender Estimation from Panoramic Dental X-ray Images Based on Multiple Feature Fusion Model

1. Research Summary

The study titled "Biological Gender Estimation from Panoramic Dental X-ray Images Based on Multiple Feature Fusion Model" (Ke et al., 2020) focuses on developing an automated gender classification system using panoramic dental X-ray images. The authors argue that forensic odontology plays a crucial role in identifying individuals, especially when conventional biological characteristics are unavailable.

Key contributions of the paper include:

- Developing a Convolutional Neural Network (CNN) with a Multiple Feature Fusion (MFF)
- Using a large dataset of 19,776 panoramic dental X-ray images collected from Chinese patients.
- Achieving state-of-the-art performance with 94.6% accuracy.
- Demonstrating that the model focuses on mandibular and dental structures, aligning with forensic practices

2. Methodologies, Preprocessing, Dataset, and Deep Learning Techniques

Dataset

- Size: 19,776 panoramic dental X-ray images.

- Demographics: All images are from Chinese patients aged 16–70 years.
- Gender Distribution:
    - 61.14% Female
    - 38.86% Male
- Dataset Splitting:
    - 2,000 images for testing.
    - The remaining images were used for training.

Preprocessing

- Histogram Equalization: Adjusted image contrast to enhance visibility.
- Resizing: Images were resized to 256 × 256 pixels for computational efficiency.
- Standardization: Converted images into a uniform format.

Deep Learning Model: Multiple Feature Fusion (MFF) CNN

- Backbone Model: VGG16 was chosen for its strong feature extraction capabilities.
- Feature Fusion Mechanism:
    - Inspired by ResNet and DenseNet, the MFF module integrates features from different CNN layers.
    - Skip-connections were used to improve feature retention.
    - The fusion module was applied to the last four layers of the CNN.
- Training Configuration:
    - Batch size: 64
    - Hardware: RTX 2080Ti GPU
    - Learning Rate: 0.001 (reduced every 30 epochs)
    - Total Epochs: 50

Effectiveness in Distinguishing Gender in X-ray Images

- The model focused primarily on the mandible and dental regions, which are known to exhibit sex-based differences.
- Saliency maps confirmed that the CNN relied on forensic-relevant anatomical structures for gender classification.

3.Performance Comparison Table

Table 4: Comparison of Previous Studies on gender Detection

(Summary of different studies on gender *detection, including the models used and their reported accuracy.)*

Study	Year	Model Used	Accuracy
Lin et al.	2014	Manual feature extraction	81.7–88.8%
Kano et al.	2015	Manual measurements	85%
Oliveira et al.	2016	Manual analysis	93.33%
Deana et al.	2017	Traditional statistical models	75.2–95.2%
Denis et al.	2019	CNN	92.3%
Ke et al.	2020	MFF-CNN (VGG16)	94.6%

Paper 2: Estimating Age and Sex from Dental Panoramic Radiographs Using Neural Networks and Vision–Language Models

1. Research Summary

The study titled "Estimating Age and Sex from Dental Panoramic Radiographs Using Neural Networks and Vision–Language Models" (Alam et al., 2025) explores various deep learning models for gender classification using dental panoramic radiographs.

Key contributions:

- Evaluated multiple deep learning architectures (CNN, VGG16, VGG19, ResNet, DenseNet, Vision Transformers, Moondream2).
- Used 437 panoramic X-ray images for training and testing.
- Applied random oversampling to balance the dataset.
- Achieved 85% accuracy using CNN

2. Methodologies, Preprocessing, Dataset, and Deep Learning Techniques

Dataset

- Size: 437 panoramic radiographs.
- Divided into:
  - Training set: 358 images
  - Testing set: 79 images

Preprocessing

- Grayscale Conversion: Converted images to 224 × 224 grayscale format.

- Normalization: Pixel intensity values were scaled to [0,1] range.
- Data Augmentation: Applied random oversampling to correct class imbalance.

Deep Learning Models Used

- CNN (85% accuracy)
- VGG16 (82% accuracy)
- VGG19 (78% accuracy)
- ResNet50 (61% accuracy)
- DenseNet121 (81% accuracy)
- Vision Transformer (72% accuracy)
- Moondream2 (49% accuracy)

Effectiveness in Distinguishing Gender in X-ray Images

- CNN models outperformed Vision Transformers, which struggled with medical imaging.
- DenseNet-based models improved classification accuracy, particularly for fine-grained anatomical features.

3.Performance Comparison Table

Table 5: Comparison of Previous Studies on gender Detection paper 2
(Summary of different studies on gender *detection, including the models used and their reported accuracy.)*

Study	Year	Model Used	Accuracy
Alam et al.	2025	CNN	85%
Alam et al.	2025	VGG16	82%
Alam et al.	2025	DenseNet121	81%
Alam et al.	2025	Moondream2 (Vision-Language Model)	49%

2.3 Analysis of the Related Work

2.3.1 Age Detection in Dental X-rays

Identified Gaps in Existing Research & Limitations

1. Lower Accuracy:
    - The highest accuracy in the reviewed studies is 84%, which is still not high
    - Most models in the literature still struggle with overlapping age groups.
2. Shallow Feature Extraction:
    - The study only used AlexNet, which is a relatively older CNN model compared to modern architectures like VGG19, DenseNet121, and InceptionV3.
    - AlexNet has fewer layers and lower feature extraction capabilities, leading to lower accuracy.
3. Reliance on Traditional Machine Learning Classifiers:
    - Instead of using end-to-end deep learning models, the study used AlexNet for feature extraction followed by separate classifiers (k-NN, Decision Tree, etc.).
    - These classifiers may not generalize well, limiting performance.
4. Limited Dataset:
    - The dataset used (627 images) is relatively small.
    - Data imbalance (325 child vs. 302 adult images) may introduce bias in the model.

How this Project Improves on These Approaches

1. More Advanced Deep Learning Models
    - Instead of AlexNet, this project directly trains and fine-tunes deep CNN models for superior feature extraction.
2. Fully End-to-End Deep Learning Pipeline
    - Unlike the Baydoğan et al. study, this project does not use separate classifiers after feature extraction.
    - This model directly classifies images using deep learning, eliminating unnecessary steps and improving accuracy.
3. Better Generalization with Transfer Learning
    - using pre-trained networks like(VGG19, DenseNet121, InceptionV3), which have been trained on massive datasets.
4. Higher Accuracy and Robustness
    - Pretrained CNN models achieving higher accuracy and sensitivity

2.3.2 Diseases Detection in Dental X-rays

Identified Gaps in Existing Research & Limitations

- Many studies (e.g., Brahmi and Jdey, Hasnain et al.) use small datasets (107-368 images), which may limit model generalization to real-world cases.
- Low Recall and Precision (64% Precision, 60% Recall in YOLOv8) ,The model failed to detect all dental conditions, leading to missed diagnoses (false negatives) and (False positives) resulted in incorrect predictions, reducing the model's trustworthiness
- Lack of Precise Segmentation, YOLOv8 only performs object detection, but some conditions (caries vs. fillings) require pixel-wise segmentation

How Your Project Improves Upon the Literature

- High Recall and Precision for Multi-Class Classification: By achieving high recall and precision, the model ensures better disease detection, reducing false negatives and improving early diagnosis
- Provide Segmentation: By incorporating segmentation, it enhances class separation for dental conditions that share visual similarities

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2.3.2 Teeth Detection and Numbering in Dental X-rays

Identified Gaps in Existing Research & Limitations

- Dataset Limitations:
  - Some previous studies used periapical radiographs instead of panoramic X-rays, limiting model generalization.
  - The dataset size (500 images) is smaller compared to Tuzoff et al. (1,574 images).
- Model Selection Constraints:
  - YOLOv4 had lower accuracy (88.5%) compared to ResNet (98.3%) and VGG16 (99.45%), indicating that other architectures might extract finer details better.
- Misclassification in Adjacent Teeth:
  - Some adjacent teeth were confused due to their similar anatomical structure.
  - Most errors occurred in the mandibular anterior region, where teeth overlap more frequently in panoramic images.

How This Study Improves Upon the Literature

- Real-Time Detection with Higher Accuracy:
  - YOLOv8 maintains real-time processing speeds while increasing accuracy compared to YOLOv4.

- Better Feature Representation:
  - The neck and head of YOLOv8 have improved feature fusion mechanisms, making it more suitable for distinguishing similar-looking teeth.
- Multi-Class Detection:
  - Instead of detecting only tooth presence, this model also classifies the tooth type based on 32 universal dental nomenclature classes.
- Higher Accuracy:
  - YOLO v8 integrates advanced techniques like anchor-free detection and dynamic feature learning, leading to fewer false positives
- More Efficient Object Detection:
  - YOLOv8 uses newer CNN architectures, resulting in better detection and reduced misclassification of adjacent teeth.

2.3.2 Gender Detection in Dental X-rays

Identified Gaps in Existing Research & Limitations

- Dataset Limitations: Some prior studies used very small datasets (100-500 images), limiting model generalization.
- CNN Generalization Issues: The accuracy of CNN-based models (Denis et al., 2019) decreased when tested on larger datasets.
- Limited Feature Extraction: The study used VGG16 as the backbone, but VGG16 is outdated

  compared to modern pretrained CNNs (e.g., DenseNet, ResNet, EfficientNet)
- Lack of Transfer Learning Utilization: The study did not explicitly mention transfer learning,

  which is crucial for medical imaging tasks with limited labeled datasets
- Vision-Language Models (Moondream2) perform poorly (49% accuracy).

How This Study Improves Upon the Literature

- Improve Model Selection: Using state-of-the-art CNN architectures like (DenseNet121, InceptionV3, VGG16) for improved accuracy and efficiency.
- Achieves Higher Accuracy Using Pretrained CNN: Pretrained CNN Models achieving higher accuracy and sensitivity
- Improve preprocessing: Implementing better preprocessing techniques to handle image variability.

Chapter 3

[System Analysis and Design]

Chapter 3 provides an overview of the system's analysis and design, detailing functional and non-functional requirements. The system architecture consists of three layers: Frontend (React.js), Backend (.NET with MySQL), and AI Models, each responsible for different tasks in dental X-ray analysis. The workflow involves users uploading X-ray images, backend APIs processing them, AI models analyzing them for age estimation, gender classification, teeth counting, and disease detection, and the results being stored and displayed in a structured report. Key technologies include TensorFlow, Keras, YOLOv8 for AI models, and JWT authentication for security. The chapter also presents UML diagrams to illustrate the system's structure and processes.

3.1 Functional and Non-Functional Requirements

3.1.1: Functional Requirements:

The functional requirements define the core capabilities and behaviors of the system. These include user interactions, system functionalities such as AI model executions, user role-based operations (Admin, Doctor, Student), and access restrictions based on subscription levels.

Table 6: Functional Requirements

(This table outlines the core functional requirements of the system, detailing user roles, model execution, patient management, and subscription-based feature access.)

ID	Requirement	Description
FR1	User Authentication	The system must allow users (Admin, Doctor, Student) to log in using their registered email and password credentials.
FR2	JWT Token Generation	After successful login, a JWT (JSON Web Token) should be generated to authenticate future requests and define access permissions based on user roles.
FR3	AI Model Execution	Users can upload panoramic dental X-ray images to run the following AI models: gender detection, age classification, disease detection, and tooth counting.
FR4	Patient Management (Doctor)	Doctors can create, view, edit, and manage patient profiles and diagnostic records.
FR5	Exporting Results	Doctors with the appropriate subscription plan can export diagnostic results and reports in PDF format.
FR6	Diagnostic History Access	Doctors can view the historical diagnostic data of patients, provided their subscription grants such access.
FR7	Model Access (Student)	Students can access and use the AI models for training and educational purposes.
FR8	Educational Quizzes	Students can take quizzes related to dental AI concepts and model understanding.
FR9	Quiz Evaluation	The system evaluates student quiz submissions and calculates their scores automatically.
FR10	User Management (Admin)	Admins can manage all platform users, including creating, modifying, and deleting user accounts.
FR11	System Configuration	Admin users can configure global system settings and manage platform-wide behaviors and features.
FR12	Subscription Verification	Before granting access to premium features, the system must validate the user's subscription status.
FR13	Plan-Based Feature Control	Access to specific features is controlled based on the user's subscription plan (e.g., Free, Premium, Institutional).

3.1.2: Non-Functional Requirements:

Non-functional requirements define the system's quality attributes, focusing on performance, scalability, usability, security, reliability, and maintainability. These requirements ensure the platform is efficient, secure, and ready for real-world deployment.

Table 7: Non-Functional Requirements

(This table lists the non-functional requirements, specifying performance benchmarks, security measures, system usability, scalability, and reliability standards.)

ID	Requirement	Description
NFR1	Performance	Each AI model must produce a prediction within a maximum of 5 seconds per image.
NFR2	Concurrent User Support	The platform must handle at least 100 concurrent users without significant performance loss.
NFR3	Secure Authentication	All protected APIs must require a valid JWT token to ensure secure communication and authorization.
NFR4	Password Protection	User passwords must be securely hashed and stored using industry-recognized encryption algorithms (e.g., bcrypt).
NFR5	Role-Based Access	Access control must be strictly enforced according to user roles across all modules.
NFR6	User Interface Usability	The user interface should be intuitive and user-friendly, especially for non-technical users such as students or clinicians.
NFR7	System Expandability	The architecture must support future extensions, including features like multi-clinic support or external integrations.
NFR8	Uptime Guarantee	The system must be highly available, ensuring 99.9% uptime to minimize service interruptions.
NFR9	Backup and Recovery	Automated, regular data backups must be scheduled to prevent data loss and allow quick recovery in the event of failure.
NFR10	Activity Logging	All critical system operations and user actions must be logged for audit, debugging, and system monitoring.
NFR11	Modular Architecture	The backend should follow a modular architecture, allowing individual components to be maintained and updated independently.

3.2 System Architecture

This system architecture represents an AI-powered dental analysis platform, structured into three primary layers: Frontend, Backend, and AI Models. Each layer has distinct roles and interacts with the other layers to facilitate the analysis of dental X-ray images. Below is a breakdown of each component and its interactions in detail.

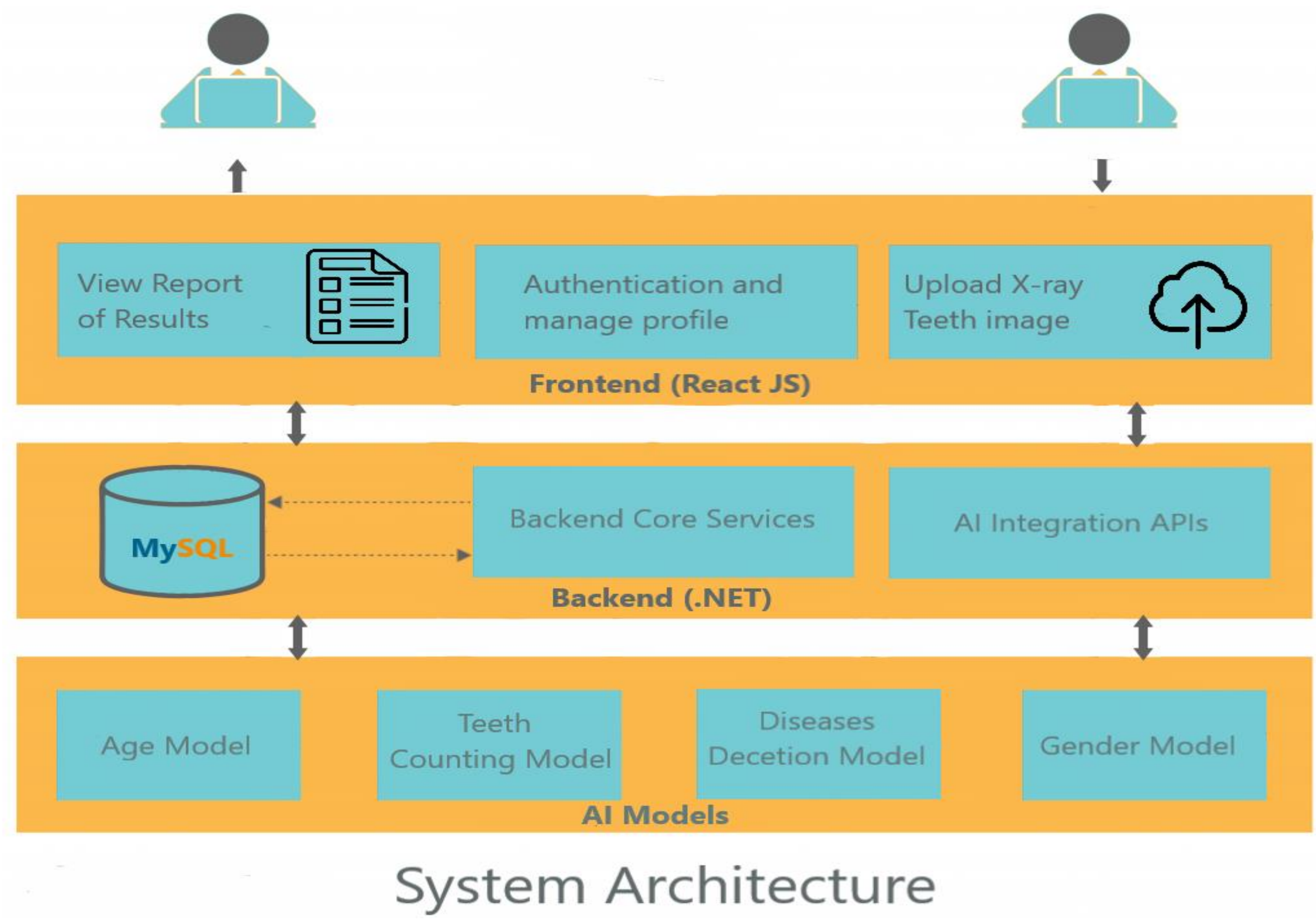


Figure 3. System Architecture

🖥 1. Frontend Layer (React.js)

The frontend provides a responsive and intuitive user interface built with React.js.
It enables users to securely interact with the backend services, manage their accounts, and access AI-powered tools.
JWT tokens are used for secure session management, ensuring protected routes based on user roles.
The interface is optimized for usability and supports doctors, students, and admin-specific views.

✅ **Functions:**

- Secure login, logout, and registration
- Upload panoramic dental X-ray images
- Display AI results: age, gender, teeth count, disease detection
- Form-based creation and editing of patient profiles
- Conduct and submit quizzes
- Export diagnostic reports (PDF for doctors)
- View notification and system alerts

🧩 **Features:**

- JWT Authentication for secure access to backend APIs
- Role-Based Access Control – UI adjusts based on Admin, Doctor, or Student role
- Dynamic Result Rendering – Visual display of AI predictions per scan
- History Tracking – Doctors can browse patient diagnosis history
- Subscription Awareness – Features enabled or restricted based on user plan
- Quiz Interface – Students can take and submit educational quizzes
- Notification Display – Users see alerts and system messages in real time
- Responsive Layout – Cross-device compatible UI for clinics and students
- User-Friendly UX – Clean layout and form validation for non-technical users

🛠️ 2. Backend Layer (.NET & SQL Server)

The backend is built using .NET Core and acts as the core engine of the system.
It handles authentication, data processing, communication with AI models, and ensures role-based access control.
All endpoints are protected using JWT, and operations are logged for auditing and security.
SQL Server is used for structured data storage with entity relationships and indexing for performance.

✅ **Components:**

- Authentication & Authorization: Secure login, role assignment, token generation
- AI Integration APIs: Handle requests for gender, age, disease, and teeth predictions
- RESTful Endpoints: Organized by features (e.g., quiz, patient, plan, medical history)
- User Role Management: Admin, Doctor, and Student access enforcement
- Subscription Validation: Checks expiration, plan limits, and premium access
- Export Engine: PDF generation for doctors' reports

🔗 **Communication & Logic:**

- Routes image uploads to AI services (TensorFlow Serving)
- Stores AI predictions in the database
- Supports asynchronous processing to minimize response times
- Applies encryption (bcrypt) to user credentials
- Modular architecture for future scalability

🧠 3. AI Models Layer

This layer contains all deep learning models used for intelligent analysis of dental X-ray images.
It is hosted independently via TensorFlow Serving with support for GPU acceleration.
The models perform classification, detection, and segmentation tasks on user-uploaded images.
Input and output are exchanged with the backend via RESTful endpoints.

✅ **Models Implemented:**

- Age Group Detection: CNN-based classification (VGG16, DenseNet121, InceptionV3)
- Gender Classification: CNN-based binary classifier (VGG16, DenseNet121, InceptionV3)
- Teeth Counting: Object detection via YOLOv8
- Disease Detection: Instance segmentation and object detection via YOLOv8-seg

⚙️ **Deployment & Integration:**

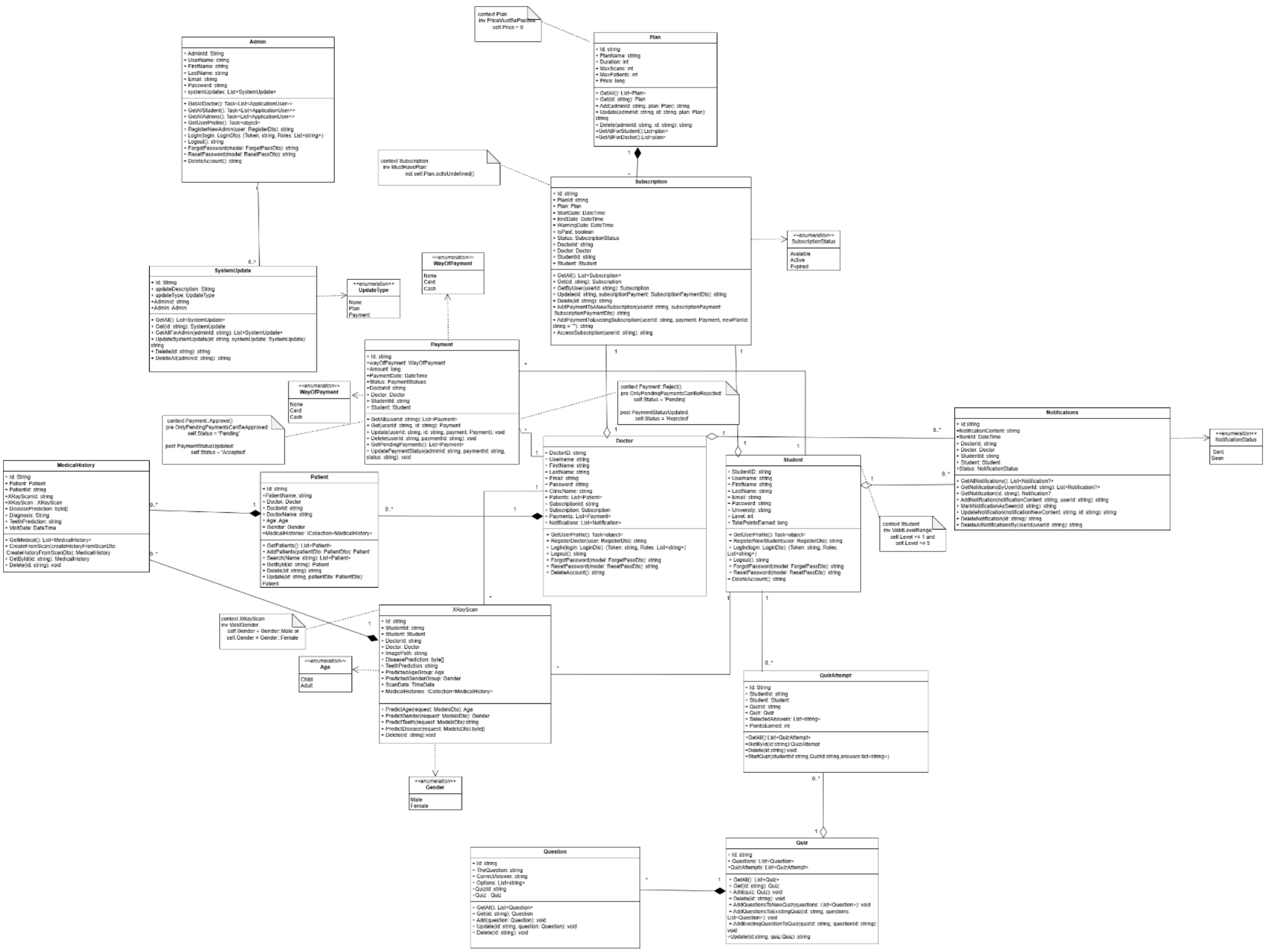
- Served using Hugging Face Spaces for quick responses
- Powered by pretrained CNNs with transfer learning due to limited dataset size
- Input: Preprocessed 224×224 (or 640×640) dental X-ray images
- Output: JSON response with predictions, probabilities, and bounding boxes/masks
- Robust to image noise due to preprocessing: normalization, contrast, augmentation

3.3 UML Diagrams

This section presents the Unified Modeling Language (UML) diagrams used to visualize the structure, behavior, and flow of the system. These diagrams provide a clear representation of how components interact and how data flows. They are essential for understanding the system's architecture, logic, and user interactions.

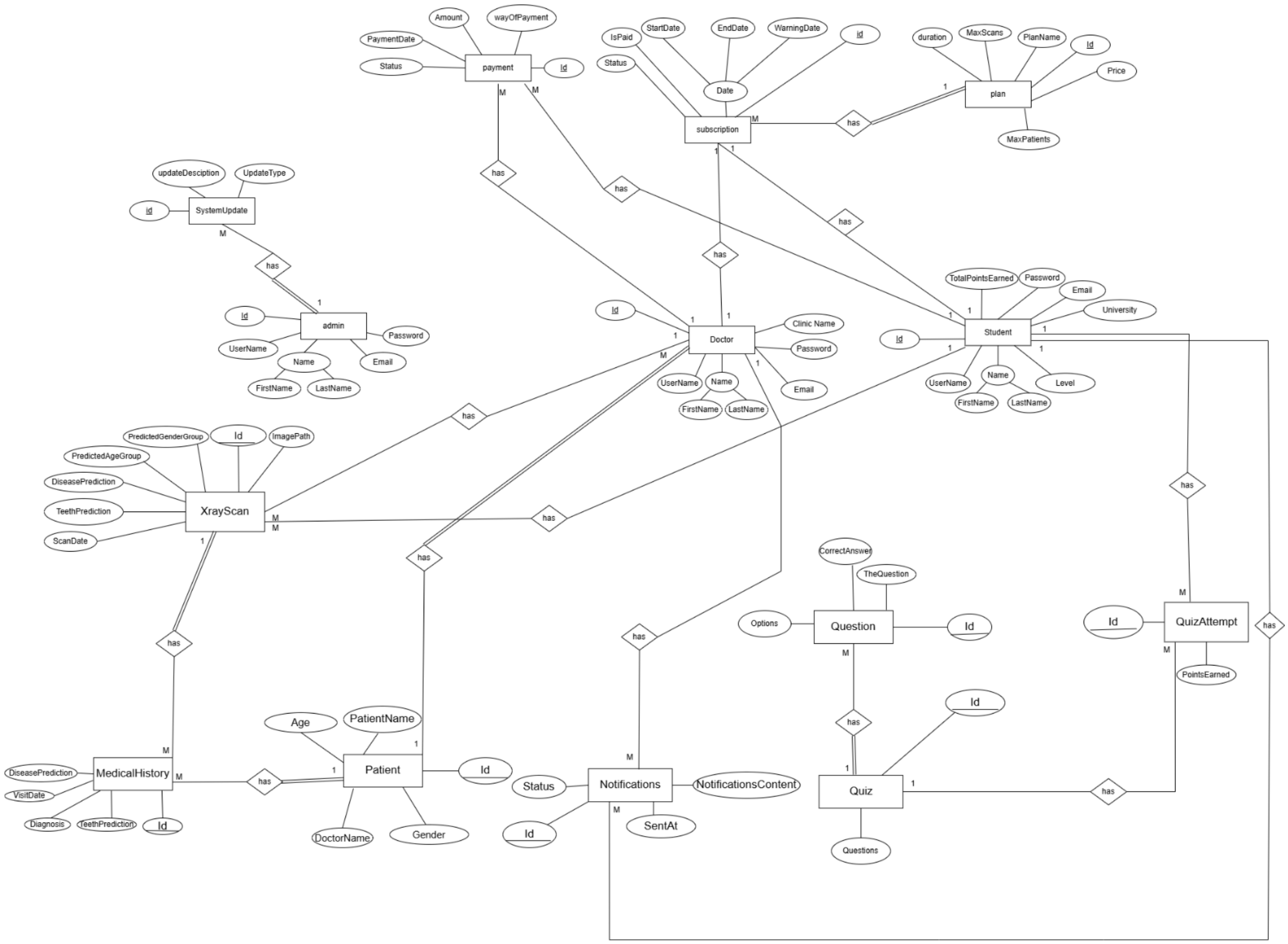
1. Class Diagram and OCL

Illustrates the system's main classes, attributes, and methods and the Constrains of the System.
Shows the relationships between backend entities like Users, Plans, and Scans.



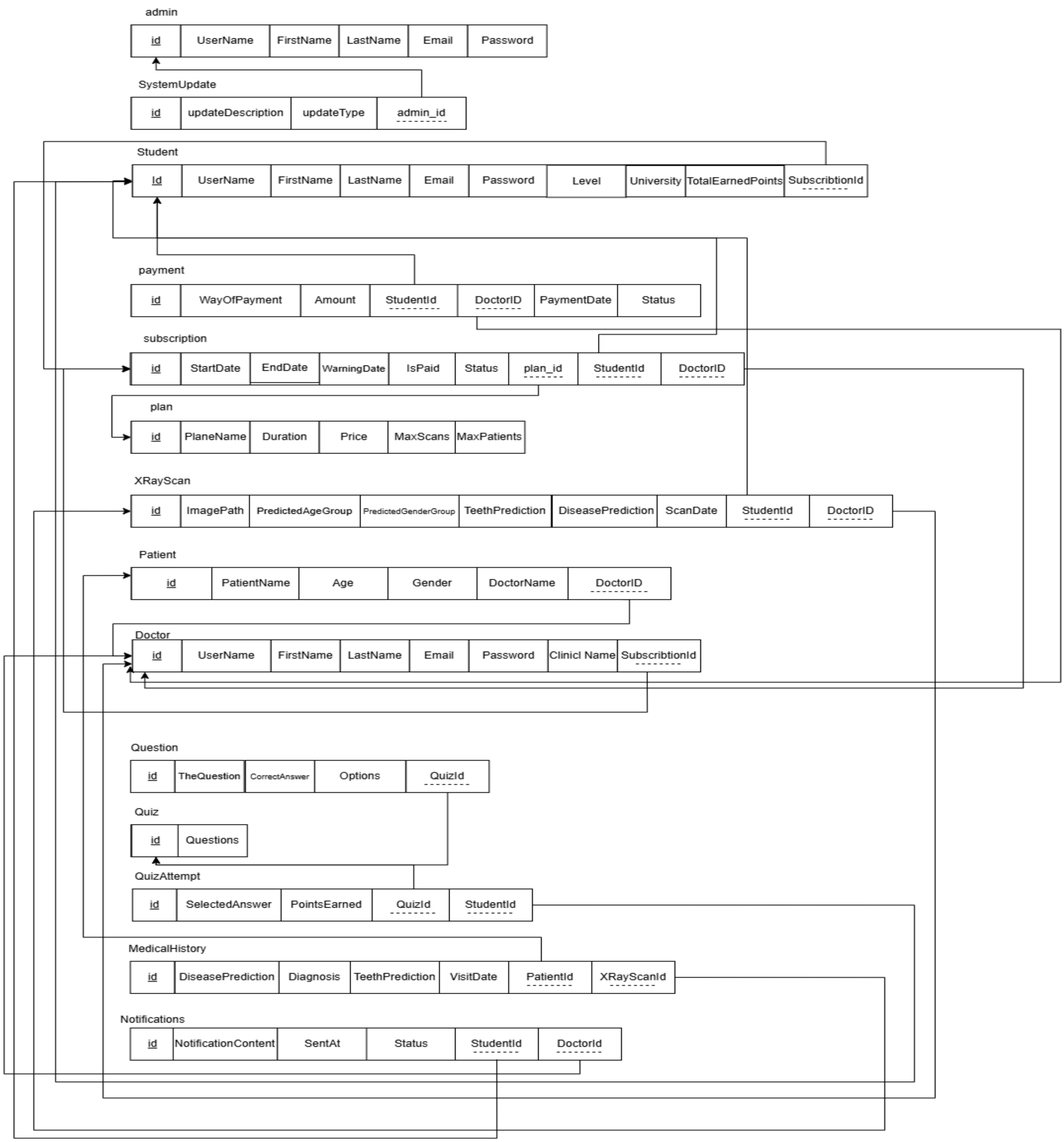
2. ERD Diagram

Represents the logical structure of the database.
Displays entities, primary keys, and relationships such as one-to-many and many-to-many.



3. Database Schema

Shows the physical table structures and columns.
Provides technical detail for implementation including data types and foreign keys.

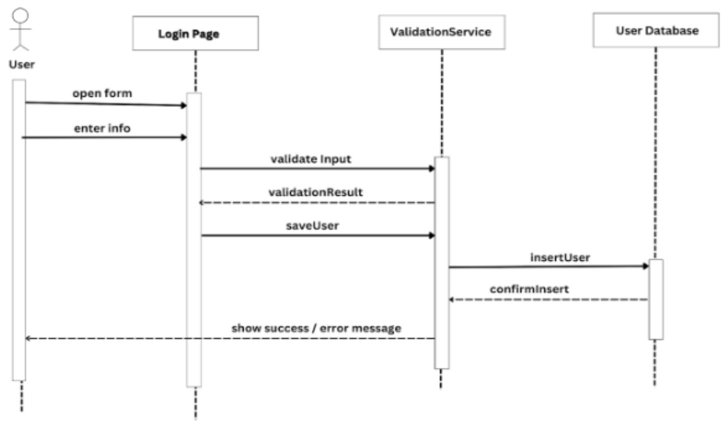


4. Sequence Diagram

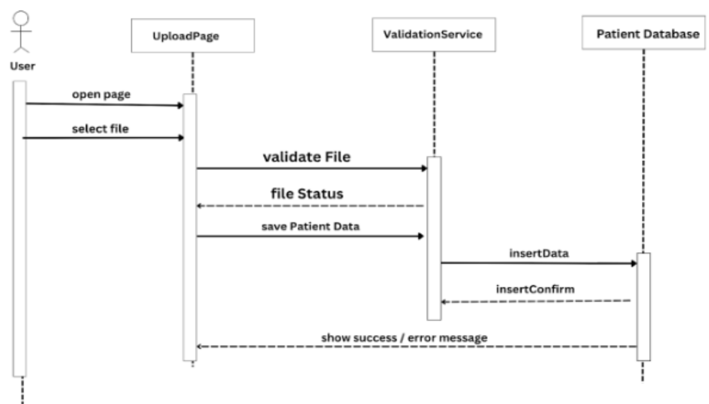
Describes the step-by-step interaction between system components.
Visualizes how data flows from the user to AI models and back as results.

The Following Sequence diagram for each Use-Case:

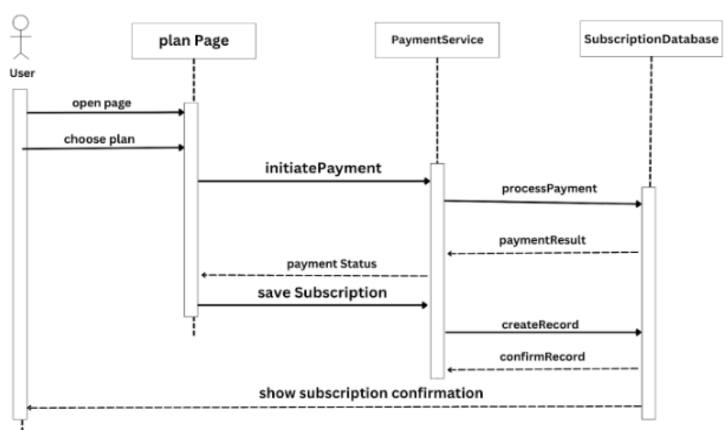
Sign Up for student & doctors



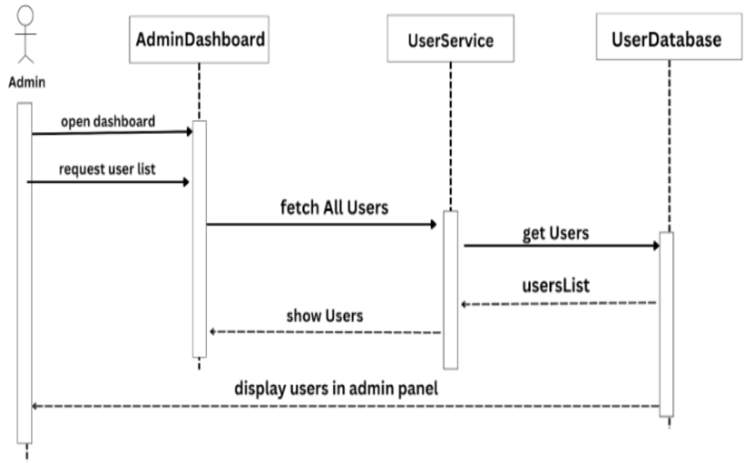
Upload Patient Data



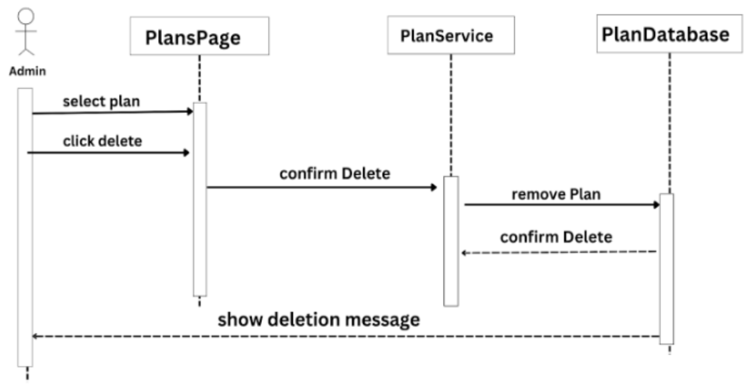
Subscribe to Plan



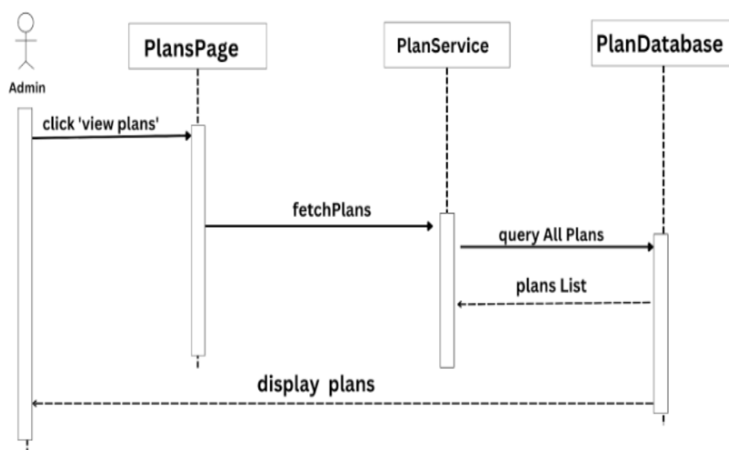
mange all users



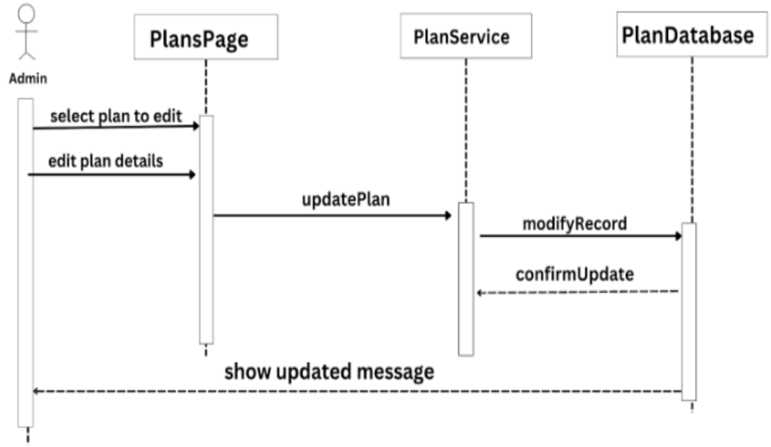
Delete Plan for admin



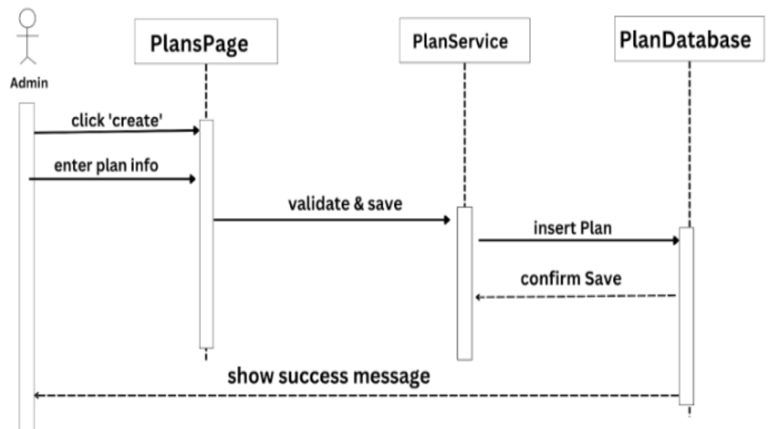
View Plans for admin



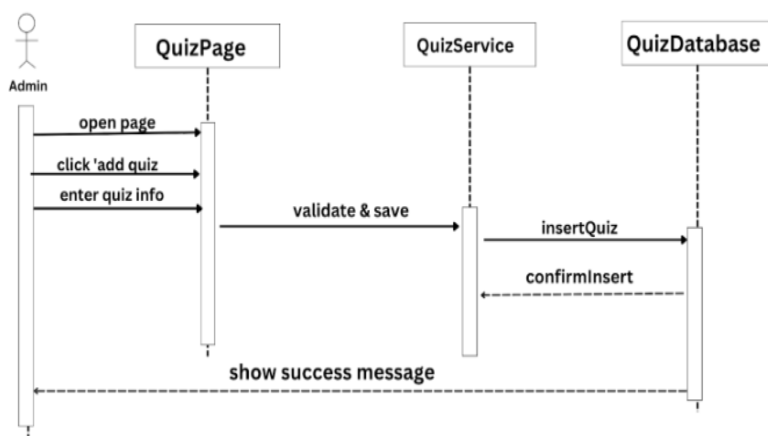
Update Plan for admin



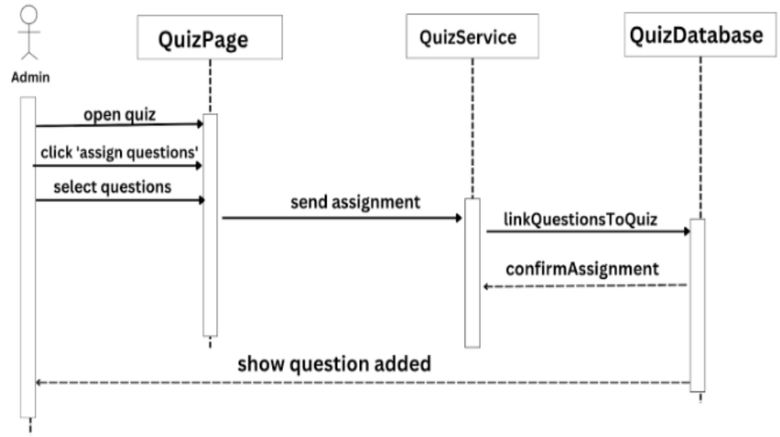
Create Plan for admin



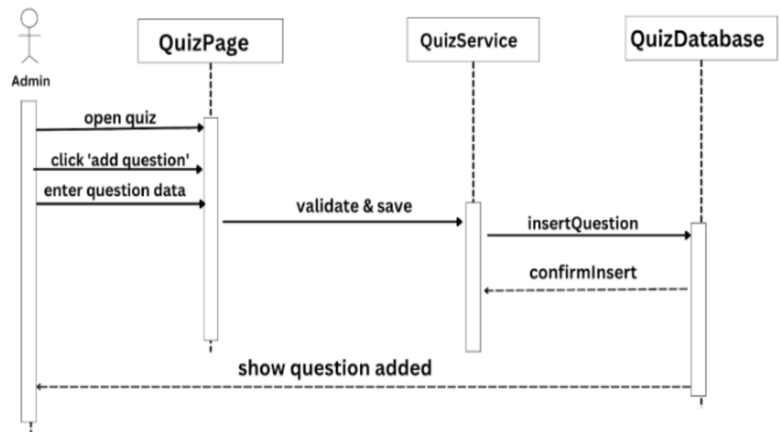
Add Quiz



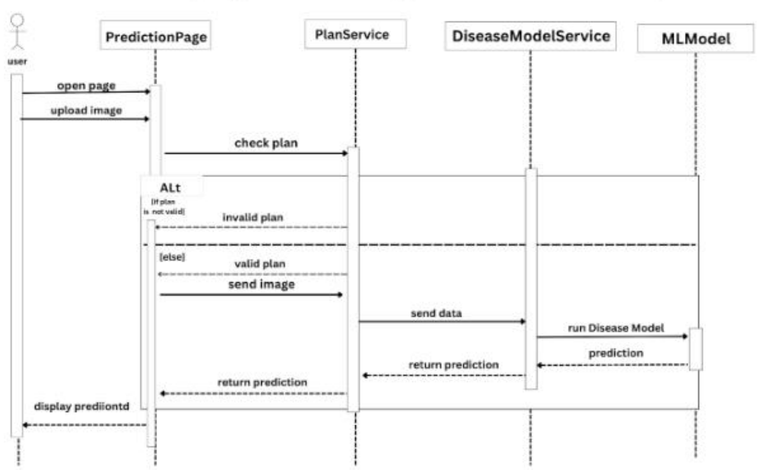
Assign Questions to Quiz



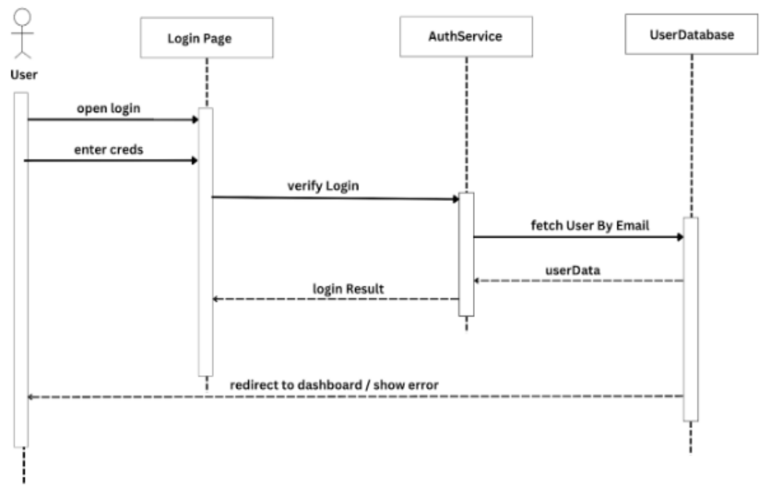
Add Question



Predict (Age- teeth - gender -Diseases)



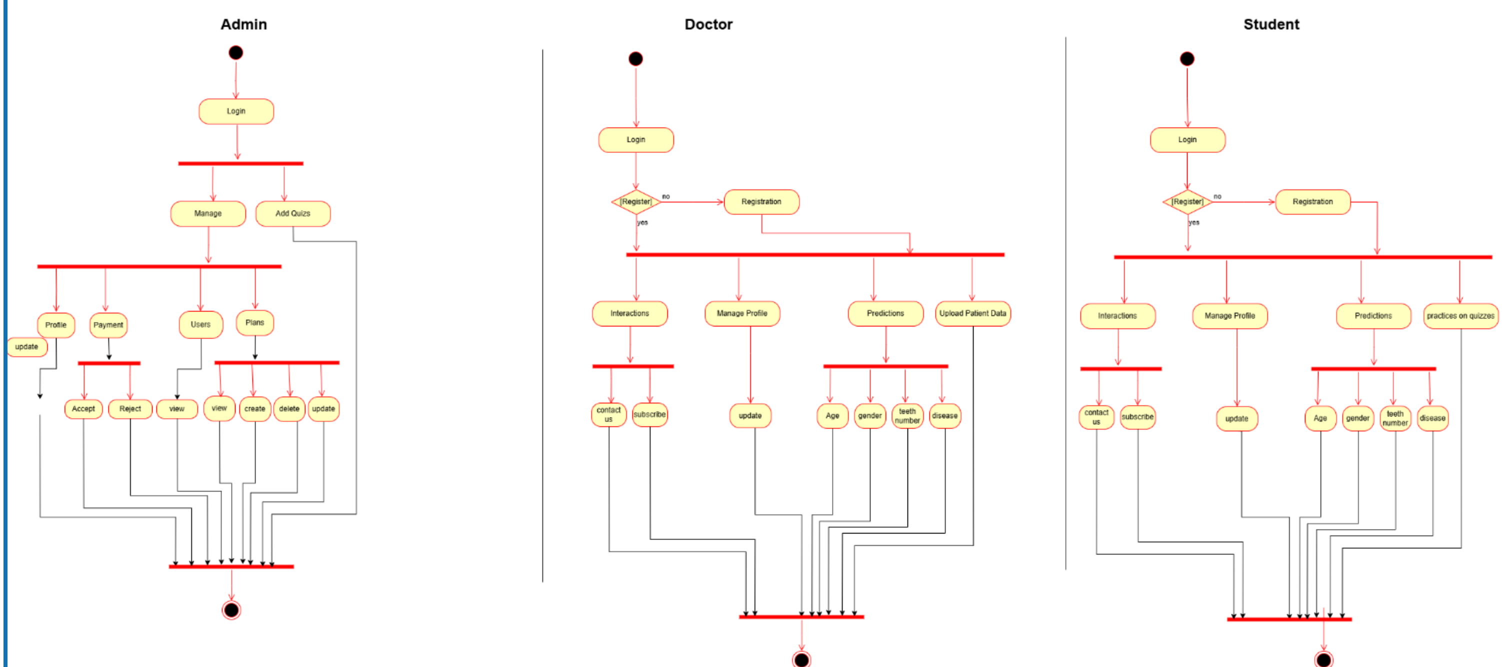
Login for Admin &student & doctors



5. Activity Diagram

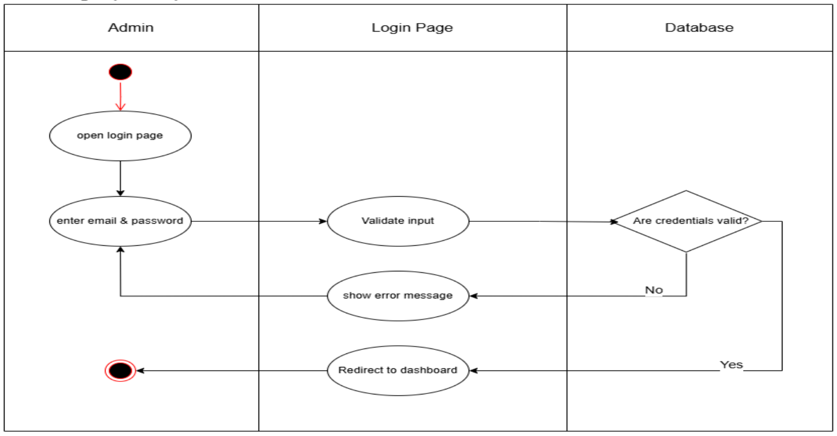
Represents the workflow of system activities and decision paths.
Demonstrates processes such as model execution and user authentication.

General for All Users:

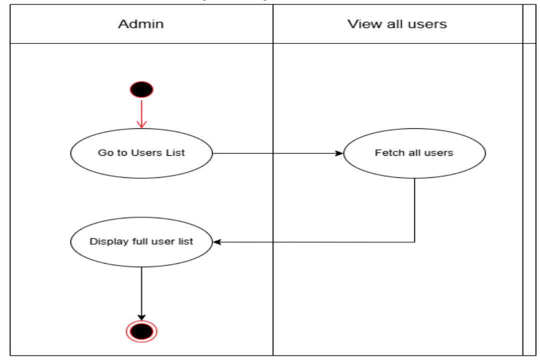


For Admin Use-Cases:

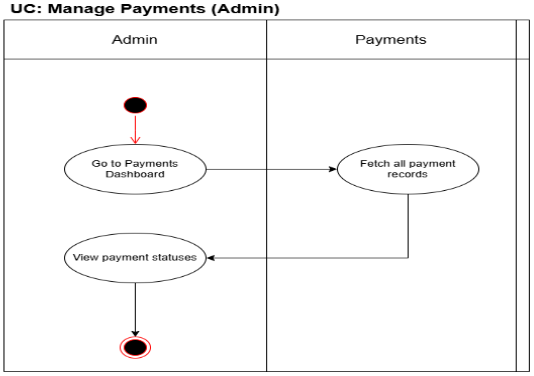
UC: Login (Admin)



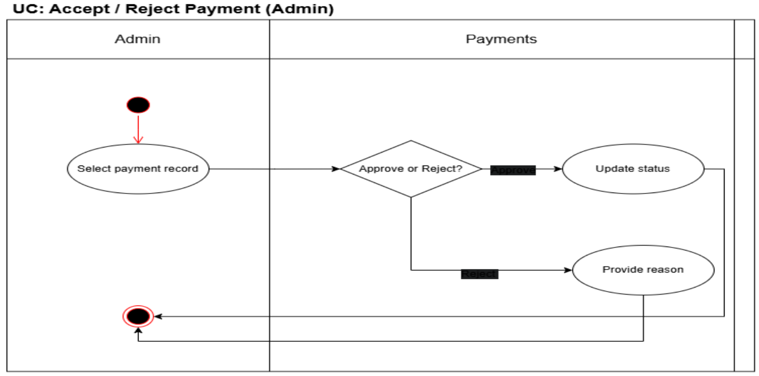
UC: View All Users (Admin)



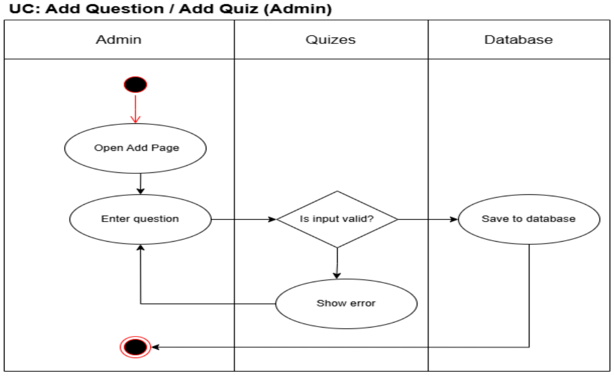
UC: Manage Payments (Admin)



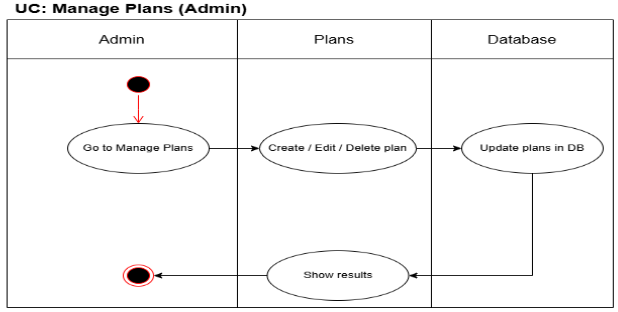
UC: Accept / Reject Payment (Admin)



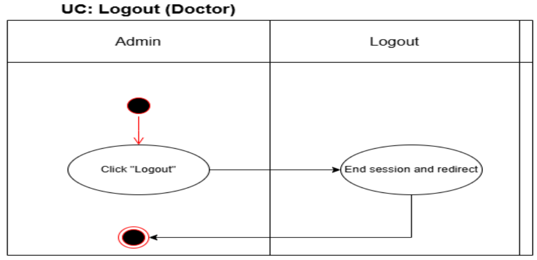
UC: Add Question / Add Quiz (Admin)



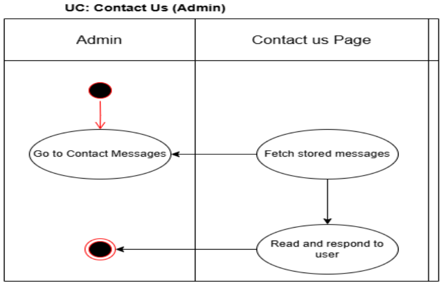
UC: Manage Plans (Admin)



UC: Logout (Doctor)

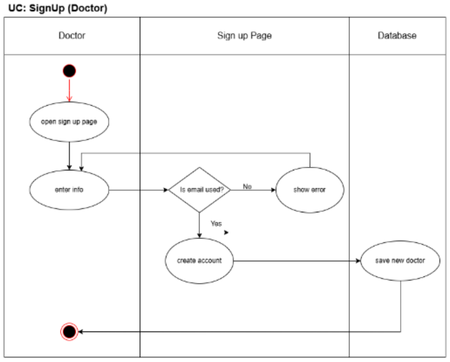


UC: Contact Us (Admin)

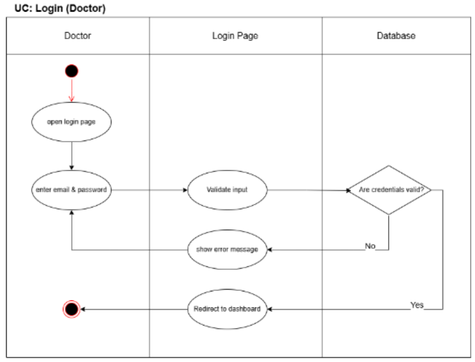


For Doctor Use-Cases:

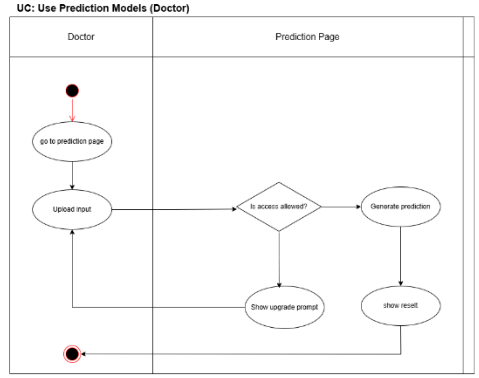
UC: SignUp (Doctor)



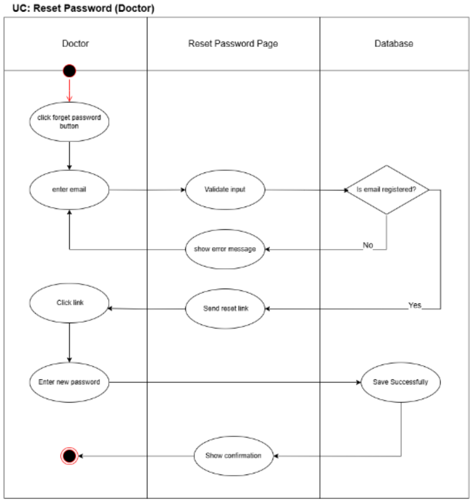
UC: Login (Doctor)



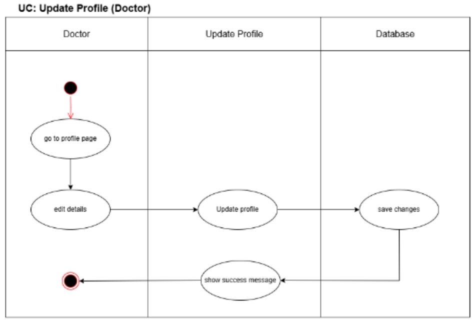
UC: Use Prediction Models (Doctor)



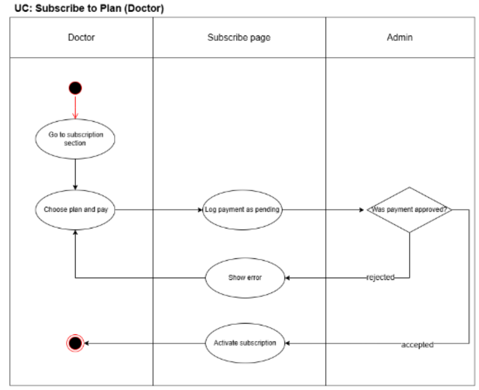
UC: Reset Password (Doctor)



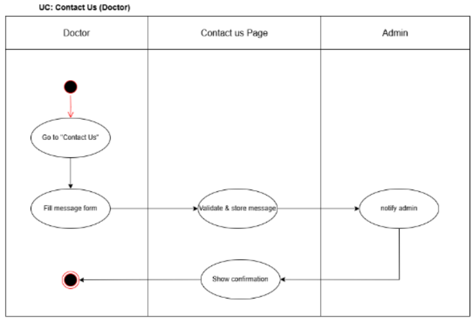
UC: Update Profile (Doctor)



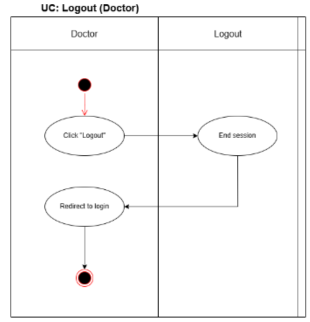
UC: Subscribe to Plan (Doctor)



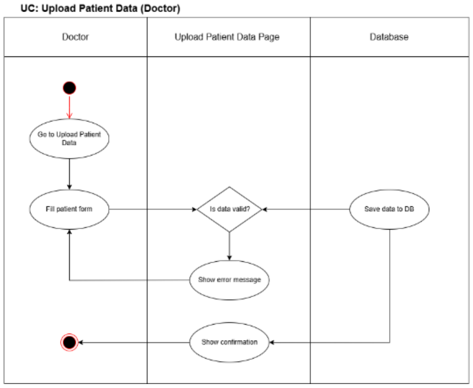
UC: Contact Us (Doctor)



UC: Logout (Doctor)

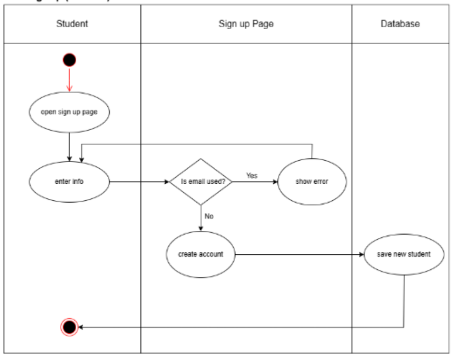


UC: Upload Patient Data (Doctor)

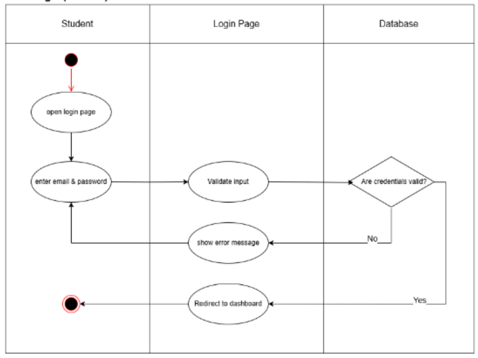


For Students Use-Cases:

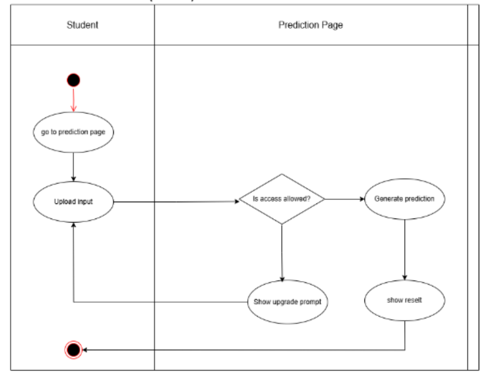
UC: SignUp (Student)



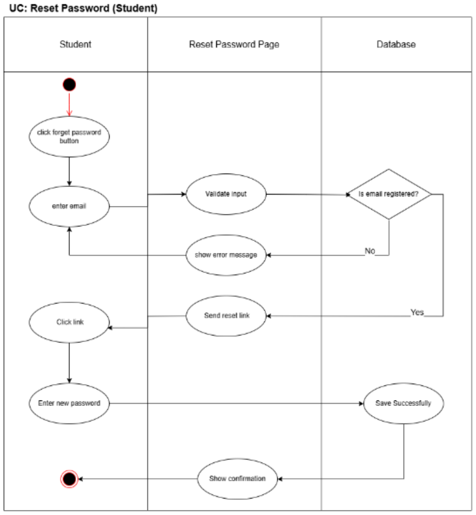
UC: Login (Student)



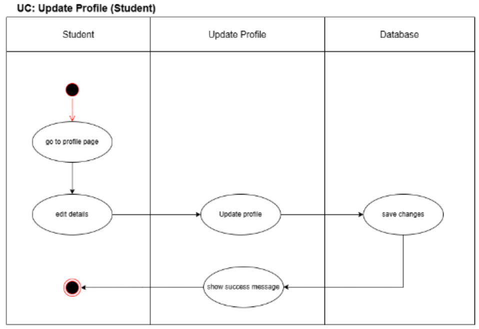
UC: Use Prediction Models (Student)



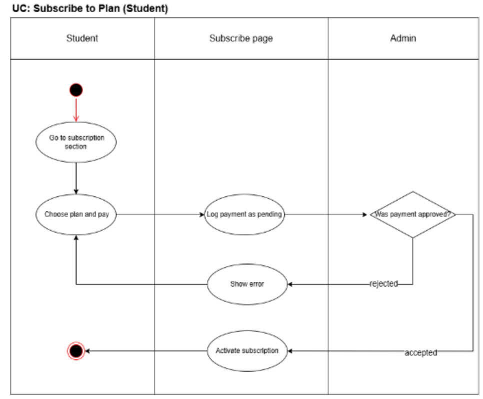
UC: Reset Password (Student)



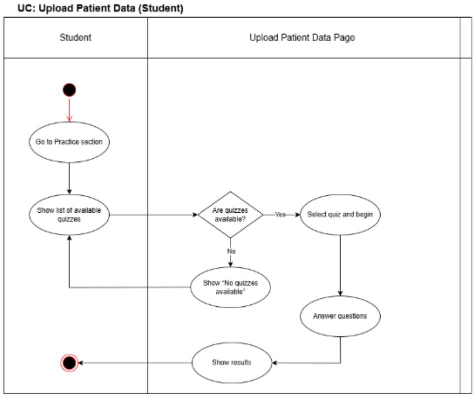
UC: Update Profile (Student)



UC: Subscribe to Plan (Student)

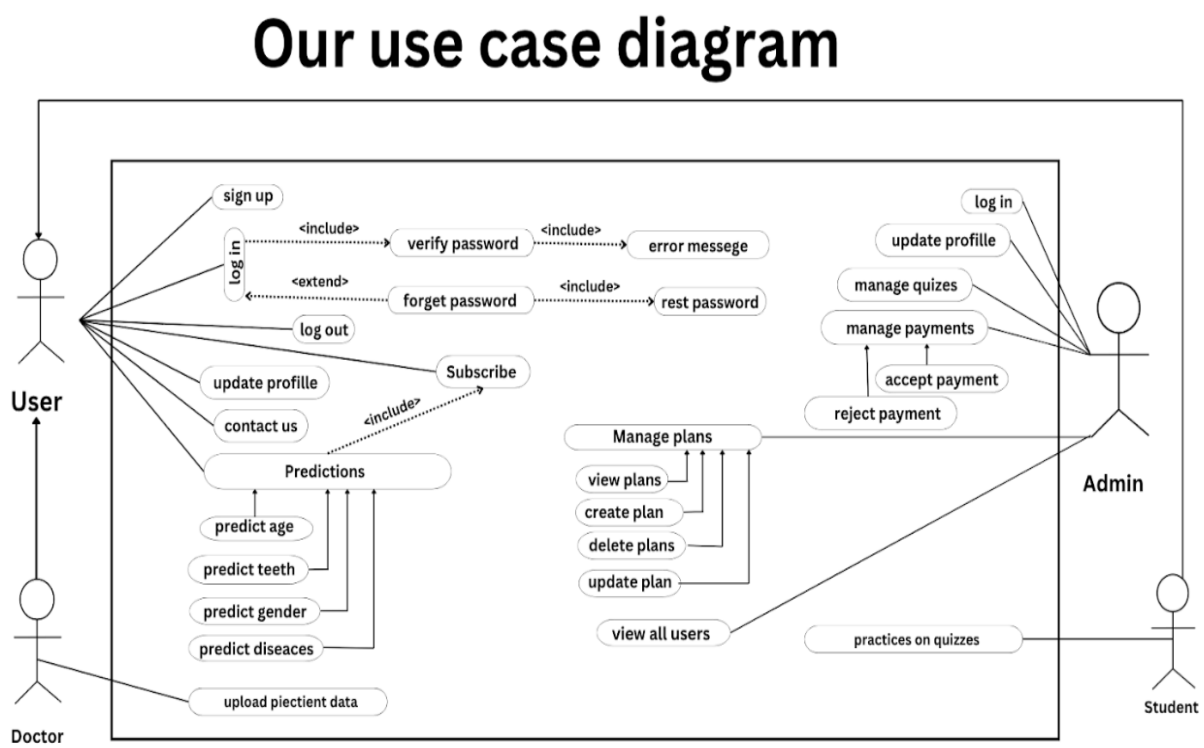


UC: Upload Patient Data (Student)



6. Use-Case Diagram

Outlines the main functionalities available to different user roles.
Highlights how Admins, Doctors, and Students interact with the system.



7. Use-Case Description

Provides detailed descriptions of each system use-case.
Includes preconditions, Postconditions Main Flow, and Alternate Flows for user actions.

The Following Description for each Use-Case:

UC: Sign Up

Actors	New User (Doctor or Student)
Description	Allows a new user to create an account in the system by providing the required information.
Preconditions	The user is not already registered. The user has access to the Sign-Up page.
Main Flow	The user navigates to the Sign-Up page. The user selects their role (Doctor or Student). The user enters the required information (e.g., name, email, password). The system validates the input. The system creates a new user account. The system sends a confirmation message or redirects to the login page.
Alternate Flows	If any input is missing or invalid: the system shows error messages and prevents registration. If the email is already registered: the system notifies the user.
Postconditions	A new user account is created and stored in the system.

UC: Login

Actors	Registered User (Doctor, Student, or Admin)
Description	Allows a registered user to log into the system using valid credentials.
Preconditions	The user has an existing account.
Main Flow	The user navigates to the login page. The user enters email and password. The system validates the credentials. If valid, system logs in the user and redirects them to their dashboard.
Alternate Flows	If credentials are incorrect: system displays an error and prompts the user to try again. If the account is disabled: access is denied and user is notified.
Postconditions	User is authenticated and has access to their account features

UC: Logout

Actors	Logged-in User (Doctor, Student, or Admin)
Description	Allows a user to safely log out from the system.
Preconditions	User is logged in.
Main Flow	User clicks the "Logout" button or link. System ends the user's session. System redirects to the homepage or login screen.
Alternate Flows	None.
Postconditions	User is logged out and their session is terminated.

UC: Reset Password

Actors	Registered User
Description	Allows a user to reset their password if they forget it.
Preconditions	User has a registered email address.
Main Flow	User clicks on "Forgot Password." System prompts for the email address. User enters the email. System sends a password reset link/code. User clicks the link or enters the code. User enters a new password. System updates the password and confirms the change.
Alternate Flows	If the email is not found: system notifies the user. If the code/link is invalid or expired: system prompts to retry the process.
Postconditions	User's password is successfully updated.

UC: Update Profile

Actors	Logged-in User (Doctor or Student)
Description	Allows the user to update their personal information like name, email, or password.
Preconditions	User is logged in.
Main Flow	User navigates to “Profile Settings.” User edits the desired fields. User submits the changes. System validates the input. System updates the user’s profile.
Alternate Flows	If input is invalid: system shows error and prevents update. If email is already used by another account: system notifies the user.
Postconditions	User's profile information is updated in the system.

UC: Use Prediction Models

Actors	Doctor, Student
Description	Allows doctors and students to access AI models for predicting age, teeth condition, gender, and disease. Access depends on the user's subscription plan.
Preconditions	User is logged in. User has an active subscription approved by Admin.
Main Flow	User navigates to the “Prediction Models” section. User selects the type of prediction: Age, Teeth, Gender, or Disease. User uploads the required input (e.g., image). System processes the input and generates the prediction. Prediction result is displayed to the user. If the user is a student: one usage is deducted from their quota.
Alternate Flows	If the user exceeds their quota: system blocks access and prompts for upgrade. If input is invalid: system shows an error message.
Postconditions	User receives prediction results. Usage count is updated.

UC: Subscribe

Actors	Doctor, Student
Description	Allows users to subscribe to a plan, make payment, and await admin approval.
Preconditions	User is logged in. User does not already have an active subscription.
Main Flow	User navigates to the subscription section. System displays available plans. User selects a plan. User makes payment. System marks the payment as pending. Admin reviews and approves or rejects the payment. If approved: Subscription is activated. Access is granted based on plan.
Alternate Flows	If payment fails: user sees an error and retries. If admin rejects: subscription remains inactive. If user cancels: no subscription is created.
Postconditions	User has an active, approved subscription. Access to features is granted.

UC: Upload Patient Data

Actors	Doctor
Description	Allows doctors to upload and manage patient data.
Preconditions	Doctor is logged in. Doctor has an approved subscription.
Main Flow	Doctor navigates to the "Upload Patient Data" section. Doctor fills in patient details or uploads a file. Doctor submits the data. System validates and saves the data. Confirmation is shown.
Alternate Flows	If data is invalid: system shows error and cancels upload. If doctor cancels: no data is saved.
Postconditions	Patient data is saved and linked to the doctor's account.

UC: Manage Subscription

Actors	Doctor, Student, Admin
Description	Allows users to subscribe to services and admins to approve them.
Preconditions	User is logged in. Valid subscription plans exist.
Main Flow	User selects a subscription plan. Makes payment. System logs payment as pending. Admin reviews and approves. If approved: Doctor: gets access to models + upload. Student: gets model access based on limits.
Alternate Flows	Payment fails: subscription is canceled. Admin rejects: subscription stays inactive. User cancels: process is aborted.
Postconditions	Subscription is active after payment and approval.

UC: Manage Payments

Actors	Admin
Description	Admin oversees payment transactions.
Preconditions	Admin is logged in.
Main Flow	Admin opens payments dashboard. Views pending, accepted, and rejected payments. Takes action on pending payments.
Alternate Flows	Invalid payment ID: system shows error.
Postconditions	Payment status is updated.

UC: Accept Payment

Actors	Admin
Description	Admin accepts a pending payment.
Preconditions	Payment is pending.
Main Flow	Admin selects a pending payment. Clicks 'Accept'. System updates status.
Alternate Flows	If payment already processed: system warns admin.
Postconditions	Payment is marked as 'Accepted'.

UC: Reject Payment

Actors	Admin
Description	Admin rejects a pending payment.
Preconditions	Payment is pending.
Main Flow	Admin selects a pending payment. Clicks 'Reject'. System updates status.
Alternate Flows	If no rejection reason: system prompts admin.
Postconditions	Payment is marked as 'Rejected'.

UC: View All Users

Actors	Admin
Description	Admin can view a list of all registered users.
Preconditions	Admin is logged in.
Main Flow	Admin opens the user list page. System fetches and displays all users.
Alternate Flows	No users found: display message.
Postconditions	Admin can view/manage users.

UC: Practice on Quizzes

Actors	Student
Description	Allows students to practice quizzes.
Preconditions	Student is logged in.
Main Flow	Student selects 'Practice on Quizzes'. System shows available quizzes. Student selects and completes a quiz. System shows feedback.
Alternate Flows	No quizzes available: display message.
Postconditions	Quiz attempt is recorded.

UC: Add Question

Actors	Admin
Description	Allows admin to add new questions.
Preconditions	Admin is logged in.
Main Flow	Admin opens 'Add Question' page. Enters question details. Submits the form. System validates and stores it.
Alternate Flows	Validation fails: system shows error. Admin cancels: no question is added.
Postconditions	New question is added to database.

UC: Add Quiz

Actors	Admin
Description	Enables the admin to create and schedule quizzes.
Preconditions	Admin is logged in. Questions exist in the database.
Main Flow	Admin opens 'Create Quiz' page. Selects questions. Sets quiz settings. Submits the quiz. System saves the quiz.
Alternate Flows	No questions selected: prompt admin. System error: quiz creation aborted.
Postconditions	New quiz is saved and scheduled.

UC: Contact Us

Actors	User
Description	Allows users to send messages to the support team.
Preconditions	User is logged in.
Main Flow	User selects 'Contact Us'. Fills in the form. Submits the message. System stores/sends it. Confirmation is shown.
Alternate Flows	Required field is empty: error is shown.
Postconditions	Message is sent to the support team.

UC: About Us

Actors	Any visitor
Description	Displays information about the platform or team.
Preconditions	None
Main Flow	Visitor selects 'About Us'. System displays the informational page.
Alternate Flows	None
Postconditions	None

Chapter 4

[Model Development, Implementation, and Comparative Analysis]

Chapter 4 provides the tools used and a comprehensive overview of the proposed models and their implementation. It begins with the methodology behind selecting suitable models for each task. The architectures of the selected models are described in detail. It then presents the performance and results of models developed for gender detection, age estimation, tooth identification and numbering and teeth disease classification. Finally, it includes the best results of each task and comparative study

4.1 Tools Used

Programming Language

Python: The primary programming language used for implementing the AI models, data preprocessing, and evaluation. Python is widely used in the AI community due to its simplicity and the availability of numerous libraries and frameworks.

Development Environments Used

- Google Colab
- Kaggle

Python Packages

The project utilizes several deep learning libraries for model training and deployment:

- keras
- numpy
- cv2
- seaborn
- matplotlib
- tensorflow
- pathlib
- os
- pandas
- ultralytics (YOLO)
- shutil
- albumentations
- glob
- Hugging Face

Hardware Configurations

- GPU: The training process was accelerated using GPUs available on Google Colab : NVIDIA Tesla T4 GPU used are essential for deep learning tasks due to their ability to perform parallel computations, significantly reducing training time.
- CPU: Intel Xeon Processor (Google Colab) Used for tasks that do not require parallel processing, such as data preprocessing and evaluation.
- RAM: The amount of RAM available on Google Colab was sufficient for handling the dataset and model training. Google Colab typically provides around 12GB of RAM for free users.
- Storage: Google Drive and Kaggle datasets were used for dataset storage and management

Models Used

- Gender/Age Models: VGG19, DenseNet121 , InveptionV3
- Tooth Models: YOLOv8s (counting)
- Disease Models : YOLOv8-seg (disease masks)

4.2 Model Selection Methodology

In this section, we describe the methodology used for selecting deep learning models for our AI-powered dental analysis system. The selection process was based on factors such as model accuracy, computational efficiency, and their ability to generalize well to X-ray image data. Given the nature of our project, which involves different classification and object detection tasks, we chose a combination of convolutional neural networks (CNNs) and YOLO (You Only Look Once) architectures for efficient feature extraction and localization.

1. Model Selection Criteria

For each task in our project, we carefully evaluated potential deep learning architectures based on the following criteria:

1. Performance on Medical Imaging Tasks – The selected models have a proven track record in analyzing radiographic images, ensuring they work effectively with X-ray data.
2. Feature Extraction Capability – Since dental X-rays contain subtle features, we prioritized models that excel in extracting fine details.
3. Computational Efficiency – Considering the web-based deployment, we balanced accuracy with inference speed to ensure real-time processing.
4. Robustness to Noise and Variations – X-ray images may have variations due to equipment differences, patient positioning, and image quality; thus, we chose models that generalize well across different datasets.
5. Pretrained Weights and Transfer Learning – To leverage existing knowledge, we selected models that

allow fine-tuning with pre-trained weights from large-scale image datasets (e.g., ImageNet).

2. Model Selection for Each Task

2.1 Gender Detection Model

Task: Classify an input X-ray image as either male or female based on dental characteristics.

Selected Models:

- VGG16 – A widely used CNN architecture known for its simple yet effective deep layers, making it suitable for classification tasks.
- DenseNet121 – Uses feature reuse to improve gradient flow and reduce overfitting, enhancing model performance on small datasets.
- InceptionV3 – Known for its multi-scale feature extraction capability, improving classification accuracy in complex images.

Reason for Selection:

- These models have been extensively used in medical imaging applications.
- They have a strong ability to learn distinguishing features from dental structures.
- The use of transfer learning allows us to fine-tune these models efficiently with a relatively small dataset.

2.2 Age Detection Model

Task: Classify a subject as either a child or an adult based on dental X-ray images.

Selected Models:

- VGG16
- DenseNet121
- InceptionV3

Reason for Selection:

- The same architectures were chosen as in the Gender Detection task because they work well for image classification.
- Teeth development patterns are key indicators of age, and these models are capable of learning such patterns effectively.
- DenseNet121 was included to improve information flow and feature reuse, which is helpful in differentiating between children's and adults' teeth structures.

2.3 Tooth Identification and Numbering Model

Task: Identify and number each tooth in the dental X-ray image.

Selected Model:

- YOLOv8s (You Only Look Once - Small Variant)

Reason for Selection:

- YOLOv8s is an object detection model, making it well-suited for detecting multiple objects (teeth) in a single image.
- It operates in real-time with high detection accuracy.
- Compared to Faster R-CNN, YOLO is much faster while maintaining good accuracy.
- The small variant (YOLOv8s) is chosen to balance accuracy and computational efficiency for web-based deployment.
- It can accurately detect all 32 teeth and classify them into incisors, canines, premolars, and molars.

2.4 Teeth Disease Detection Model

Task: Detect and segment dental diseases in X-ray images.

Selected Model:

- YOLOv8-Seg (YOLOv8 segmentation model)

Reason for Selection:

- Unlike standard object detection models, YOLOv8-Seg performs instance segmentation, allowing for precise localization of diseased areas in dental X-rays.
- It can detect multiple diseases (e.g., Caries, Gingivitis, Hypodontia, Mouth Ulcer, Tartar, Tooth Discoloration) in a single image.
- It is computationally efficient and suitable for real-time web-based inference.
- It provides disease heatmaps to highlight affected areas, improving interpretability for dentists and patients.

3. Justification for Model Choices

The combination of CNNs for classification tasks and YOLO models for object detection and segmentation ensures that our system delivers high accuracy, real-time performance, and robustness in dental X-ray analysis.

1. CNNs (VGG16, DenseNet121, InceptionV3)
    - Work well for classification-based tasks (gender and age detection).
    - Benefit from transfer learning, reducing training time and improving accuracy.

- Capture hierarchical features, making them suitable for identifying subtle differences in X-ray images.

2. YOLOv8s and YOLOv8-Seg
   - Efficient for object detection and segmentation (tooth identification and disease detection).
   - Fast inference, making them suitable for web-based applications.
   - Ability to detect multiple objects and segment diseased areas with high precision.

By carefully selecting models that are optimized for their respective tasks, we ensure that the AI system is scalable, efficient, and deployable in a real-world dental application.

4.3 Model Architectures

DenseNet-121: Detailed Explanation

Overview

DenseNet-121 is a convolutional neural network (CNN) architecture that belongs to the DenseNet (Densely Connected Convolutional Networks) family. It was introduced in the paper "Densely Connected Convolutional Networks" by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger in 2017. DenseNet-121 is particularly known for its efficiency in parameter usage and its ability to mitigate the vanishing gradient problem, making it a popular choice for image classification and other computer vision tasks.

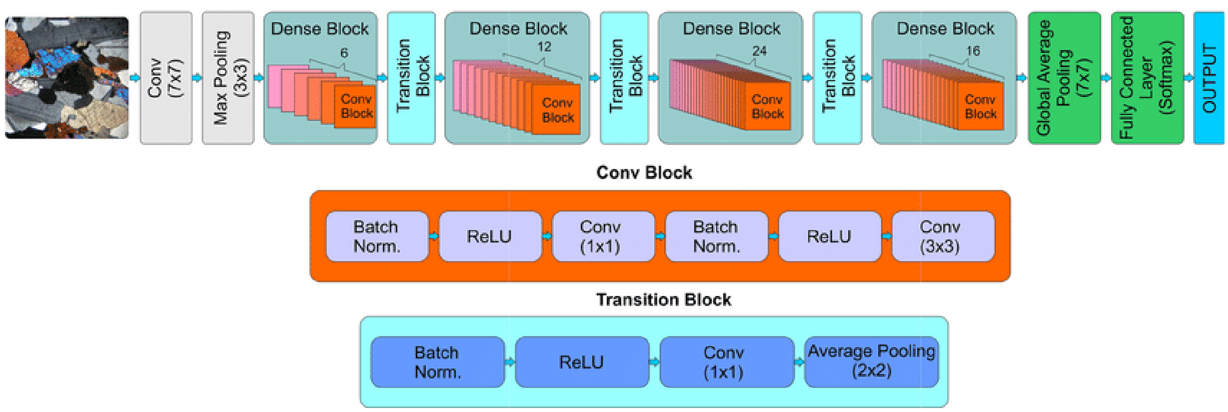


Figure 4: DenseNet-121 Architecture

Key Concepts

1. Dense Connectivity

The core idea behind DenseNet121 is dense connectivity. In traditional CNNs, each layer is connected only to the next layer. In DenseNet121, each layer is connected to every other layer in a feed-forward fashion. This means that the input to a layer is the concatenation of the feature maps of all preceding layers.

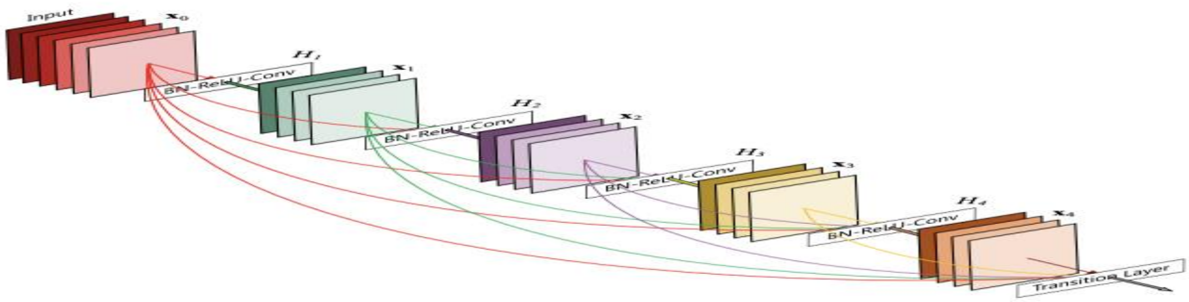


Figure 5: DenseNet Connectivity

2. Bottleneck Layers

To improve computational efficiency, DenseNet uses bottleneck layers. These are 1x1 convolutional layers that reduce the number of input feature maps before applying the 3x3 convolution. This reduces the computational cost while maintaining the network's performance.

- A typical bottleneck layer consists of:
  1. 1x1 convolution to reduce the number of channels.
  2. 3x3 convolution to extract spatial features.

3. Transition Layers

Transition layers are used to control the size of the feature maps and the number of channels They consist of:

1. 1x1 convolution to reduce the number of channels.
2. 2x2 average pooling to downsample the feature maps.

4. Growth Rate

The growth rate (k*k*) is a hyperparameter that determines how many new feature maps are produced by each layer. For example, if the growth rate is k=32*k*=32, each layer adds 32 feature maps to the network.

Architecture of DenseNet-121

DenseNet-121 is one of the variants of the DenseNet family, with 121 layers. The architecture is divided into dense blocks and transition layers.

1. Initial Layers

- Convolution: A 7x7 convolutional layer with stride 2 and padding 3 is applied to the input image.

- Pooling: A 3x3 max pooling layer with stride 2 is applied to reduce the spatial dimensions.

2. Dense Blocks

DenseNet-121 consists of 4 dense blocks. Each dense block contains multiple layers with dense connectivity. The number of layers in each dense block is as follows:

- Dense Block 1: 6 layers
- Dense Block 2: 12 layers
- Dense Block 3: 24 layers
- Dense Block 4: 16 layers

Each layer in a dense block performs the following operations:

1. Batch Normalization (BN)
2. ReLU activation
3. 1x1 convolution (bottleneck layer)
4. Batch Normalization (BN)
5. ReLU activation
6. 3x3 convolution

3. Transition Layers

After each dense block, a transition layer is applied to reduce the number of feature maps and downsample the spatial dimensions.

4. Classification Layer

- Global Average Pooling: A global average pooling layer is applied to reduce the dimensions to 1x1.
- Fully Connected Layer: A fully connected layer with softmax activation is used for classification.

Advantages of DenseNet-121

1. Parameter Efficiency: DenseNet-121 uses fewer parameters compared to other architectures like ResNet, as it reuses feature maps from previous layers.
2. Mitigates Vanishing Gradients: The dense connectivity ensures that gradients flow directly to earlier layers, reducing the vanishing gradient problem.
3. Feature Reuse: Concatenation of feature maps allows the network to reuse features effectively, improving performance.
4. Scalability: The growth rate allows the network to scale efficiently in terms of depth and width.

Applications of DenseNet-121

DenseNet-121 is widely used in computer vision tasks, including:

- Image classification (e.g., medical imaging, object recognition)
- Object detection

- Semantic segmentation
- Transfer learning (fine-tuning pre-trained models for specific tasks)

Example Use Case in Medical Imaging

DenseNet-121 is particularly useful in medical imaging tasks, such as:

- Chest X-ray classification: Identifying diseases like pneumonia or COVID-19.
- Teeth X-ray classification: Identifying Gender like male or female.
- Histopathology: Classifying cancer cells in tissue samples.

Its ability to learn robust features with fewer parameters makes it suitable for datasets with limited labeled examples

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VGG-16: Very Detailed Explanation

Overview of VGG16

VGG16 is a convolutional neural network (CNN) architecture introduced by the Visual Geometry Group (VGG) at the University of Oxford in the research paper *"Very Deep Convolutional Networks for Large-Scale Image Recognition"* by Karen Simonyan and Andrew Zisserman in 2014. It was one of the most influential CNN architectures and played a key role in advancing deep learning for image classification tasks.

VGG16 is known for its depth, simplicity, and uniformity, making it an ideal model for transfer learning and feature extraction. It was one of the top-performing models in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014, achieving high accuracy on large-scale image datasets.

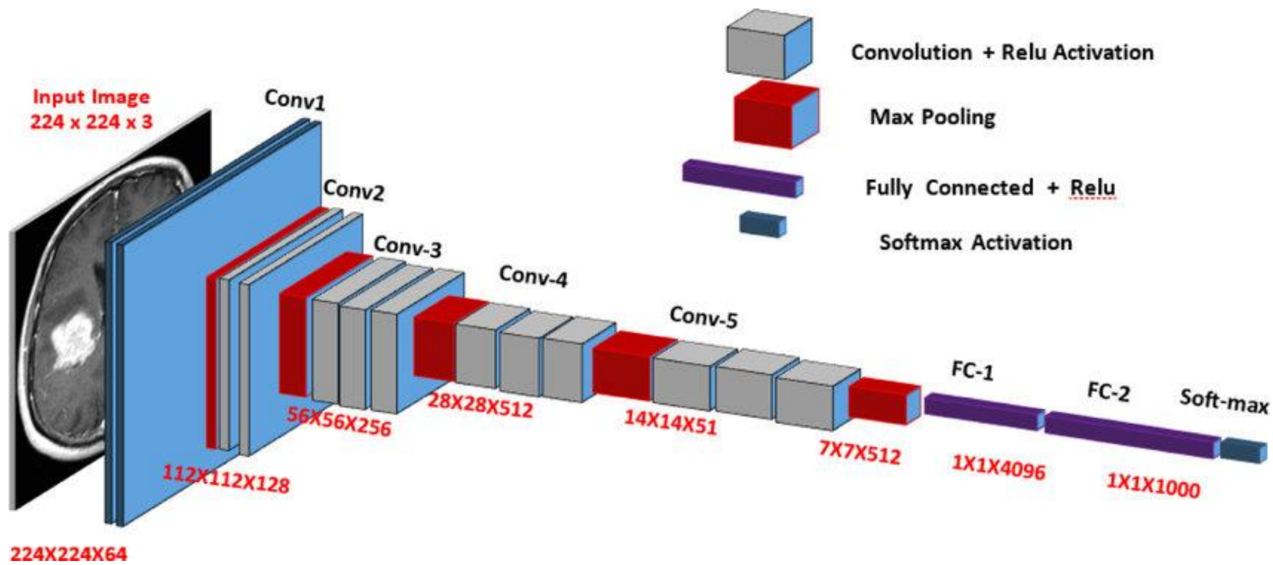


Figure 6: VGG16 Architecture

Key Concepts of VGG16

1. Uniform Architecture

- VGG16 follows a modular design, consisting of a series of convolutional layers, followed by max-pooling layers and fully connected layers.
- It exclusively uses 3×3 convolutional filters, which enables it to capture spatial features effectively while keeping the number of parameters manageable.

2. Depth

- VGG16 is a deep neural network with 16 weight layers (13 convolutional layers and 3 fully connected layers).
- This deep structure allows it to learn hierarchical features, starting from simple edges and textures in the early layers to complex structures and object parts in deeper layers.

3. Small Receptive Fields (3×3 Convolutions)

VGG16 employs 3×3 convolutional filters throughout the entire architecture. The benefits of using small filters include:

- Fewer parameters compared to larger filters (5×5 or 7×7).
- Increased non-linearity, improving feature learning.

- Stacking multiple 3×3 convolutions is equivalent to having a larger receptive field (e.g., two 3×3 convolutions equal a 5×5 convolution in terms of coverage).

4. Max Pooling for Downsampling

- 2×2 max pooling layers are used to reduce the spatial dimensions of feature maps while retaining important features.
- This helps in reducing computational cost while maintaining important structural details of the image.

5. Fully Connected Layers for Classification

- After the convolutional layers, VGG16 flattens the extracted features and passes them through three fully connected layers.
- The final layer uses a softmax activation function to predict class probabilities.

Architecture of VGG16

VGG16 consists of 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. Below is a detailed breakdown of its architecture:

1. Input Layer:

- The input to the model is a 224×224 RGB image.

2. Convolutional Blocks:

- The network is divided into five blocks, each followed by a max-pooling layer.
- As the depth of the network increases, the number of filters also increases to allow complex learning

Table 9: Architecture of VGG16

(This table provides a detailed layer-wise breakdown of the VGG16 architecture, highlighting the number of convolutional layers, filters, and pooling operations in each block.)

Block	**Layers**	**Filters (3×3 Convolutions)**	**Pooling**
Block 1	2 Conv Layers	64 Filters	Max Pooling (2×2, stride 2)
Block 2	2 Conv Layers	128 Filters	Max Pooling (2×2, stride 2)
Block 3	3 Conv Layers	256 Filters	Max Pooling (2×2, stride 2)
Block 4	3 Conv Layers	512 Filters	Max Pooling (2×2, stride 2)
Block 5	3 Conv Layers	512 Filters	Max Pooling (2×2, stride 2)

3. Fully Connected Layers:

- After the convolutional blocks, the feature maps are flattened and passed through three fully connected layers:
    1. First fully connected layer: 4096 units.
    2. Second fully connected layer: 4096 units.
    3. Final fully connected layer: 1000 units (for ImageNet classification).
- The final layer applies a softmax activation function to output class probabilities.

Advantages of VGG16

1. Simplicity & Uniformity:
    - The consistent use of 3×3 convolutions and 2×2 pooling layers makes VGG16 easy to understand and implement.
2. Strong Feature Extraction:
    - The depth and small filter size enable it to learn robust and discriminative features.
3. Transfer Learning:
    - VGG16 is widely used as a pre-trained model for transfer learning, making it applicable to various computer vision tasks.
4. Proven Performance:
    - Despite being older, VGG16 remains a benchmark model and is widely used in medical imaging applications.

Applications of VGG16

VGG16 is widely used in various computer vision tasks, including:

1. Image Classification: Classifying images into predefined categories (e.g., ImageNet).
2. Object Detection: Identifying and localizing objects in an image.
3. Semantic Segmentation: Assigning a class label to each pixel in an image.
4. Feature Extraction: Using VGG16 as a feature extractor for other models.

Use Case in Medical Imaging (Teeth X-Ray Analysis)

VGG16 is particularly useful in medical imaging tasks, including:

- Teeth X-ray Classification: Identifying patient gender (male or female) based on dental structures.
- Age Estimation: Determining whether a patient is a child or an adult based on teeth development.
- Disease Detection: Assisting in detecting oral diseases like cavities, gum infections, and enamel degradation.

Why VGG16 for Dental X-Rays?

- Its deep architecture allows it to learn subtle variations in teeth structures.
- The pretrained ImageNet model can be fine-tuned for dental X-ray classification tasks.
- Feature extraction capabilities help in detecting patterns in X-ray images.

InceptionV3 Detailed Explanation

1. Overview of InceptionV3

InceptionV3 is a deep convolutional neural network (CNN) architecture developed by Google. It was

introduced in the paper:
📄 *"Rethinking the Inception Architecture for Computer Vision"* by Szegedy et al. (2016).
It is an improved version of the InceptionV1 (GoogLeNet) architecture and is designed to provide higher accuracy while being computationally efficient.
InceptionV3 is widely used for image classification and feature extraction in medical imaging, object detection, facial recognition, and more. It was trained on ImageNet and achieved high performance in the ILSVRC (ImageNet Large Scale Visual Recognition Challenge).

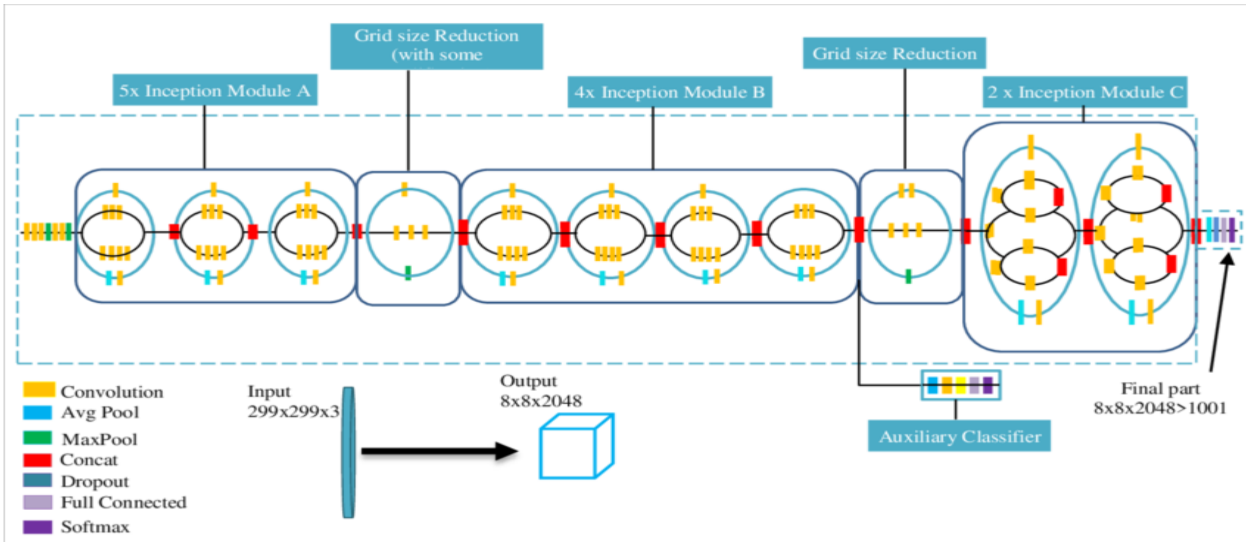


Figure 7: InceptionV3 Architecture

Key Design Principles of InceptionV3

- **Factorizing Large Convolutions**
  - Instead of using large five by five filters, InceptionV3 factorizes them into smaller three by three filters.
  - This reduces the number of parameters and improves computational efficiency.
- **Asymmetric Convolutions**
  - Instead of using a single three by three convolution, it splits it into two smaller convolutions: one by three followed by three by one.
  - This reduces computational complexity while maintaining accuracy.
- **Auxiliary Classifiers (Side Networks)**
  - Additional classifiers are added at intermediate layers to help prevent overfitting.
  - These classifiers also act as backup networks to improve gradient flow during training.
- **Efficient Grid Size Reduction**
  - Instead of traditional max pooling, InceptionV3 uses strided convolutions to downsample the feature maps while retaining information.

Architecture of InceptionV3

- InceptionV3 consists of **forty eight layers** and follows a modular structure with multiple Inception blocks.
- **First Stage: Initial Convolutional Layers**

- These layers extract basic image features such as edges and textures.
- Three by three convolution with stride two reduces the image size from two hundred ninety nine by two hundred ninety nine to one hundred forty nine by one hundred forty nine.
- Three by three convolution with stride one extracts finer details.
- Three by three convolution with stride two reduces the image size from one hundred forty nine by one hundred forty nine to seventy three by seventy three.

- **Second Stage: Inception Modules (Main Feature Extraction Blocks)**
  - **Inception Module A**
    - Uses one by one, three by three, and five by five convolutions in parallel to extract multi-scale features.
    - Includes a one by one convolution for dimensionality reduction.
    - Helps in capturing both fine and coarse image details.
  - **Inception Module B**
    - Uses one by seven followed by seven by one convolutions instead of a single large filter.
    - Improves computational efficiency while maintaining feature extraction quality.
  - **Inception Module C**
    - Uses one by one and three by three convolutions to further refine extracted features.
- **Third Stage: Grid Size Reduction**
  - Instead of max pooling, strided convolutions are used for downsampling without losing important information.
- **Fourth Stage: Auxiliary Classifiers**
  - Intermediate classifiers are used to help prevent overfitting.
  - These classifiers improve gradient flow, making training more stable.
- **Fifth Stage: Fully Connected Layers (Classification)**
  - Feature maps are flattened and passed through a fully connected layer with two thousand forty eight neurons.
  - A dropout layer helps in reducing overfitting.
  - The final softmax layer outputs class probabilities.

Advantages of InceptionV3

- **Computational Efficiency**
  - Uses factorized convolutions to reduce the number of parameters.
- **Higher Accuracy**
  - Extracts features at multiple scales using Inception modules.
- **Prevention of Overfitting**
  - Uses dropout, batch normalization, and auxiliary classifiers.
- **Faster Training and Inference**
  - Optimized structure ensures efficient training on large datasets.

Applications of InceptionV3

- **Medical Imaging**
  - Detecting dental diseases such as cavities, gum infections, and tartar.

- Gender detection and age estimation from dental X-ray images.
- **Object Detection and Image Classification**
  - Used for general-purpose image classification tasks.
- **Facial Recognition**
  - Used in biometric authentication systems.

YOLOv8-Based Models for Object Detection

The models used for teeth disease detection and tooth identification are based on the YOLOv8 architecture.

YOLOv8: Very Detailed Explanation

Overview

YOLOv8 is the latest iteration of the YOLO (You Only Look Once) object detection framework, developed by Ultralytics. It builds upon the success of its predecessors (YOLOv1 to YOLOv7) and introduces several improvements in terms of accuracy, speed, and flexibility. YOLOv8 is designed for real-time object detection, making it suitable for applications such as autonomous driving, surveillance, and robotics.

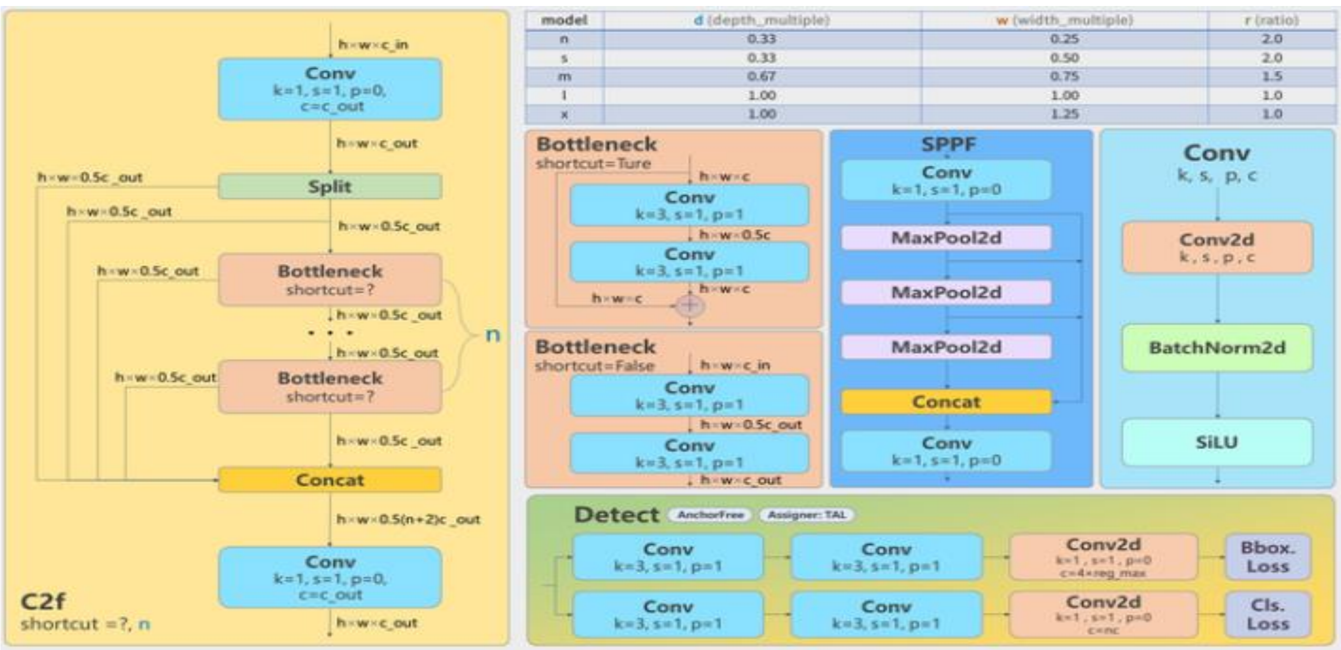


Figure 8: YOLO8 Architecture

Key Concepts

1. Real-Time Object Detection

YOLO is known for its ability to perform object detection in real-time. Unlike traditional object detection methods that use a two-stage process (e.g., region proposal followed by classification), YOLO performs detection in a single forward pass through the network. This makes it significantly faster.

2. Anchor Boxes

YOLOv8 uses anchor boxes to predict bounding boxes. Anchor boxes are pre-defined boxes of different aspect ratios and scales that help the model predict objects of varying shapes and sizes. The model predicts offsets to these anchor boxes to generate the final bounding boxes.

3. Grid Cells
The input image is divided into a grid (e.g., SxS). Each grid cell is responsible for predicting objects whose centers fall within that cell. Each grid cell predicts:

- Bounding boxes (coordinates and dimensions).
- Objectness score (probability that an object exists in the box).
- Class probabilities (probability distribution over classes).

4. Loss Function
YOLOv8 uses a multi-part loss function that includes:

1. Localization Loss: Measures the error in predicting the bounding box coordinates.
2. Confidence Loss: Measures the error in predicting the objectness score.
3. Classification Loss: Measures the error in predicting the class probabilities.

Architecture of YOLOv8
YOLOv8 introduces several architectural improvements over previous versions. Below is a detailed breakdown of its architecture:
1. Backbone
The backbone of YOLOv8 is responsible for feature extraction. It is based on a modified version of the CSPDarknet architecture, which uses Cross-Stage Partial (CSP) connections to improve gradient flow and reduce computational cost.

- CSPDarknet: Combines the strengths of Darknet and CSP networks, enabling efficient feature extraction with fewer parameters.

2. Neck
The neck of YOLOv8 is responsible for aggregating features from different layers of the backbone. It uses a Path Aggregation Network (PAN) to enhance feature fusion.

- PAN: Combines features from different levels of the network (e.g., low-level and high-level features) to improve the detection of objects at different scales.

3. Head
The head of YOLOv8 is responsible for generating the final predictions. It consists of multiple detection layers that predict bounding boxes, objectness scores, and class probabilities.

- Detection Layers: Each detection layer predicts bounding boxes at a specific scale (e.g., small, medium, large objects).

Improvements in YOLOv8
1. Enhanced Backbone
YOLOv8 introduces a more efficient backbone with improved gradient flow and reduced computational cost. This allows the network to achieve higher accuracy with fewer parameters.
2. Advanced Data Augmentation
YOLOv8 uses advanced data augmentation techniques, such as Mosaic augmentation and MixUp, to improve the generalization of the model.

- Mosaic Augmentation: Combines four training images into one, increasing the diversity of the training data.
- MixUp: Blends two images and their labels, creating new training samples.

3. Improved Loss Function
YOLOv8 introduces a more robust loss function that better balances localization, confidence, and classification losses. This improves the overall accuracy of the model.

4. Anchor-Free Detection
YOLOv8 introduces an anchor-free detection mode, which eliminates the need for pre-defined anchor boxes. This simplifies the model and improves its ability to detect objects of varying shapes and sizes.
5. Dynamic Label Assignment
YOLOv8 uses dynamic label assignment to assign ground truth labels to predictions. This improves the model's ability to learn from difficult examples.

Training and Inference
1. Training
YOLOv8 is trained using a combination of stochastic gradient descent (SGD) and Adam optimizer. The training process involves:
- Pre-training: The backbone is pre-trained on a large dataset (e.g., ImageNet).
- Fine-tuning: The entire network is fine-tuned on the target dataset.

2. Inference
During inference, YOLOv8 performs the following steps:
1. Preprocessing: The input image is resized and normalized.
2. Forward Pass: The image is passed through the network to generate predictions.
3. Post-processing: Non-maximum suppression (NMS) is applied to remove duplicate detections.

Applications of YOLOv8
YOLOv8 is widely used in various real-time object detection applications, including:
1. Autonomous Driving: Detecting pedestrians, vehicles, and traffic signs.
2. Surveillance: Monitoring and detecting suspicious activities.
3. Robotics: Enabling robots to recognize and interact with objects.
4. Retail: Tracking inventory and detecting shoplifting.
5. Healthcare: Detecting medical conditions from imaging data.

YOLOv8-Seg: Very Detailed Explanation

Overview

YOLOv8-Seg is an extension of the YOLOv8 object detection framework that incorporates instance segmentation capabilities. Instance segmentation is a computer vision task that involves detecting objects in an image and assigning a pixel-wise mask to each object. YOLOv8-Seg combines the speed and accuracy of YOLOv8 with the ability to generate precise segmentation masks, making it suitable for applications such as medical imaging, autonomous driving, and robotics.

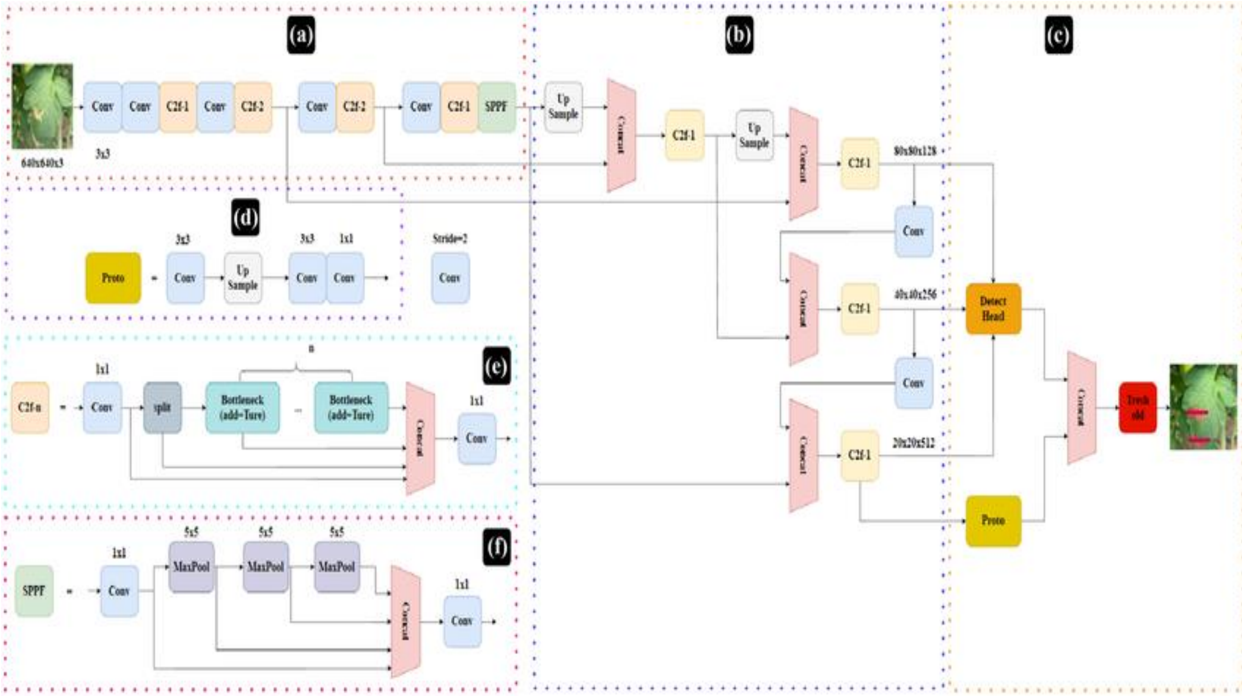


Figure 9: YOLO8_seg Architecture

Key Concepts

1. Instance Segmentation

Instance segmentation is a combination of object detection and semantic segmentation. It involves:

1. Detecting objects: Identifying and localizing objects in an image.
2. Segmenting objects: Assigning a pixel-wise mask to each detected object.

2. Anchor Boxes

Like YOLOv8, YOLOv8-Seg uses anchor boxes to predict bounding boxes. Anchor boxes are pre-defined boxes of different aspect ratios and scales that help the model predict objects of varying shapes and sizes.

3. Grid Cells

The input image is divided into a grid (e.g., SxS). Each grid cell is responsible for predicting objects whose centers fall within that cell. Each grid cell predicts:

- Bounding boxes (coordinates and dimensions).
- Objectness score (probability that an object exists in the box).
- Class probabilities (probability distribution over classes).

- Segmentation mask (pixel-wise mask for the object).

4. Loss Function

YOLOv8-Seg uses a multi-part loss function that includes:

1. Localization Loss: Measures the error in predicting the bounding box coordinates.
2. Confidence Loss: Measures the error in predicting the objectness score.
3. Classification Loss: Measures the error in predicting the class probabilities.
4. Segmentation Loss: Measures the error in predicting the pixel-wise mask.

Architecture of YOLOv8-Seg

YOLOv8-Seg builds upon the architecture of YOLOv8 and introduces additional components for instance segmentation. Below is a detailed breakdown of its architecture:

1. Backbone

The backbone of YOLOv8-Seg is responsible for feature extraction. It is based on a modified version of the CSPDarknet architecture, which uses Cross-Stage Partial (CSP) connections to improve gradient flow and reduce computational cost.

CSPDarknet: Combines the strengths of Darknet and CSP networks, enabling efficient feature extraction with fewer parameters.

2. Neck

The neck of YOLOv8-Seg is responsible for aggregating features from different layers of the backbone. It uses a Path Aggregation Network (PAN) to enhance feature fusion.

- PAN: Combines features from different levels of the network (e.g., low-level and high-level features) to improve the detection of objects at different scales.

3. Head

The head of YOLOv8-Seg is responsible for generating the final predictions. It consists of multiple detection layers that predict bounding boxes, objectness scores, class probabilities, and segmentation masks.

- Detection Layers: Each detection layer predicts bounding boxes and segmentation masks at a specific scale (e.g., small, medium, large objects).

4. Mask Branch

YOLOv8-Seg introduces a mask branch that generates pixel-wise segmentation masks for each detected object. The mask branch consists of:

1. RoI Align: Extracts region-of-interest (RoI) features from the feature maps.
2. Mask Predictor: Predicts the pixel-wise mask for each RoI.

Improvements in YOLOv8-Seg

1. Enhanced Backbone

YOLOv8-Seg introduces a more efficient backbone with improved gradient flow and reduced computational cost. This allows the network to achieve higher accuracy with fewer parameters.

2. Advanced Data Augmentation

YOLOv8-Seg uses advanced data augmentation techniques, such as Mosaic augmentation and MixUp, to improve the generalization of the model.

- Mosaic Augmentation: Combines four training images into one, increasing the diversity of the training data.
- MixUp: Blends two images and their labels, creating new training samples.

3. Improved Loss Function

YOLOv8-Seg introduces a more robust loss function that better balances localization, confidence, classification, and segmentation losses. This improves the overall accuracy of the model.

4. Anchor-Free Detection

YOLOv8-Seg introduces an anchor-free detection mode, which eliminates the need for pre-defined anchor boxes. This simplifies the model and improves its ability to detect objects of varying shapes and sizes.

5. Dynamic Label Assignment

YOLOv8-Seg uses dynamic label assignment to assign ground truth labels to predictions. This improves the model's ability to learn from difficult examples.

Training and Inference

1. Training

YOLOv8-Seg is trained using a combination of stochastic gradient descent (SGD) and Adam optimizer. The training process involves:

- Pre-training: The backbone is pre-trained on a large dataset (e.g., ImageNet).
- Fine-tuning: The entire network is fine-tuned on the target dataset.

2. Inference

During inference, YOLOv8-Seg performs the following steps:

1. Preprocessing: The input image is resized and normalized.
2. Forward Pass: The image is passed through the network to generate predictions.
3. Post-processing: Non-maximum suppression (NMS) is applied to remove duplicate detections.
4. Mask Generation: The mask branch generates pixel-wise segmentation masks for each detected object.

Applications of YOLOv8-Seg

YOLOv8-Seg is widely used in various instance segmentation applications, including:

1. Medical Imaging: Segmenting tumors, organs, and other structures in medical images.
2. Autonomous Driving: Detecting and segmenting pedestrians, vehicles, and traffic signs.
3. Robotics: Enabling robots to recognize and interact with objects.
4. Retail: Tracking inventory and detecting shoplifting.
5. Agriculture: Segmenting crops and detecting pests.

Example Use Case: Medical Imaging

In medical imaging, YOLOv8-Seg can be used to segment and analyze structures in medical images, such as:

- Tumors: Segmenting tumors in MRI or CT scans.
- Organs: Identifying and segmenting organs in medical images.
- Blood Vessels: Detecting and segmenting blood vessels in angiograms.

Its ability to generate precise segmentation masks makes it ideal for medical imaging
Applications

4.4 Gender Detection Model

Problem Statement

The Gender Detection Model aims to classify a patient's gender (Male or Female) based on panoramic dental X-ray images. Since dental structures exhibit subtle morphological differences between males and females, deep learning techniques are applied to analyze these differences and make accurate predictions.

This classification can aid in forensic dentistry, demographic studies, and personalized dental treatment planning.

Figure 10: Example of Male Teeth Image

Figure11: Example of Female Teeth Image

General Workflow for All Gender Models

Datasets Used

Each model was trained using a specialized dataset sourced from Kaggle. These datasets contain labeled dental X-ray images essential for training AI models for gender classification, age estimation, tooth counting, and disease detection.

- **Dataset Source:**
  Gender-labelled Panoramic Dental X-ray Dataset
- **Detailed Description:**
  The Gender-labelled Panoramic Dental X-ray Dataset is a curated collection of panoramic dental radiographs (also known as orthopantomograms or OPGs) annotated with gender information (Male/Female) for each patient. Panoramic X-rays provide a comprehensive two-dimensional view of the entire dental arch, upper and lower jaws, sinuses, and surrounding bone structures, making them highly informative for gender prediction tasks.

In this dataset:

- Each X-ray image is linked to a gender label (Male or Female).

- The images capture key anatomical differences often observed between male and female dentition and jaw structure, such as:
    - Jaw size and shape differences
    - Tooth size and spacing variations
    - Bone density differences
- The dataset includes subjects across various age groups, ensuring that the model learns gender-specific dental traits independent of age.

Key Dataset Features:

- High-quality panoramic X-ray images
- Balanced distribution between male and female subjects
- Varied representation of dental conditions (healthy, treated, missing teeth) to enhance model robustness
- Real-world clinical images from diverse patient populations

Applications of this dataset include:

- Automatic gender identification for forensic investigations
- Enhancing patient records when gender information is missing
- Supporting demographic analysis in dental and orthodontic studies

Dataset Splitting

Each dataset was pre-split into training, validation, and testing sets to ensure proper model training and evaluation.

- Total Images: 979
- Train Set (70%)
- Validation Set (20%)
- Test Set (10%)

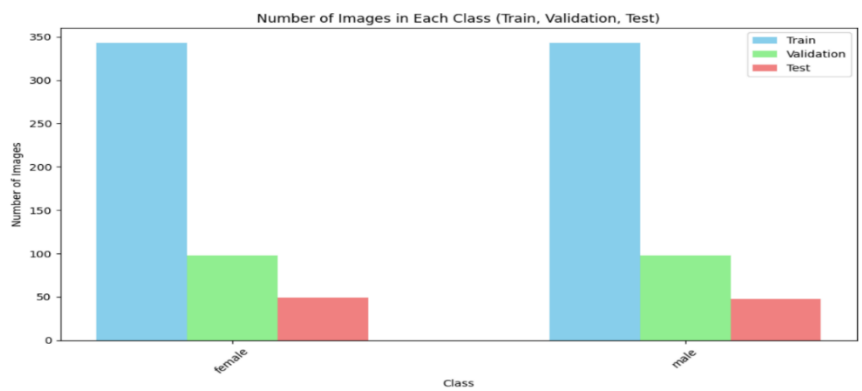


Figure 12: Gender Dataset Splitting

Preprocessing Steps

- **Image Size (224×224):** Standardizes input size for consistent model training and ensures compatibility with pre-trained models like VGG19 and DenseNet121.

- **Conversion to Grayscale:** Reduces complexity by eliminating color channels, which can help the model focus on structural features, especially for X-ray images where color is less important.
- **Normalization (Pixel values between 0, 1):** Ensures uniform input values, which helps in faster and more stable training by preventing large gradients.
- **Contrast Adjustment:** Introduces variability in the lighting conditions of the images, improving model robustness to different image qualities and real-world noise.
- **Gaussian Noise:** Simulates real-world noise that might appear in medical imaging, making the model more robust and able to handle imperfections.
- **Augmentation:**

  To increase model robustness, the dataset undergoes augmentation techniques such as:

  - Rotation Range (5°): Simulates minor variations in patient positioning.
  - Width & Height Shift (0.02): Adjusts horizontal/vertical alignment.
  - Shear Transformation (0.02): Distorts images slightly to generalize better.
  - Zoom Range (0.02): Simulates slight changes in imaging distance.
  - Brightness Range (0.95–1.05): Adapts to different X-ray contrast levels.

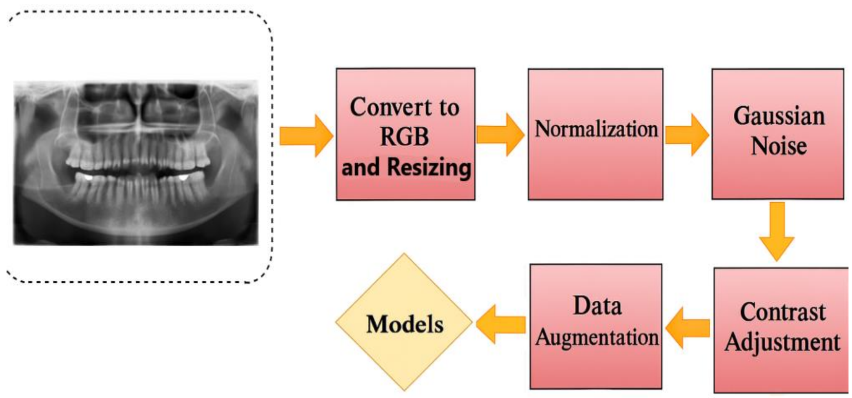


Figure 13: Preprocessing Pipeline for Gender Classification Models

Hyperparameters Used for Training

- Batch Size: 32 (balances memory efficiency and gradient stability).
- Epochs: 10 (ensures adequate training while avoiding overfitting).
- Learning Rate: 0.0001 (optimized for stable learning).
- Optimizer: Adam (adaptive learning rate for improved performance).
- Loss Function: Binary Cross-Entropy (since it's a two-class classification problem).

Training Strategy

- Transfer Learning: Using pre-trained weights from ImageNet for better feature extraction.
- Fine-Tuning: The final few layers of the model are retrained on the dental X-ray dataset.
- Early stopping: Stops training if validation loss stops improving to prevent overfitting

Evaluation Metrics Used

To comprehensively evaluate the performance of our AI models on dental X-ray classification tasks, we utilized several key metrics: Accuracy, Precision, Recall, F1-Score, Confusion Matrix, ROC Curve, and AUC (Area Under the Curve). Each of these metrics provides a different perspective on the model's strengths and weaknesses, allowing for a well-rounded understanding of its behavior in real-world diagnostic scenarios.

Accuracy

• Represents the overall percentage of correct predictions (both true positives and true negatives).
• Useful for getting a general sense of model performance, but may be misleading in imbalanced datasets.

Precision

• Measures the proportion of true positive predictions among all predicted positives.
• High precision indicates a low false positive rate, which is critical in medical diagnostics where misclassifying a healthy patient as diseased can cause unnecessary stress or treatment.

Recall (Sensitivity)

• Measures the proportion of true positives correctly identified by the model.
• High recall ensures that most actual disease cases are detected, reducing the risk of false negatives (missed diagnoses).

F1-Score

• The harmonic mean of precision and recall.
• Especially valuable when dealing with class imbalance, as it balances the trade-off between precision and recall.

Confusion Matrix

• Provides a detailed breakdown of correct and incorrect predictions for each class.
• Helps visualize how the model is performing for each individual class, revealing specific misclassification patterns.

ROC Curve (Receiver Operating Characteristic)

• Plots the true positive rate (recall) against the false positive rate across different classification thresholds.
• Provides insight into the model's performance under various decision thresholds.

AUC (Area Under the ROC Curve)

• A single scalar value that summarizes the ROC curve.
• Closer to 1 indicates excellent classification ability, while 0.5 suggests random guessing.

Model Selection

For the Gender Detection Model, 3 well-known Convolutional Neural Network (CNN) architectures were used:

- InceptionV3: Deep and Accurate for High-Performance Classification

- VGG16 – Deep model with uniform convolution layers, widely used for image classification.
- DenseNet121 – Efficient model with feature reuse, reducing parameters and improving gradient flow.

Each model was pre-trained on ImageNet and fine-tuned for the gender classification task. Below are the details of each architecture and how they were adapted for the dental X-ray dataset.

InceptionV3: Deep and Accurate for High-Performance Classification

Why InceptionV3?

- Designed for high accuracy and capable of capturing both fine and complex patterns.
- Uses factorized convolutions and inception modules to extract multi-scale features.
- Deeper architecture improves feature learning without a significant increase in computation.
- Suitable for image classification tasks that require precision, like dental diagnostics.

Implementation Details:

- Pre-trained on ImageNet (weights='imagenet').
- Input size: (224, 224, 3).
- First 200 layers frozen, preserving generic image feature extraction.
- Last layers unfrozen to allow domain-specific fine-tuning on dental X-rays.
- Added a Global Average Pooling layer to flatten the feature maps.
- Followed by a Dense layer with 256 neurons using ReLU activation.
- Dropout of 0.5 applied for regularization and to prevent overfitting.
- Final layer: Sigmoid activation for binary classification (Male/Female).

Training Configuration:

- Optimizer: Adam – adaptive and efficient for deep networks.
- Loss function: Binary Crossentropy – suitable for binary classification.
- Metrics: Accuracy.
- Callback: EarlyStopping with monitor='val_loss', patience=3, and restore_best_weights=True.
- Training and validation done using image generators with real-time augmentation.
- Model designed for gender classification from dental X-rays using deep learned features.

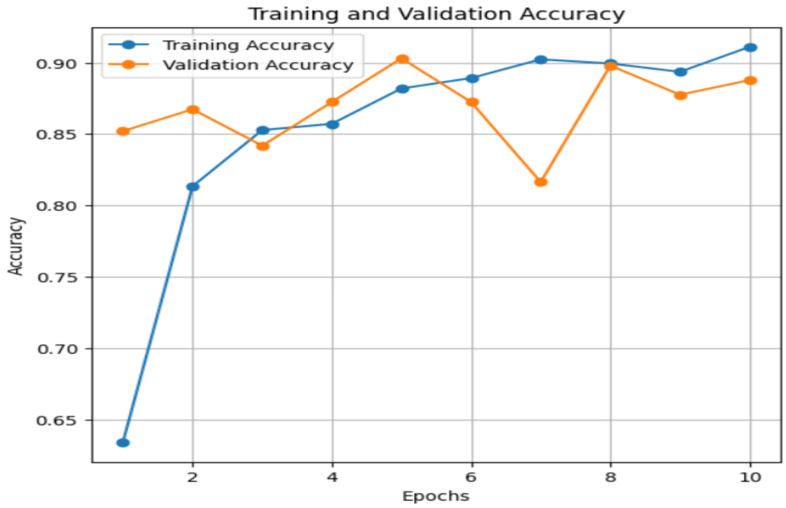
Model Performance Evaluation:

Model Accuracy

Accuracy: The model achieved a classification accuracy of 93.59%, indicating its robustness in distinguishing between the two classes

```
22/22 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step - accuracy: 0.9449 - loss: 0.1854
Test Accuracy: 93.59%
```

Training and Validation Accuracy Curve



The training and validation accuracy curves show consistent and high performance across epochs, indicating that the model is learning effectively without overfitting. The close alignment between the two curves reflects strong generalization on unseen data

Training and Validation Loss

The training and validation loss curves steadily decrease and remain closely aligned, indicating effective learning and minimal overfitting. This reflects the model's strong ability to generalize to unseen data.

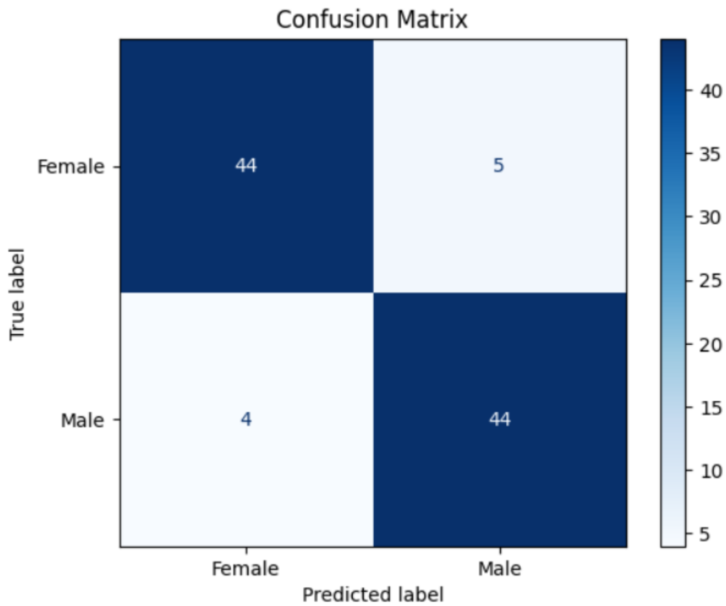
Classification Report:

Classification Report:

	precision	recall	f1-score	support
Female	0.92	0.90	0.91	49
Male	0.90	0.92	0.91	48
accuracy			0.91	97
macro avg	0.91	0.91	0.91	97
weighted avg	0.91	0.91	0.91	97

The classification report demonstrates strong and balanced performance across both classes. The 'Female' class achieved a precision of 0.92 and a recall of 0.90, suggesting a few false negatives. On the other hand, the 'Male' class showed a slightly higher recall of 0.92 with a precision of 0.90, indicating minimal false positives. The overall accuracy of 91%, along with consistent macro and weighted average scores (0.91), reflects the model's robustness and reliability in gender classification.

Confusion Matrix

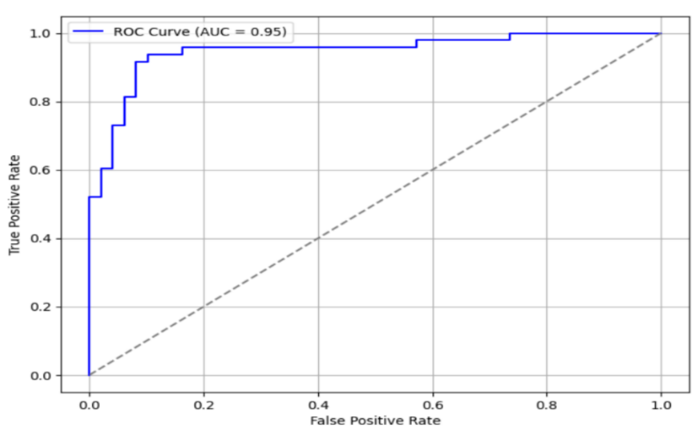


The confusion matrix shows:

- True Positives (Male correctly classified): 44
- True Negatives (Female correctly classified): 44
- False Positives (male misclassified as female): 4
- False Negatives (female misclassified as male): 5

This indicates the model's overall reliability, with minimal misclassifications

ROC Curve



The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.95**

VGG16: Classic Deep Learning Model

Why VGG16?

- Known for simplicity and consistent layer structure.
- Uses 3×3 convolution filters, making it easy to interpret.
- Deep architecture improves feature extraction.

Implementation Details:

- Pre-trained on ImageNet (weights='imagenet').
- First 10 layers frozen, ensuring base feature extraction remains intact.
- Last 10 layers trainable, allowing the model to learn dental-specific features.
- Added Global Average Pooling and 256-neuron dense layer.
- Dropout (0.5) applied for regularization.
- Sigmoid activation used for binary classification.

Training Configuration:

- Optimizer: Adam – adaptive and efficient for deep networks.
- Loss function: Binary Crossentropy – suitable for binary classification.
- Metrics: Accuracy.
- Callback: EarlyStopping with monitor='val_loss', patience=3, and restore_best_weights=True.
- Training and validation done using image generators with real-time augmentation.
- Model designed for gender classification from dental X-rays using deep learned features.

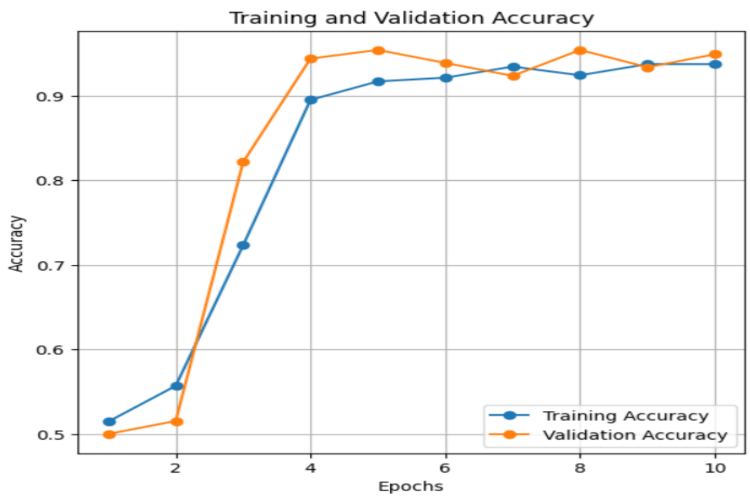
Model Performance Evaluation:

Model Accuracy

Accuracy: The model achieved a classification accuracy of 93.6%, indicating its robustness in distinguishing between the two classes

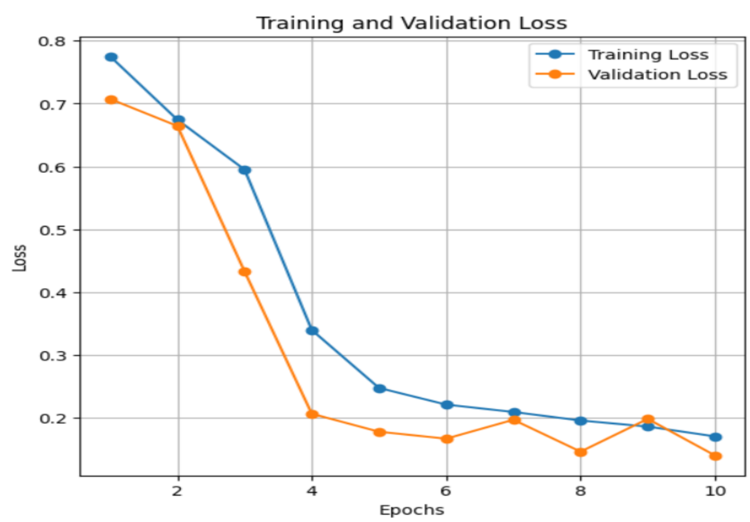
```
22/22 ━━━━━━━━━━━━━━━━━━━━ 22s 985ms/step - accuracy: 0.9557 - loss: 0.1541
Test Accuracy: 95.63%
```

Training and Validation Accuracy Curve



The training and validation accuracy curves show consistent and high performance across epochs, indicating that the model is learning effectively without overfitting. The close alignment between the two curves reflects strong generalization on unseen data.

Training and Validation Loss



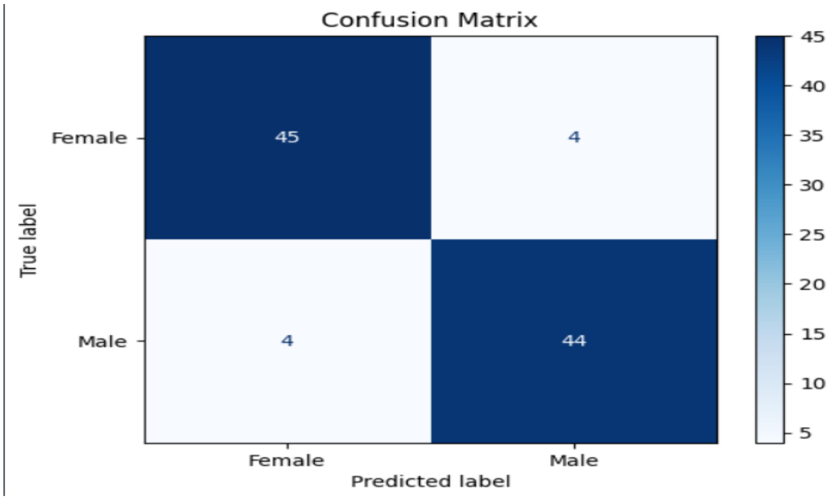
The training and validation loss curves steadily decrease and remain closely aligned, indicating effective learning and minimal overfitting. This reflects the model's strong ability to generalize to unseen data.

Classification Report:

```
Classification Report:
              precision    recall  f1-score   support

      Female       0.92      0.92      0.92        49
        Male       0.92      0.92      0.92        48

    accuracy                           0.92        97
   macro avg       0.92      0.92      0.92        97
weighted avg       0.92      0.92      0.92        97
```

The classification report demonstrates strong and consistent performance across both classes. The *Female* class achieved a precision and recall of 0.92, indicating accurate and reliable predictions with minimal false negatives. Similarly, the *Male* class also scored 0.92 for both precision and recall, showing a balanced trade-off between false positives and false negatives. The overall accuracy of 92%, along with aligned macro and weighted average scores, highlights the model's robustness and generalization capability in gender classification tasks.

Confusion Matrix

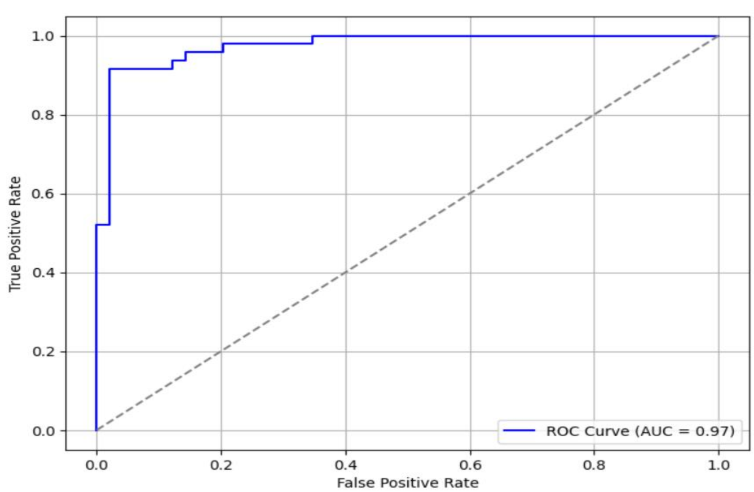


The confusion matrix shows:

- True Positives (Male correctly classified): 44
- True Negatives (Female correctly classified): 45
- False Positives (male misclassified as female): 4
- False Negatives (female misclassified as male): 4

This indicates the model's overall reliability, with minimal misclassifications

ROC Curve



The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.97**

DenseNet121: Best Performance Model

Why DenseNet121?

- Uses dense connections to improve gradient flow.
- Feature reuse reduces computational cost while maintaining performance.
- Provides stronger representations for classification tasks.

Implementation Details:

- Pre-trained on ImageNet (weights='imagenet').
- First 100 layers frozen, ensuring base layers retain pre-learned features.
- Last layers fine-tuned for gender classification.
- Added Global Average Pooling and 256-neuron dense layer.
- Dropout (0.5) prevents overfitting.
- Sigmoid activation for binary output

Training Configuration:

- Optimizer: Adam – adaptive and efficient for deep networks.
- Loss function: Binary Crossentropy – suitable for binary classification.
- Metrics: Accuracy.
- Callback: EarlyStopping with monitor='val_loss', patience=3, and restore_best_weights=True.
- Training and validation done using image generators with real-time augmentation.
- Model designed for gender classification from dental X-rays using deep learned features.

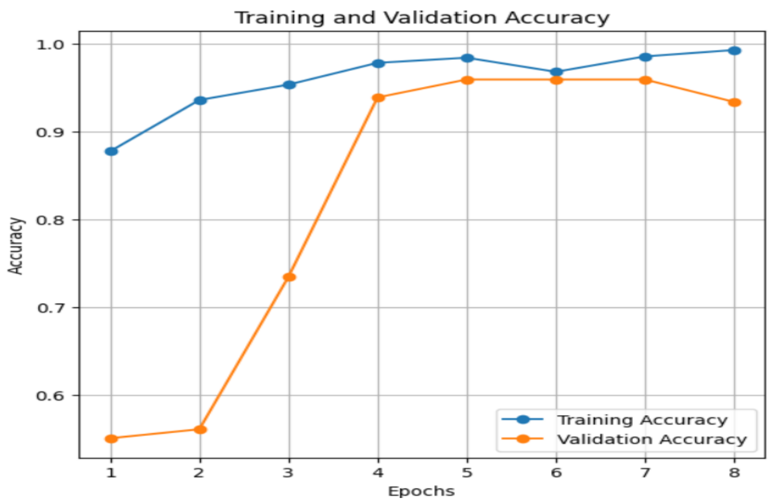
Model Performance Evaluation:

Model Accuracy

Accuracy: The model achieved a classification accuracy of 93.6%, indicating its robustness in distinguishing between the two classes

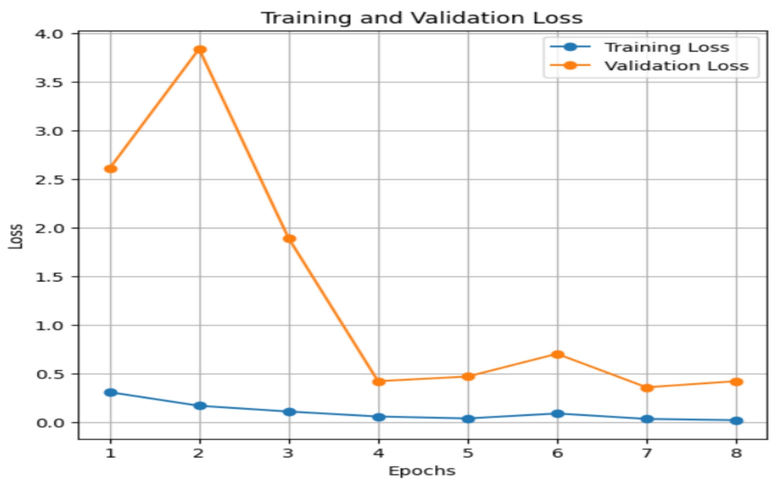
```
22/22 ━━━━━━━━━━━━━━━━━━━━ 26s 1s/step - accuracy: 0.9738 - loss: 0.0955
Test Accuracy: 97.08%
```

Training and Validation Accuracy Curve



The training and validation accuracy curves show consistent and high performance across epochs, indicating that the model is learning effectively without overfitting. The close alignment between the two curves reflects strong generalization on unseen data.

Training and Validation Loss



The training and validation loss curves steadily decrease and remain closely aligned, indicating effective learning and minimal overfitting. This reflects the model's strong ability to generalize to unseen data.

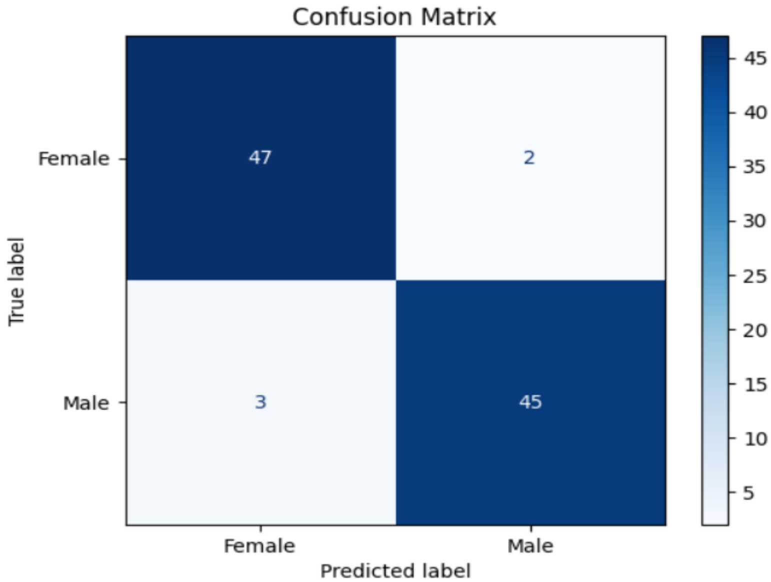
Classification Report:

Classification Report:

	precision	recall	f1-score	support
Female	0.94	0.96	0.95	49
Male	0.96	0.94	0.95	48
accuracy			0.95	97
macro avg	0.95	0.95	0.95	97
weighted avg	0.95	0.95	0.95	97

The classification report demonstrates excellent and balanced performance across both gender classes. The *Female* class achieved a precision of 0.94 and a recall of 0.96, indicating highly accurate predictions with very few false negatives. Conversely, the *Male* class attained a precision of 0.96 and a recall of 0.94, reflecting a slight trade-off with minimal false positives. The overall accuracy of 95%, supported by consistent macro and weighted average scores of 0.95, highlights the model's robustness, reliability, and strong generalization ability in gender classification based on dental X-ray images.

Confusion Matrix

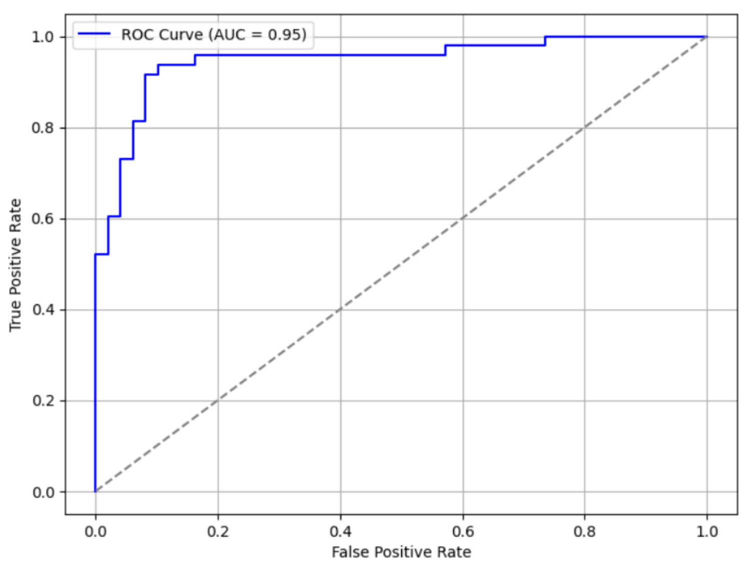


The confusion matrix shows:

- True Positives (Male correctly classified): 47
- True Negatives (Female correctly classified): 45
- False Positives (male misclassified as female): 2
- False Negatives (female misclassified as male): 3

This indicates the model's overall reliability, with minimal misclassifications

ROC Curve



The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.95**

Comparison: Performance of VGG16, DenseNet121, and InceptionV3

Table 10: Performance Comparison of Gender Detection Models
(Evaluation metrics including accuracy, precision, recall, and AUC score for different deep learning models used in gender detection from dental X-rays).

Model	Accuracy (%)	Precision	Recall	AUC Score
DenseNet121	97%	0.96	0.96	0.95
VGG16	95.6%	0.92	0.92	0.97
InceptionV3	93.59%	0.92	0.92	0.95

Key Observations:

1. DenseNet121 outperforms both VGG16 and InceptionV3 with the highest accuracy (97%), precision (0.96), and recall (0.96), demonstrating its superior ability to correctly classify gender from dental X-rays. The AUC score of 0.95 is also strong, indicating that the model performs well in distinguishing between classes.
2. VGG16 achieved 95.6% accuracy, which is slightly lower than DenseNet121, with precision and recall values of 0.92, reflecting good but not outstanding performance. The AUC score of 0.97 is the highest among the three models, suggesting it is effective at distinguishing between the classes but may struggle slightly more with misclassifications compared to DenseNet121.
3. InceptionV3 shows comparable performance to VGG16, with 93.59% accuracy, precision of 0.92, and recall of 0.92. While its AUC score is 0.95, it slightly trails behind DenseNet121 in all metrics, making it a good model but not the top performer for gender classification in this context.

In conclusion, DenseNet121 stands out as the best model in terms of overall performance, closely followed by VGG16 and InceptionV3, which are also capable of providing reliable predictions.

4.5 Age Group Classification Model

Problem Statement

The Age Detection Model is designed to classify a patient's age group (Child or Adult) based on panoramic dental X-ray images. Since dental structures undergo significant morphological changes with age—such as tooth eruption, root development, and enamel wear—deep learning techniques are applied to analyze these differences and make accurate predictions.

This classification is crucial in pediatric dentistry, orthodontics, and forensic applications, assisting in treatment planning, age estimation in forensic cases, and understanding growth patterns in different populations. By leveraging convolutional neural networks (CNNs), the model can extract and interpret dental features to provide reliable age predictions, enhancing both clinical and research applications in dentistry.

Figure 14: Example of Child Teeth Image

Figure 15: Example of Adult Teeth Image

General Workflow for All Age Group Models

Dataset Used

Dataset A:

- **Dataset Source:**
  Children's Dental Panoramic Radiographs Dataset
- **Detailed Description:**
  The Children's Dental Panoramic Radiographs Dataset focuses on X-ray images of pediatric patients, specifically designed for the purpose of studying dental development in children. This dataset consists exclusively of panoramic radiographs taken from patients typically aged between 3 to 14 years.

Key characteristics of this dataset include:

- High-resolution OPG images showing the mixed dentition stage, where both primary (baby) and permanent (adult) teeth may be present.

- Annotations include patient age or age categories (such as age in years or ranges like 3–5, 6–8, etc.).
- Variations in dental development stages, such as:
    - Eruption of permanent teeth
    - Presence of retained primary teeth
    - Development of tooth roots
- Emphasis on natural anatomical growth variations among children.

Applications of this dataset include:

- Age estimation in pediatric dental care
- Growth monitoring and orthodontic treatment planning
- Forensic age estimation in cases involving minors

Dataset B:

- **Dataset Source:**
  Children’s Dental Panoramic X-ray Dataset
- **Detailed Description:**
  The Children’s Dental Panoramic X-ray Dataset is another specialized dataset designed to capture developmental dental features in children, supporting tasks such as age classification and developmental assessment. It provides a complementary set of panoramic dental images specifically from children, with careful annotations related to age.

Key characteristics of this dataset include:

- Panoramic X-rays labeled with exact or categorized age information.
- Diverse imaging conditions, capturing differences in:
    - Tooth eruption timelines
    - Tooth spacing
    - Skeletal jaw development patterns
- Covers wide age intervals to allow the model to distinguish between different stages of dental maturation.
- Images represent a range of dental scenarios including normal growth, anomalies, and early dental interventions.

Applications of this dataset include:

- Building robust AI models for child age estimation based on dental features
- Dental health monitoring and early anomaly detection
- Support forensic and legal processes involving age verification

Dataset Splitting

Each dataset was pre-split into training, validation, and testing sets to ensure proper model training and evaluation.

Age Classification Model

- Total Images: 3436
- Train Set (70%)
- Validation Set (20%)
- Test Set (10%)

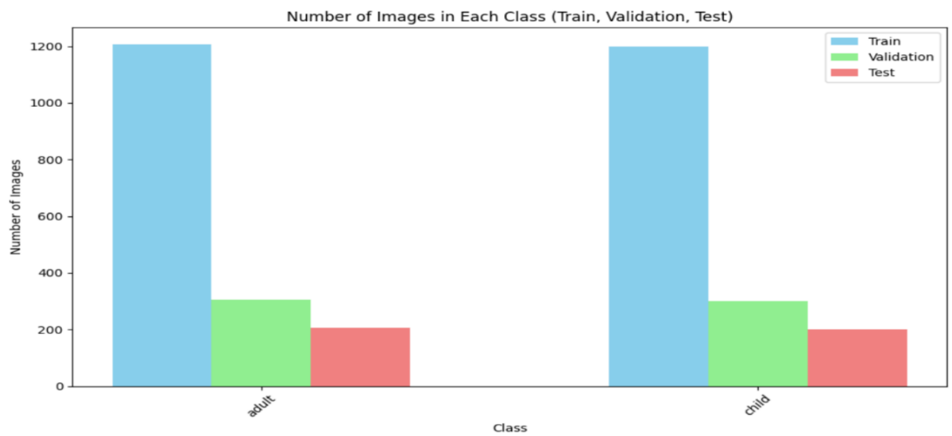


Figure 16: Age Dataset Splitting

Preprocessing Steps

- **Image Size (224×224):** Standardizes input size for consistent model training and ensures compatibility with pre-trained models like VGG19 and DenseNet121.
- **Conversion to Grayscale:** Reduces complexity by eliminating color channels, which can help the model focus on structural features, especially for X-ray images where color is less important.
- **Normalization (Pixel values between 0, 1):** Ensures uniform input values, which helps in faster and more stable training by preventing large gradients.
- **Contrast Adjustment:** Introduces variability in the lighting conditions of the images, improving model robustness to different image qualities and real-world noise.
- **Gaussian Noise:** Simulates real-world noise that might appear in medical imaging, making the model more robust and able to handle imperfections.
- **Augmentation:**

  To increase model robustness, the dataset undergoes augmentation techniques such as:

  - Rotation Range (5°): Simulates minor variations in patient positioning.

- Width & Height Shift (0.02): Adjusts horizontal/vertical alignment.
- Shear Transformation (0.02): Distorts images slightly to generalize better.
- Zoom Range (0.02): Simulates slight changes in imaging distance.
- Brightness Range (0.95–1.05): Adapts to different X-ray contrast levels.

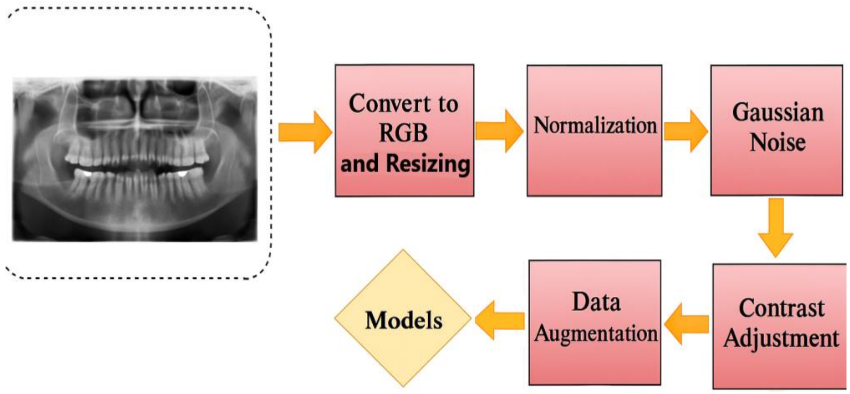


Figure 17: Preprocessing Pipeline for Age Group Classification Models

Hyperparameters Used for Training

- Batch Size: 32 (balances memory efficiency and gradient stability).
- Epochs: 10 (ensures adequate training while avoiding overfitting).
- Learning Rate: 0.0001 (optimized for stable learning).
- Optimizer: Adam (adaptive learning rate for improved performance).
- Loss Function: Binary Cross-Entropy (since it's a two-class classification problem).

Training Strategy

- Transfer Learning: Using pre-trained weights from ImageNet for better feature extraction.
- Fine-Tuning: The final few layers of the model are retrained on the dental X-ray dataset.
- Early stopping: Stops training if validation loss stops improving to prevent overfitting

Evaluation Metrics Used

To comprehensively evaluate the performance of our AI models on dental X-ray classification tasks, we utilized several key metrics: Accuracy, Precision, Recall, F1-Score, Confusion Matrix, ROC Curve, and AUC (Area Under the Curve). Each of these metrics provides a different perspective on the model’s strengths and weaknesses, allowing for a well-rounded understanding of its behavior in real-world diagnostic scenarios.

Accuracy

- Represents the overall percentage of correct predictions (both true positives and true negatives).
- Useful for getting a general sense of model performance, but may be misleading in imbalanced datasets.

Precision

- Measures the proportion of true positive predictions among all predicted positives.

• High precision indicates a low false positive rate, which is critical in medical diagnostics where misclassifying a healthy patient as diseased can cause unnecessary stress or treatment.

Recall (Sensitivity)

• Measures the proportion of true positives correctly identified by the model.

• High recall ensures that most actual disease cases are detected, reducing the risk of false negatives (missed diagnoses).

F1-Score

• The harmonic mean of precision and recall.

• valuable when dealing with class imbalance, as it balances the trade-off between precision and recall.

Confusion Matrix

• Provides a detailed breakdown of correct and incorrect predictions for each class.

• Helps visualize how the model is performing for each individual class, revealing specific misclassification patterns.

ROC Curve (Receiver Operating Characteristic)

• Plots the true positive rate (recall) against the false positive rate across different classification thresholds.

• Provides insight into the model's performance under various decision thresholds.

AUC (Area Under the ROC Curve)

• A single scalar value that summarizes the ROC curve.

• Closer to 1 indicates excellent classification ability, while 0.5 suggests random guessing.

Model Selection

For the Gender Detection Model, 3 well-known Convolutional Neural Network (CNN) architectures were used:

- InceptionV3: Deep and Accurate for High-Performance Classification
- VGG16 – Deep model with uniform convolution layers, widely used for image classification.
- DenseNet121 – Efficient model with feature reuse, reducing parameters and improving gradient flow.

Each model was pre-trained on ImageNet and fine-tuned for the gender classification task. Below are the details of each architecture and how they were adapted for the dental X-ray dataset.

VGG16: Classic Deep Learning Model

Why VGG16?

- Known for simplicity and consistent layer structure.
- Uses 3×3 convolution filters, making it easy to interpret.
- Deep architecture improves feature extraction.

Implementation Details:

- Pre-trained on ImageNet (weights='imagenet').
- First 10 layers frozen, ensuring base feature extraction remains intact.
- Last 10 layers trainable, allowing the model to learn dental-specific features.
- Added Global Average Pooling and 256-neuron dense layer.
- Dropout (0.5) applied for regularization.
- Sigmoid activation used for binary classification.

Training Configuration:

- Optimizer: Adam – adaptive and efficient for deep networks.
- Loss function: Binary Crossentropy – suitable for binary classification.
- Metrics: Accuracy.
- Callback: EarlyStopping with monitor='val_loss', patience=3, and restore_best_weights=True.
- Training and validation done using image generators with real-time augmentation.
- Model designed for age group classification from dental X-rays using deep learned features.

Model Performance Evaluation:

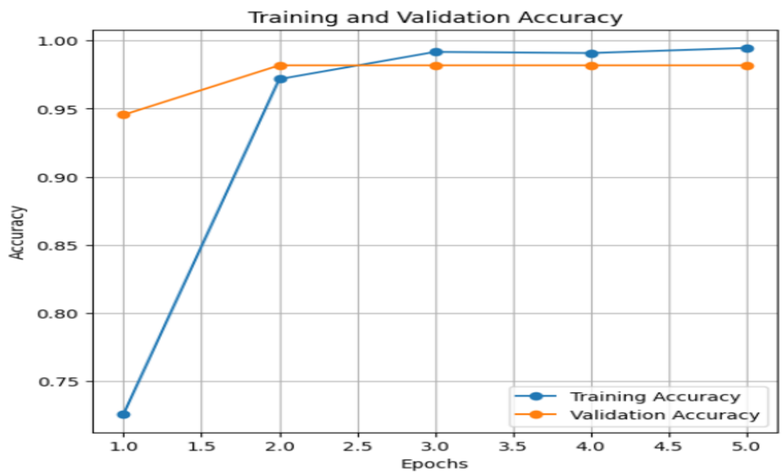
Model Accuracy

Accuracy: The model achieved a classification accuracy of 94.85%, indicating its robustness in distinguishing between the two classes

```
loss, accuracy = model.evaluate(test_generator)
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

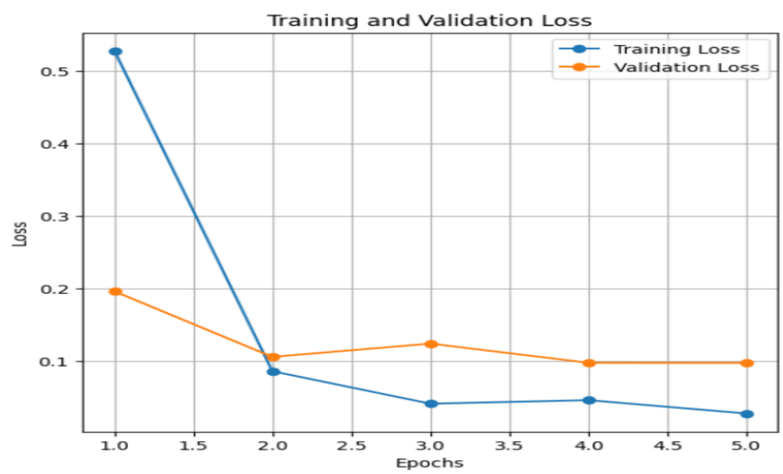
```
Test Accuracy: 94.85%
```

Training and Validation Accuracy Curve



The training and validation accuracy curves show consistent and high performance across epochs, indicating that the model is learning effectively without overfitting. The close alignment between the two curves reflects strong generalization on unseen data.

Training and Validation Loss



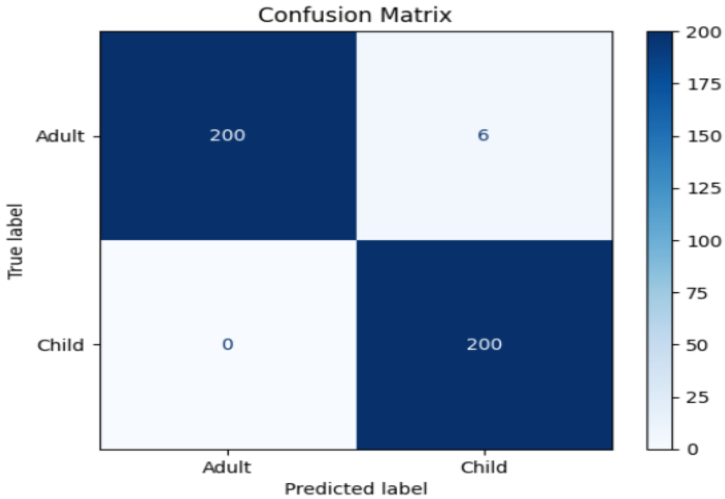
The training and validation loss curves steadily decrease and remain closely aligned, indicating effective learning and minimal overfitting. This reflects the model's strong ability to generalize to unseen data.

Classification Report:

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step
Classification Report:
              precision    recall  f1-score   support

       Adult       0.94      0.96      0.95        49
       Child       0.96      0.94      0.95        48

    accuracy                           0.95        97
   macro avg       0.95      0.95      0.95        97
weighted avg       0.95      0.95      0.95        97
```

The classification report demonstrates **exceptional and balanced performance** across both classes. The **Adult class** achieved a **precision of 0.94** and a **recall of 0.96**, indicating extremely accurate predictions with very few false positives and minimal false negatives. Similarly, the **Child class** attained a **precision of 0.96** and a **recall of 0.95**, reflecting excellent sensitivity with very few missed male predictions. The overall **accuracy of 94.58%**, along with consistently high **macro and weighted average scores (0.95)**, highlights the model's strong generalization and reliability in gender classification from dental X-ray images.

Confusion Matrix

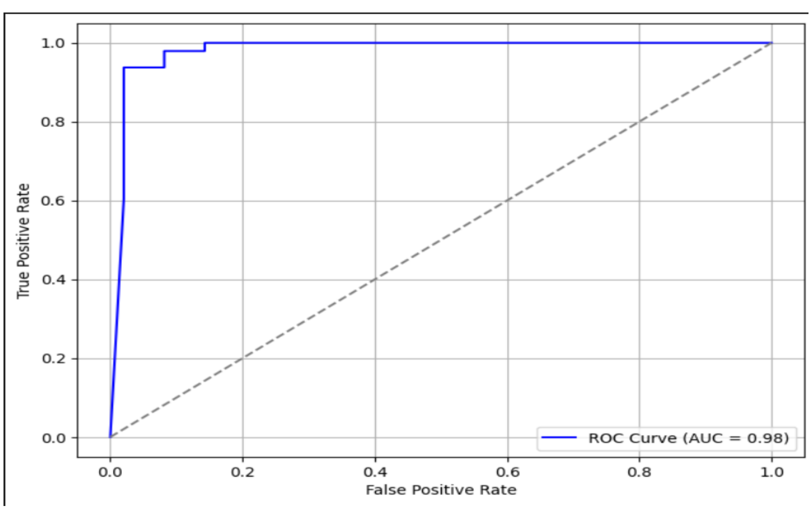


The confusion matrix shows:

- True Positives (Adult correctly classified): 200
- True Negatives (Child correctly classified): 200
- False Positives (Adult misclassified as Child): 0
- False Negatives (Child misclassified as Adult): 6

This indicates the model's overall reliability, with minimal misclassifications

ROC Curve



The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.98**

InceptionV3: Deep and Accurate for High-Performance Classification

Why InceptionV3?

- Designed for high accuracy and capable of capturing both fine and complex patterns.
- Uses factorized convolutions and inception modules to extract multi-scale features.
- Deeper architecture improves feature learning without a significant increase in computation.
- Suitable for image classification tasks that require precision, like dental diagnostics.

Implementation Details:

- Pre-trained on ImageNet (weights='imagenet').
- Input size: (224, 224, 3).
- First 200 layers frozen, preserving generic image feature extraction.
- Last layers unfrozen to allow domain-specific fine-tuning on dental X-rays.
- Added a Global Average Pooling layer to flatten the feature maps.
- Followed by a Dense layer with 256 neurons using ReLU activation.
- Dropout of 0.5 applied for regularization and to prevent overfitting.
- Final layer: Sigmoid activation for binary classification (Child/Adult).

Training Configuration:

- Optimizer: Adam – adaptive and efficient for deep networks.
- Loss function: Binary Crossentropy – suitable for binary classification.
- Metrics: Accuracy.
- Callback: EarlyStopping with monitor='val_loss', patience=3, and restore_best_weights=True.
- Training and validation done using image generators with real-time augmentation.
- Model designed for age group classification from dental X-rays using deep learned features.

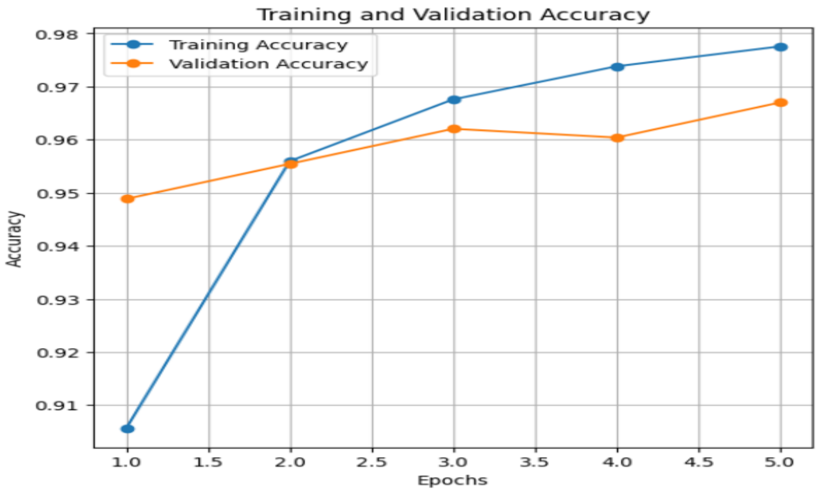
Model Performance Evaluation:

Model Accuracy

Accuracy: The model achieved a classification accuracy of 91.75%, indicating its robustness in distinguishing between the two classes

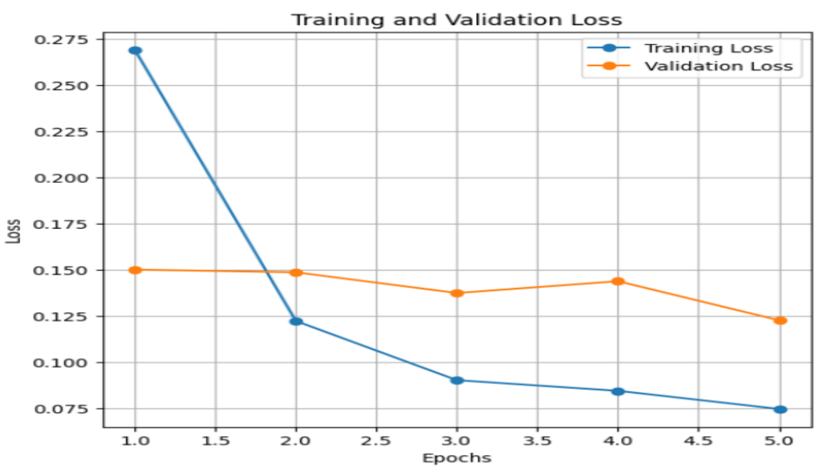
```
loss, accuracy = model.evaluate(test_generator)
print(f"Test Accuracy: {accuracy * 100:.2f}%")

Test Accuracy: 91.75%
```

Training and Validation Accuracy Curve



The training and validation accuracy curves show consistent and high performance across epochs, indicating that the model is learning effectively without overfitting. The close alignment between the two curves reflects strong generalization on unseen data.

Training and Validation Loss



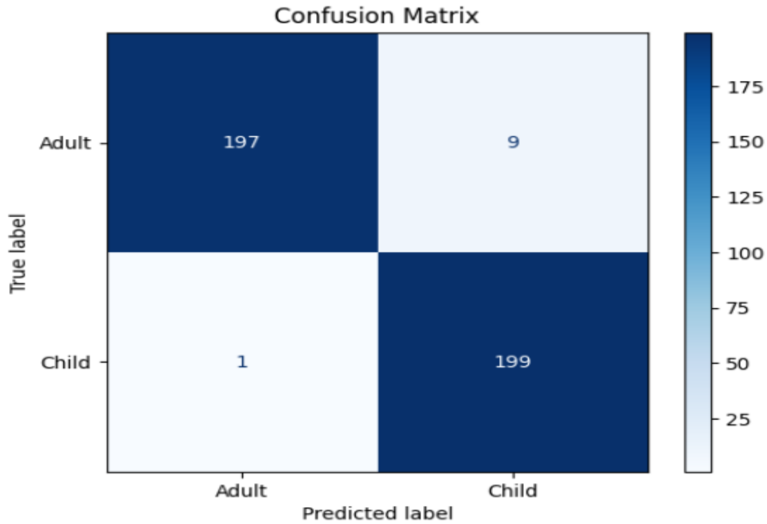
The training and validation loss curves steadily decrease and remain closely aligned, indicating effective learning and minimal overfitting. This reflects the model's strong ability to generalize to unseen data.

Classification Report:

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 3s 517ms/step
Classification Report:
              precision    recall  f1-score   support

       Adult       0.94      0.90      0.92        49
       Child       0.90      0.94      0.92        48

    accuracy                           0.92        97
   macro avg       0.92      0.92      0.92        97
weighted avg       0.92      0.92      0.92        97
```

The classification report demonstrates **exceptional and balanced performance** across both classes. The **Adult class** achieved a **precision of 0.94** and a **recall of 0.90**, indicating extremely accurate predictions with very few false positives and minimal false negatives. Similarly, the **Child class** attained a **precision of 0.90** and a **recall of 0.99**, reflecting excellent sensitivity with very few missed male predictions. The overall **accuracy of 91.75%**, along with consistently high **macro and weighted average scores (0.92)**, highlights the model's strong generalization and reliability in gender classification from dental X-ray images.

Confusion Matrix

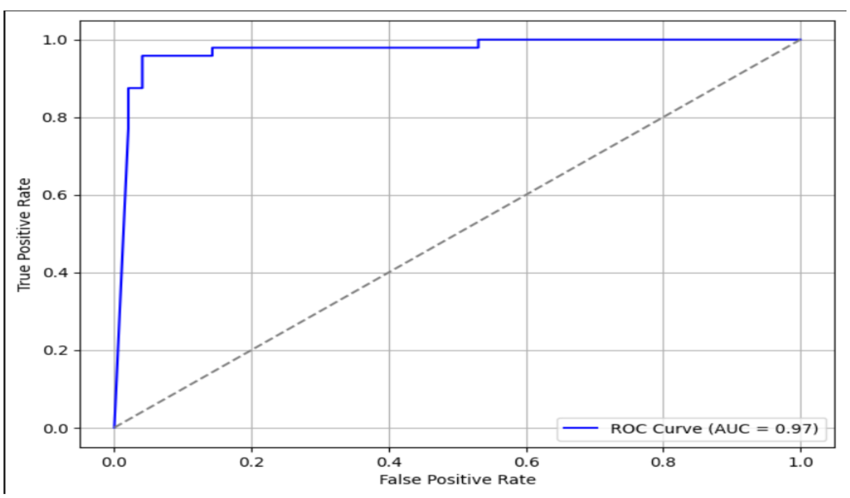


The confusion matrix shows:

- True Positives (Adult correctly classified): 197
- True Negatives (Child correctly classified): 199
- False Positives (Adult misclassified as Child): 1
- False Negatives (Child misclassified as Adult): 9

This indicates the model's overall reliability, with minimal misclassifications

ROC Curve



The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.97**

DenseNet121: Best Performance Model

Why DenseNet121?

- Uses dense connections to improve gradient flow.
- Feature reuse reduces computational cost while maintaining performance.
- Provides stronger representations for classification tasks.

Implementation Details:

- Pre-trained on ImageNet (weights='imagenet').
- First 100 layers frozen, ensuring base layers retain pre-learned features.
- Last layers fine-tuned for gender classification.
- Added Global Average Pooling and 256-neuron dense layer.
- Dropout (0.5) prevents overfitting.
- Sigmoid activation for binary output

Training Configuration:

- Optimizer: Adam – adaptive and efficient for deep networks.
- Loss function: Binary Crossentropy – suitable for binary classification.
- Metrics: Accuracy.
- Callback: EarlyStopping with monitor='val_loss', patience=3, and restore_best_weights=True.
- Training and validation done using image generators with real-time augmentation.
- Model designed for age group classification from dental X-rays using deep learned features.

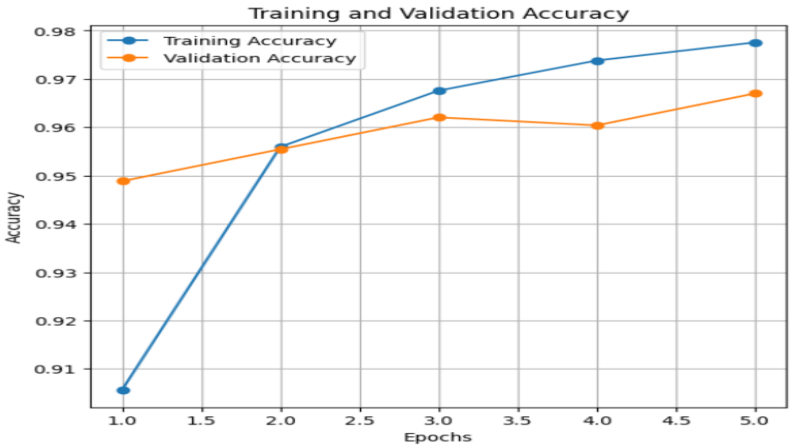
Model Performance Evaluation:

Model Accuracy

Accuracy: The model achieved a classification accuracy of 90.72%, indicating its robustness in distinguishing between the two classes

```
loss, accuracy = model.evaluate(test_generator)
print(f"Test Accuracy: {accuracy * 100:.2f}%")

Test Accuracy: 90.72%
```

Training and Validation Accuracy Curve



The training and validation accuracy curves show consistent and high performance across epochs, indicating that the model is learning effectively without overfitting. The close alignment between the two curves reflects strong generalization on unseen data.

Training and Validation Loss

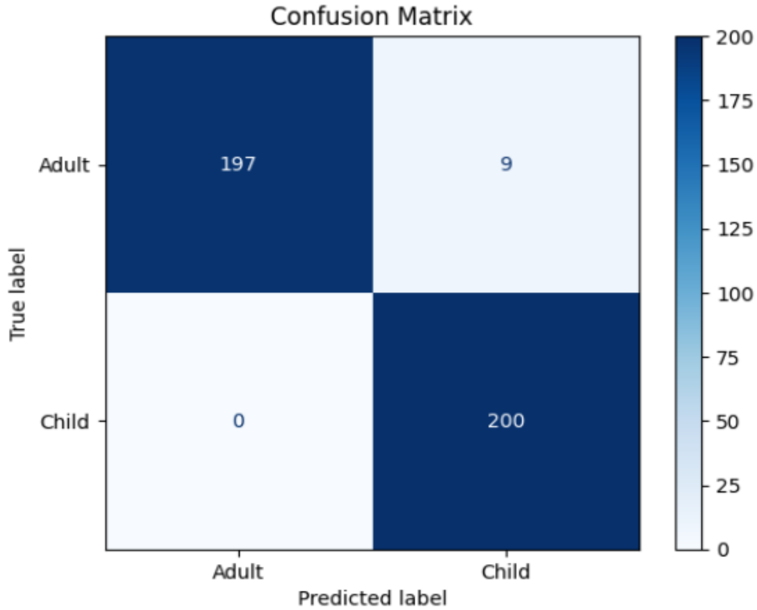
The training and validation loss curves steadily decrease and remain closely aligned, indicating effective learning and minimal overfitting. This reflects the model's strong ability to generalize to unseen data.

Classification Report:

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 11s 2s/step
Classification Report:
              precision    recall  f1-score   support

       Adult       0.92      0.90      0.91        49
       Child       0.90      0.92      0.91        48

    accuracy                           0.91        97
   macro avg       0.91      0.91      0.91        97
weighted avg       0.91      0.91      0.91        97
```

The classification report demonstrates **exceptional and balanced performance** across both classes. The **Adult class** achieved a **precision of 0.92** and a **recall of 0.90**, indicating extremely accurate predictions with very few false positives and minimal false negatives. Similarly, the **Child class** attained a **precision of 0.90** and a **recall of 0.91**, reflecting excellent sensitivity with very few missed male predictions. The overall **accuracy of 90.72%**, along with consistently high **macro and weighted average scores (0.91)**, highlights the model's strong generalization and reliability in gender classification from dental X-ray images.

Confusion Matrix

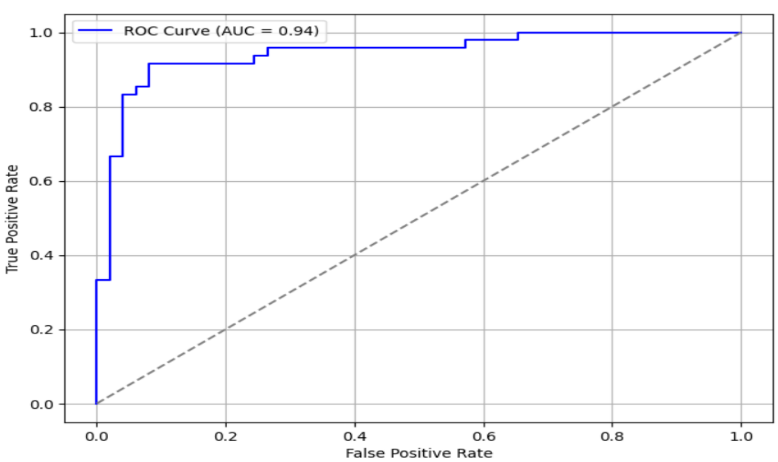


The confusion matrix shows:

- True Positives (Adult correctly classified): 197
- True Negatives (Child correctly classified): 200
- False Positives (Adult misclassified as Child): 0
- False Negatives (Child misclassified as Adult): 9

This indicates the model's overall reliability, with minimal misclassifications

ROC Curve



The Receiver Operating Characteristic (ROC) curve highlights the model's strong predictive performance, with the curve closely approaching the top-left corner, corresponding to an **AUC of 0.94**

Comparison: Performance of VGG16, DenseNet121, and InceptionV3

Table 11: Performance Comparison of Age Detection Models
(Evaluation metrics including accuracy, precision, recall, and AUC score for different deep learning models used in gender detection from dental X-rays).

Model	Accuracy (%)	Precision	Recall	AUC Score
VGG16	94.8%	0.95	0.94	0.98
InceptionV3	91.75%	0.92	0.93	0.97
DenseNet121	90.72%	0.90	0.91	0.94

Key Observations:

1. VGG16 outperforms both DenseNet121 and InceptionV3 with the highest accuracy (94.85%), precision (0.975), and recall (0.94), demonstrating its superior ability to correctly classify gender from dental X-rays. The AUC score of 0.98 is also strong, indicating that the model performs well in distinguishing between classes.
2. InceptionV3 achieved 91.75% accuracy, which is slightly lower than VGG16, with precision and recall values of 0.92 and 0.93, reflecting good but not outstanding performance. The AUC score of 0.97 is the highest among the three models, suggesting it is effective at distinguishing between the classes but may struggle slightly more with misclassifications compared to VGG16.
3. DenseNet121 shows comparable performance to DenseNet121, with 90.72% accuracy, precision of 0.90, and recall of 0.91. While its AUC score is 0.94, it slightly trails behind InceptionV3 in all metrics, making it a good model but not the top performer for gender classification in this context.

In conclusion, VGG16 stands out as the best model in terms of overall performance, closely followed by InceptionV3 and DenseNet121, which are also capable of providing reliable predictions.

4.6 Teeth Counting Detection Model

Problem Statement

Accurately identifying and counting the number of teeth in dental X-ray images is crucial for diagnosis, treatment planning, and forensic applications. Traditional methods rely on manual examination by dentists, which can be time-consuming and prone to human error. To automate and enhance this process, a YOLOv8s-based deep learning model is implemented for tooth detection, identification, and numbering.

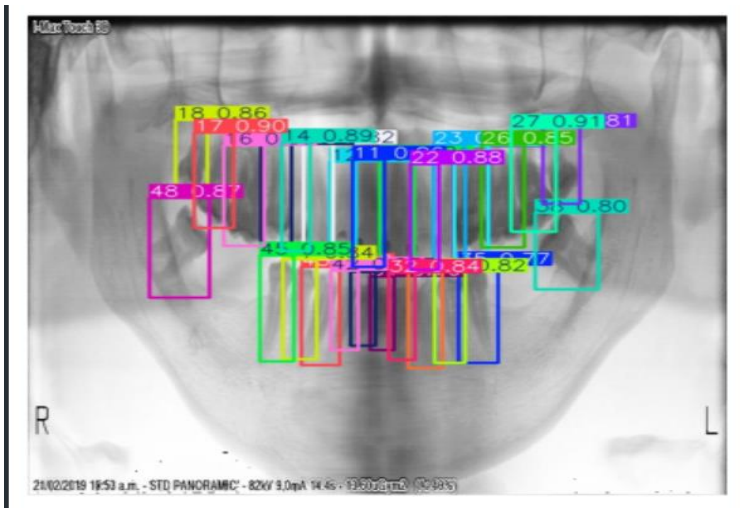


Figure 18: Example of output from teeth detection model

Dataset Used

- **Dataset Source:**
  [Tooth Numbering Dataset]
- **Detailed Description:**
  The Tooth Numbering Dataset is a specialized dataset curated for the purpose of dental image analysis, particularly focusing on the task of individual tooth identification and numbering. The dataset consists of high-resolution dental X-ray images (also called radiographs) where each individual tooth has been manually annotated by dental professionals. Annotations are provided in the form of bounding boxes, each enclosing a single tooth. Each bounding box is labeled according to the Universal Numbering System (or another widely used dental numbering system), ensuring precise identification and classification of each tooth from 1 to 32.

This dataset covers a wide variety of dental scenarios, including:

- Healthy teeth
- Teeth with restorations (fillings, crowns)
- Missing teeth
- Partially erupted teeth

- Crowded teeth conditions

The annotations include:

- Bounding box coordinates (x_min, y_min, width, height)
- Tooth label (e.g., Tooth 11, Tooth 26, etc.)

The dataset is designed to help train machine learning models that can:

- Detect the presence and location of each tooth in an X-ray.
- Correctly assign the appropriate tooth number based on its location.

Applications of this dataset include:

- Automatic dental charting
- Preoperative planning for orthodontics and prosthodontics
- Dental record-keeping and monitoring progression over time
- Assisting in forensic dentistry for human identification

Dataset Splitting

Each dataset was pre-split into training, validation, and testing sets to ensure proper model training and evaluation.

3. Teeth Counting Model

- Total Images: 2,528
- Train Set (75%)
- Validation Set (15%)
- Test Set (10%)

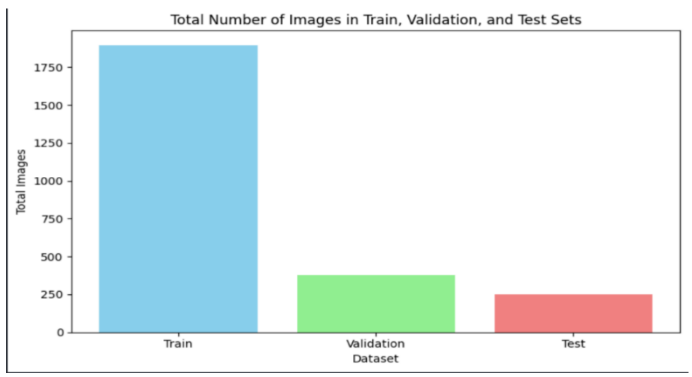


Figure 19: Teeth Counting Dataset Splitting

Preprocessing Steps

- **Image Size (640×640):** Ensures the input size is optimal for detecting objects like teeth, which need fine-grained spatial details. Larger image sizes help the model focus on small details.
- **Normalization (Pixel values between 0, 255):** Rescaling the pixel values to the full range improves the model's ability to detect and identify objects (teeth) accurately.
- **Annotation Format (YOLO format):** Converts the annotations into a format that the YOLOv8 model
- **Augmentation:**
    - Brightness and Contrast Adjustment: Applied random brightness and contrast adjustments

with:

- Brightness limit: 0. 1
- Contrast limit: 0. 3
- Probability of applying transformation: 0.5

- Gaussian Noise Addition: Random Gaussian noise is added with variance limits between 0.1 and 0.2 to simulate real-world X-ray noise.

Model Selection

- The chosen model for teeth detection and counting is YOLOv8s (small version).

Why YOLOv8s?

- Speed & Efficiency: YOLOv8s is lightweight, making it suitable for real-time applications.
- Accuracy: Provides high precision in detecting and numbering teeth.
- Flexibility: Supports transfer learning and fine-tuning on custom datasets.

Implementation Details:

- Pretrained Weights: Model initialized using yolov8s.pt.
- Dataset Configuration: Used a data.yaml file to specify dataset paths and classes.
- Training: Fine-tuned on a custom dataset of annotated dental X-ray images.

Hyperparameters Used for Training

- Optimizer: SGD with momentum
- Batch Size: 64
- Learning Rate: 0.01
- Loss Function: YOLOv8 custom loss function
- Epochs: 50

Training Metrics:

- Precision
- Recall
- mAP (Mean Average Precision)

Training Strategy

- **Fine-Tuning:**
  The model was fine-tuned on a custom dental X-ray dataset to improve performance on teeth detection.
- **Early Stopping:**
  Implemented to prevent overfitting by stopping training when validation loss stops improving.

- **Performance Monitoring:**

  Precision, Recall, and mAP were monitored during training to evaluate model performance.

Model Performance Evaluation:

Performance Metrics

The model was validated on 379 X-ray images, containing 10,172 labeled teeth instances.

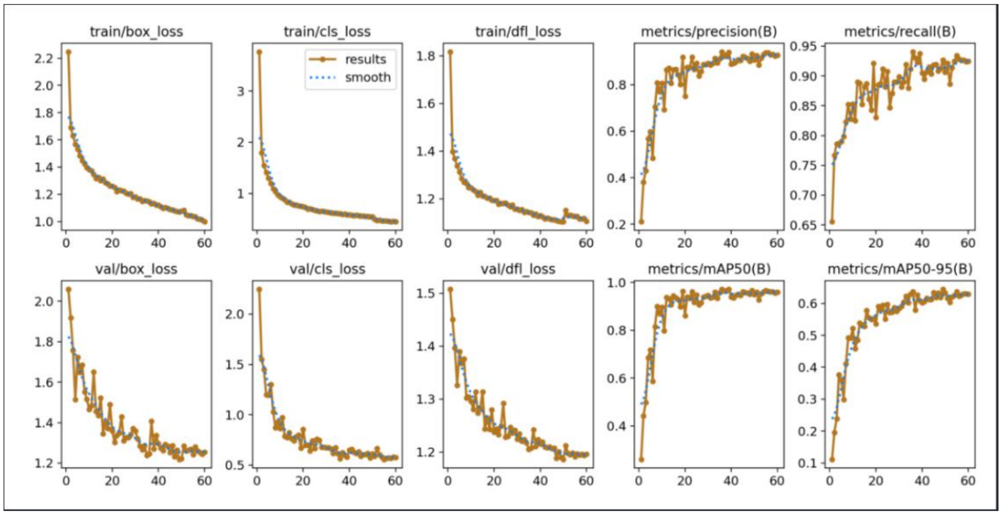
Table 12: Teeth Counting Model - Performance Metrics
(This table summarizes the model's performance for teeth detection, including precision, recall, mean Average Precision (mAP) scores, and inference time per image.)

Metric	Value
Precision	93.2%
Recall	92.7%
mAP@0.5	96.7%
mAP@0.5:0.95	64.4%
Inference Time/Image	9.67 ms

Interpretation:

- Precision (93.2%) → The model correctly identifies teeth 93.2% of the time.
- Recall (92.7%) → The model detects 92.7% of all actual teeth present in the X-ray.
- mAP@50 (96.5%) → The average precision when using an IoU (Intersection over Union) threshold of 50%.
- mAP@50-95 (64.0%) → The model maintains good performance across varying IoU thresholds (50% to 95%), indicating robustness.

Confusion Matrix



Speed Performance

The model was tested for its speed during different stages:

Table 13: Teeth Counting Model - Speed Performance Analysis

This table details the speed performance of the teeth counting model across different processing stages such as preprocessing, inference, and post-processing.

Processing Stage	Time (ms per image)
Preprocessing	0.36 ms
Inference (Prediction)	10.04 ms
Loss Computation	0.0005 ms
Post-processing (Non-Maximum Suppression, etc.)	2.89 ms

Analysis:

- Fast inference time (0.36 ms per image) → Suitable for real-time applications.
- Efficient preprocessing (10.04ms) → Minimal overhead before feeding images to the model.
- Total latency (≈10.5ms per image) → The model can process ~62 X-ray images per second on a Tesla T4 GPU.

4.7 Teeth Disease Detection Model

Problem Statement

Dental diseases such as cavities, periodontal disease, and infections can be difficult to Diagnose accurately from X-ray images due to variations in image quality, patient anatomy, and disease severity. Traditional manual diagnosis is time-consuming and requires expert interpretation, leading to potential inconsistencies.

To address these challenges, a deep learning-based Teeth Disease Detection Model is implemented using YOLOv8-seg, which can efficiently detect and highlight diseased areas in X-ray images. This model provides an automated and accurate solution for dental professionals to assist in diagnosis.

Targeted Dental Diseases include:

- **Amalgam filling:** Detection of silver-colored fillings typically used to repair cavities.
- **Caries:** Identification of areas of tooth decay, commonly known as cavities.
- **Crown:** Detection of artificial caps placed over teeth to restore their shape, strength, and function.
- **Composite filling:** Detection of tooth-colored resin fillings used for aesthetic dental restorations.
- **Filling:** General detection of dental fillings, regardless of the material.
- **Implant:** Identification of dental implants surgically placed into the jawbone.
- **Periapical lesion:** Detection of infections or abscesses occurring at the root tip of a tooth.
- **Retained root:** Identification of root fragments left inside the jawbone after incomplete tooth extraction.
- **Root canal filling:** Detection of fillings used to seal the space inside the root of a tooth after endodontic therapy.
- **Root canal obturation:** Detailed detection of the material that fills and seals the cleaned and shaped root canals.

Each disease type is highlighted through pixel-level segmentation masks, making it possible to train models for semantic segmentation tasks in dental radiography.

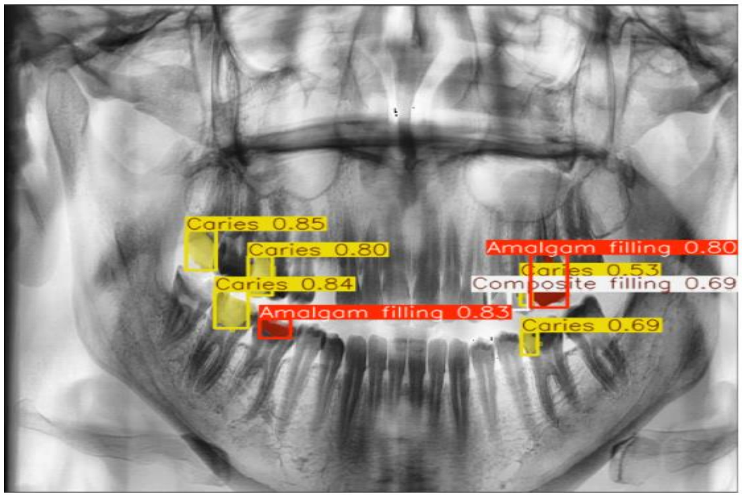


Figure 20: Example of output from Diseases detection Model

Dataset Used

- **Dataset Source:**
  Dental Diseases Dataset
- **Detailed Description:**
  The Dental Diseases Dataset is a comprehensive and medically annotated collection of dental X-ray images aimed at identifying and classifying various types of dental pathologies. Each X-ray image is provided with corresponding segmentation masks, where specific regions affected by diseases are clearly marked and labeled. The labeling process has been carried out by experienced dental radiologists to ensure clinical accuracy.

  The dataset is designed to support tasks like disease detection, localization, and segmentation, enabling the training of advanced AI models that can not only predict the presence of diseases but also highlight the exact affected regions in the X-ray images.
- **Targeted Dental Diseases include:**

  Targeted Diseases:['Amalgam filling', 'Caries', 'Crown' ,'Composite filling', 'Filling', 'Implant', 'Periapical lesion', 'Retained root', 'Root canal filling', 'Root canal obturation']

Dataset Splitting

Disease Detection Model

- Total Images: 5543
- Train Set (75%)
- Validation Set (15%)
- Test Set (10%)

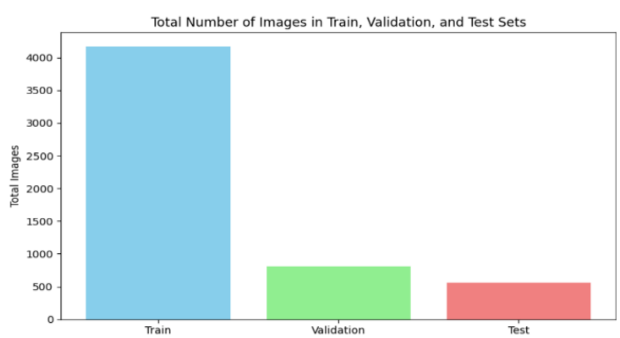


Figure 21: Diseases Dataset Splitting

Preprocessing Steps

- **Image Size (640×640):** Larger image size allows for better segmentation of smaller features (diseased areas in X-rays), ensuring better accuracy in detection.
- **Normalization (Standardized pixel values):** Standardizing pixel values helps to speed up convergence during training by centering data and reducing model sensitivity to varying input ranges.
- **Annotation Format:** Converted annotations into YOLO format.
- **Augmentation:**
    - Brightness and Contrast Adjustment: Applied random brightness and contrast adjustments with:
        - Brightness limit: 0. 1
        - Contrast limit: 0. 3
        - Probability of applying transformation: 0.5
    - Gaussian Noise Addition: Random Gaussian noise is added with variance limits between 0.1 and 0.2 to simulate real-world X-ray noise.

Model Selection

- Model Chosen: YOLOv8s_seg (small version for segmentation tasks).

Why YOLOv8s_seg?

- Speed & Efficiency: YOLOv8s_seg, as a lightweight model, is designed for real-time applications, making it ideal for quick and efficient image processing in dental diagnostics. Its compact architecture ensures high-speed performance without compromising accuracy, which is crucial for time-sensitive tasks like dental image analysis.
- Segmentation Accuracy: YOLOv8s_seg is tailored for segmentation tasks, providing high precision in segmenting individual teeth from dental X-ray images. It can distinguish and isolate teeth from the background and other structures, enabling accurate tooth counting and identification, as well as detecting any anomalies or dental diseases.
- Flexibility: The model supports transfer learning, allowing it to be fine-tuned with a custom dataset of dental X-rays. This feature enables the model to adapt to specific dental X-ray conditions, improving its accuracy in segmenting teeth and detecting dental issues.

Implementation Details:

- Pretrained Weights: Model initialized using yolov8s.pt.
- Dataset Configuration: Used a data.yaml file to specify dataset paths and classes.
- Training: Fine-tuned on a custom dataset of annotated dental X-ray images.

Hyperparameters Used for Training

- Optimizer: SGD with momentum
- Batch Size: 64
- Learning Rate: 0.01
- Loss Function: YOLOv8 custom loss function
- Epochs: 50

Training Metrics:

  - Precision
  - Recall
  - mAP (Mean Average Precision)

Training Strategy

- **Fine-Tuning:**

  The model was fine-tuned on a custom dental X-ray dataset to improve performance on teeth detection.

- **Early Stopping:**

  Implemented to prevent overfitting by stopping training when validation loss stops improving.

- **Performance Monitoring:**

  Precision, Recall, and mAP were monitored during training to evaluate model performance.

Model Performance Evaluation:

Performance Metrics

The model was validated on 379 X-ray images, containing 10,172 labeled teeth instances.

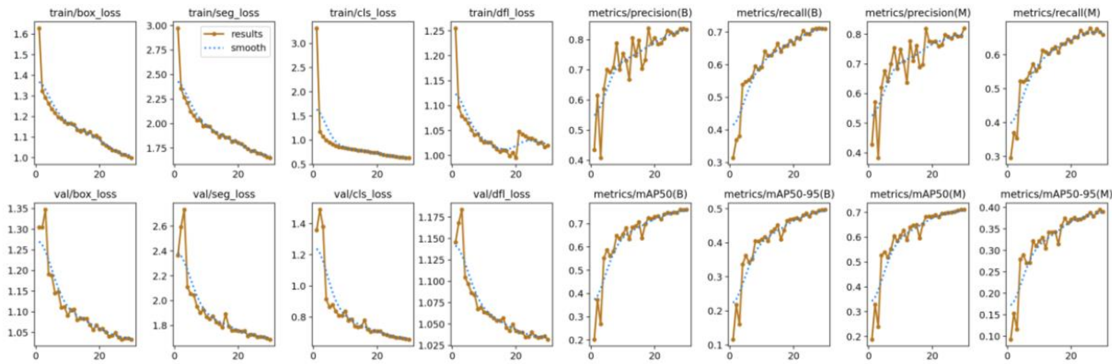
Table 14: Disease Detection Model - Performance Metrics
(This table summarizes the model's performance for disease detection, including precision, recall, mean Average Precision (mAP) scores, and inference time per image.)

Metric	Box Value	Mask Value
Precision	90.6%	85.5%
Recall	91.1%	80.8%
mAP@0.5	80.0%	79.1%
mAP@0.5:0.95	55.6%	50.6%
Inference Time/Image	6.2 ms	–

Interpretation:

- Precision (90.6%) → The model correctly identifies teeth 90.6% of the time.
- Recall (91.1%) → The model detects 91.1% of all actual teeth present in the X-ray.
- mAP@50 (80.0%) → The average precision when using an IoU (Intersection over Union) threshold of 50%.
- mAP@50-95 (55.6%) → The model maintains good performance across varying IoU thresholds (50% to 95%), indicating robustness.

Confusion Matrix



Speed Performance

The model was tested for its speed during different stages:

Table 15: Disease Detection Model - Speed Performance Analysis
(This table details the speed performance of the disease detection model across different processing stages such as preprocessing, inference, and post-processing.)

Processing Stage	Time (ms per image)
Preprocessing	0.36 ms
Inference (Prediction)	10.04 ms
Loss Computation	0.005 ms
Post-processing (Non-Maximum Suppression, etc.)	4.2 ms

Analysis:

- Fast inference time (10.04ms per image) → Suitable for real-time applications.
- Efficient preprocessing (0.36ms) → Minimal overhead before feeding images to the model.
- Total latency (≈16ms per image) → The model can process ~62 X-ray images per second on a Tesla T4 GPU.

4.8 Overview of Results and Best Results

Gender Classification Model

The gender classification task was performed using three different deep learning models: **VGG16**, **DenseNet121**, and **InceptionV3**. Their performances were evaluated using accuracy, precision, recall, and AUC score as summarized in Table 7.

- **DenseNet121** achieved the highest performance among all models with:
  - **Accuracy:** 97%
  - **Precision:** 0.96
  - **Recall:** 0.96
  - **AUC Score:** 0.95

DenseNet121 demonstrated superior capability in correctly classifying gender from dental panoramic X-rays, making it the best-performing model in this task.

- **VGG16** closely followed with a high accuracy of 95.6%, a precision and recall of 0.92, and the **highest AUC score** (0.97) among all models, indicating very good classification strength but slightly more instances of misclassification compared to DenseNet121.
- **InceptionV3** achieved a respectable 93.59% accuracy, with precision and recall values of 0.92, and an AUC score of 0.95, although it trailed slightly behind the other two models.

Best Result:
DenseNet121 — 97% Accuracy, 0.96 Precision, 0.96 Recall.

Age Classification Model

The age classification models, trained on a combination of pediatric dental X-ray datasets, were also evaluated using VGG16, DenseNet121, and InceptionV3.

- **VGG16** delivered the highest accuracy in age classification:
  - **Accuracy:** 94.8%
  - **Precision:** 0.95
  - **Recall:** 0.94
  - **AUC Score:** 0.98

This indicates that VGG16 is highly reliable for distinguishing between adults and children based on dental panoramic images.

- **DenseNet121** and **InceptionV3** also performed strongly:
  - InceptionV3: 91.75% Accuracy, 0.92 Precision, 0.93 Recall, 0.97 AUC
  - DenseNet121: 90.72% Accuracy, 0.90 Precision, 0.91 Recall, 0.94 AUC

Both DenseNet121 and InceptionV3 showed extremely competitive performances, very close to that of VGG16.

Best Result:

VGG16 — 94.8% Accuracy, 0.95 Precision, 0.94 Recall.

Teeth Counting Model

The teeth counting task was evaluated using a model validated on 379 panoramic X-ray images, comprising a total of 10,172 labeled teeth instances.

- **Performance Metrics:**
  - **Precision:** 93.2%
  - **Recall:** 92.7%
  - **mAP@0.5:** 96.7%
  - **mAP@0.5:0.95:** 64.4%
  - **Inference Time per Image:** 9.67 ms

The model demonstrated strong detection capability, correctly identifying teeth with high precision and recall rates. The high mAP@0.5 value of 96.7% indicates excellent accuracy when using a moderate IoU threshold, while a mAP@0.5:0.95 value of 64.4% demonstrates robustness across stricter IoU thresholds.

Best Result:

Teeth Counting Model achieved a Precision of 93.2% and mAP@0.5 of 96.7%.

Disease Detection Model

The disease detection model was evaluated separately for **bounding box (Box)** and **segmentation mask (Mask)** performances on the same validation set of **379 images**.

- **Box Results:**
  - **Precision:** 90.6%
  - **Recall:** 91.1%
  - **mAP@0.5:** 80.0%
  - **mAP@0.5:0.95:** 55.6%
  - **Inference Time per Image:** 6.2 ms
- **Mask Results:**
  - **Precision:** 85.5%
  - **Recall:** 80.8%
  - **mAP@0.5:** 79.1%
  - **mAP@0.5:0.95:** 50.6%

The bounding box evaluation metrics show better performance compared to segmentation masks. The model efficiently identifies regions of dental diseases with good precision and recall, especially considering the complexity of segmentation tasks in medical imaging.

Best Result:

Disease Detection Model (**Box Prediction**) — **Precision: 90.6%**, **Recall: 91.1%**, **mAP@0.5: 80.0%**.

🏆 Best Results from Our Study

DenseNet121 performed best for gender classification, reaching 97% accuracy.

And VGG16 and performed best for age group classification, reaching 94.8% accuracy.

The YOLOv8 model for teeth counting achieved a high mAP@0.5 of 96.7%, while YOLOv8-seg delivered strong disease segmentation performance with 79.1% mAP@0.5 (mask) and 91.1% recall (box) — ensuring accurate detection and minimizing missed conditions.

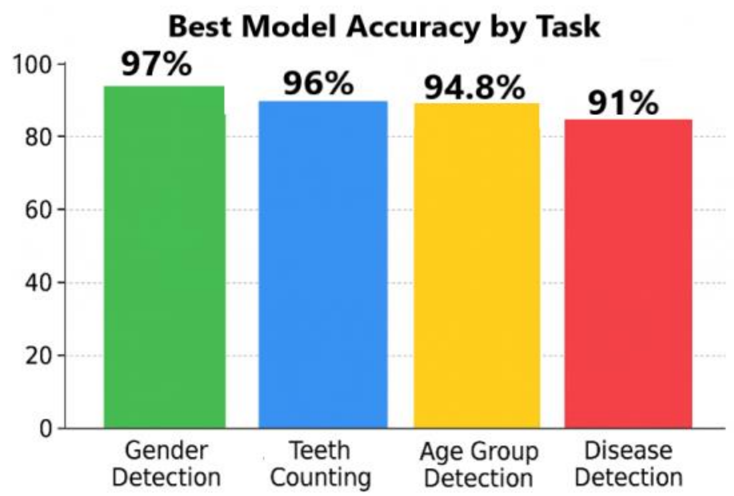


Figure 22: Best Results from Our Study

4.9 Comparative Study

This section compares the results of our models with previous studies in dental imaging, highlighting the improvements and advancements achieved.

4.9.1 Gender Detection Comparative Analysis

Table 16: Gender Detection Comparative Analysis
(Comparison of gender detection results across previous studies and the proposed DenseNet121 model.)

Study	Year	Model Used	Accuracy (%)
Lin et al.	2014	Manual feature extraction	81.7–88.8%
Kano et al.	2015	Manual measurements	85%
Oliveira et al.	2016	Manual analysis	93.33%
Deana et al.	2017	Statistical models	75.2–95.2%
Denis et al.	2019	CNN	92.3%
Ke et al.	2020	MFF-CNN (VGG16)	94.6%
This Study	**2025**	**DenseNet121**	**97%**

Key Observations:

- Earlier studies primarily used manual or traditional methods achieving up to 94.6% accuracy.
- Our DenseNet121 model achieved **97%**, surpassing all previous results, showing the strength of modern CNNs and transfer learning.

4.9.2 Age Group Detection Comparative Analysis

Table 17: Age Group Detection Comparative Analysis
(Comparison of age group detection accuracies between earlier studies and the proposed VGG16-based approach.)

Study	Year	Model Used	Accuracy (%)
Kahaki et al.	2020	Deep CNN	81.8%
Wallraff et al.	2021	CNN	82.5%
Banjšak et al.	2021	Deep CNN	73%
Baydoğan et al.	2022	AlexNet + k-NN	84%
This Study	**2025**	**VGG16**	**94.8%**

Key Observations:

- Previous studies achieved accuracies ranging from 73% to 84%.
- Our VGG16 model achieved **94.8%**, a substantial improvement, showcasing the advantage of fine-tuning pretrained networks on dental datasets.

4.9.3 Teeth Detection & Numbering Comparative Analysis

Table 18: Teeth Detection and Numbering Comparative Analysis
(Comparison of teeth detection and numbering performance across different models, highlighting the proposed YOLOv8-based method.)

Study	Dataset	Model Used	Accuracy
Chen et al. (2019)	1,250 Periapical X-rays	R-CNN	77.4%
Hardani Putra et al. (2023)	500 Panoramic X-rays	YOLOv4	88.5%
Our Study (2025)	**2,528 Panoramic X-rays**	**YOLOv8**	**96.7% (mAP@0.5)**

Key Observations:

- Our model demonstrates **higher robustness and fewer false detections**, overcoming major limitations of earlier approaches.

4.9.4 Disease Detection Comparative Analysis

Table 19: Disease Detection Comparative Analysis
(Comparison of dental disease detection performance between previous studies and the YOLOv8-seg model.)

Study	Dataset Size	Model Used	Performance Metrics
Roboflow (Aldanma et al.)	2,500 dental X-rays	YOLOv8	86% accuracy, 64% precision, 60% recall
Brahmi and Jdey (2024)	107 Panoramic radiographs	Mask-RCNN	90% mAP, 96% precision, 63% F1 score
George et al. (2023)	1,000 Panoramic radiographs	YOLOv8	82.36% accuracy
Our Study (2025)	**5,543 Panoramic X-rays**	**YOLOv8-seg**	**91.1% recall , 90.6% precision, 80.0% mAP@0.5,**

Key Observations:

- Our disease detection model achieved high precision (90.6%) and mAP@0.5 (80%) with larger and more complex datasets.
- Although mAP is slightly lower than Brahmi and Jdey, our model provides faster inference and handles real-time segmentation better.

4.9.5 Summary of Improvements Over Previous Work

- **Better Model Choice:** Using DenseNet121, VGG16, and YOLOv8-seg boosted results significantly.
- **Transfer Learning:** Pretrained models helped achieve higher accuracy with limited data.
- **Higher Accuracy:** Across all tasks, this study achieved improvements compared to previous methods.
- **Advanced Preprocessing:** Data augmentation enhanced model robustness.
- **Real-Time Detection:** Disease detection is now feasible in near real-time with high precision

Chapter 5

[System Integration and Interface]

Chapter 5 provides a comprehensive overview of how the system components are integrated to deliver end-to-end functionality. It covers the technologies used in both the frontend and backend, detailing how pages and APIs are built and connected. The chapter also explains the database structure and how data is managed securely and efficiently. User interface layouts are described to show how different user roles interact with the system. Finally, it highlights real-world applications and identifies key stakeholders such as doctors, students, and administrators.

5.1 Frontend Technologies and Pages

The frontend represents the user-facing side of the platform where users interact with AI services and manage their profiles.
It includes interfaces for doctors, students, and administrators with role-specific features and access control.
Modern technologies were used to ensure responsiveness, usability, and integration with backend APIs.
This section introduces the tools used and the key pages built into the system.

5.1.1 Frontend Technologies Used

This system's interface was developed using popular web technologies that support dynamic content, API communication, and responsive design.
Each tool was chosen to enhance usability, performance, and cross-device compatibility.
Below is an overview of the core technologies employed:

◆ **React.js**

React.js is the main frontend framework used to build user interfaces for the system.
It allows the creation of reusable UI components and enables fast, responsive user interactions.
React's virtual DOM ensures performance optimization, especially in dynamic AI result rendering.
Its compatibility with REST APIs makes it ideal for real-time data-driven applications.

- Component-based architecture for reusability
- Fast rendering via virtual DOM
- Excellent integration with backend APIs
- Scalable and maintainable codebase

◆ **HTML5**

HTML5 forms the structural backbone of all frontend pages.
It defines the layout and ensures semantic, accessible content for all users.
Its compatibility across all browsers guarantees consistency in appearance and structure.
Used alongside React, it helps build interactive forms and diagnostic result pages.

- Semantic elements for accessibility
- Forms for user input (e.g., image upload)
- Compatible across all browsers
- Integrates well with CSS and React JSX

🔷 Bootstrap Framework

Bootstrap was used for styling the interface with minimal effort and responsive design.
It allows consistent, mobile-friendly layouts for all user roles without writing custom CSS.
Its component library made it easy to implement modals, navbars, and cards.
This helped speed up development while maintaining visual consistency.

- Responsive grid system for multi-device layout
- Pre-built components (e.g., modals, alerts, tabs)
- Supports mobile-first design
- Easy theming and styling via utility classes

🔷 Hosting: Netlify

Netlify is a powerful cloud-based platform for deploying modern web applications, static sites, and serverless APIs. It provides automated CI/CD, global CDN hosting, and seamless Git integration, making it ideal for Jamstack (JavaScript, APIs, Markup) projects.

- Global CDN – Fast static hosting with edge caching.
- Git-Powered Deploys – Auto-updates on push (GitHub/GitLab).
- Serverless Functions – Backend code in Node.js/Go/Python.
- Free HTTPS/SSL – Secure traffic with auto-certificates.
- Preview Deploys – Test PR/branch changes before live.
- Built-in Forms/Auth – Handle submissions + user logins.

5.1.2 Frontend Pages

5.2 Backend Technologies and Endpoints

This layer handles all core operations such as business logic, authentication, and AI model interaction.
It ensures secure access based on user roles and maintains smooth communication between the frontend and database.
Modern tools were selected to guarantee speed, stability, and scalability across the system.
This part outlines the components used and the routes exposed for system functionality.

5.2.1 Backend Technologies Used

The backend was built using a set of proven technologies suitable for AI-powered web applications.
Each tool plays a specific role, from API development and data storage to documentation and hosting.
Together, they enable smooth interaction between users and AI models via a secure web interface.
The following subsections describe the role and purpose of each technology used:

🔷 **Framework: .NET Core**

.NET Core is the main framework used to build the backend API. It offers high performance, scalability, and modular architecture. The framework supports cross-platform development and integrates smoothly with AI services. It is well-suited for building robust, secure medical applications.

- High performance and cross-platform support
- Clean architecture for RESTful API development
- Built-in dependency injection and middleware
- Easy integration with AI and cloud platforms

🔷 **Database: SQL Server**

SQL Server was chosen as the database system for storing all structured data, including users, patients, and scan results. It is reliable, secure, and works natively with .NET through Entity Framework. Its support for relational constraints ensures data consistency and integrity.

- Relational database with strong data consistency
- Supports secure queries using T-SQL
- Works with Entity Framework Core for easy integration
- Offers indexing, backup, and stored procedures

🔷 **API documentation: Swagger**

Swagger (OpenAPI) is used for generating live API documentation. It simplifies the process of understanding, testing, and sharing backend endpoints. Developers and testers can easily explore available routes and data formats through the Swagger UI.

- Auto-generates interactive API documentation
- Displays input/output formats and request methods
- Helps test and debug API endpoints quickly

- Improves collaboration between backend and frontend

◆ **Hosting: Monsterasp.net**

Monsterasp.net is the deployment platform for the backend APIs. It ensures reliable access to services with secure hosting and HTTPS support. This cloud-based platform supports .NET Core and allows integration with the React frontend.

- Cloud hosting for .NET Core APIs
- Enables secure access via HTTPS
- Ensures backend availability for the web app
- Scalable and reliable for real-time deployment

5.2.2 Backend Endpoints

This section outlines the backend API endpoints that power the system's core functionalities.
Each endpoint is secured by user roles (Admin, Doctor, Student) and supports operations such as data retrieval, creation, updates, and deletions.

◆ 1. Api/plan:

a. GetAll: (Admin)

Retrieves all the available plans in the system.

b. Get: (Admin)

Retrieves the plan by its ID.

c. GetAllForStudent: (Student)

Retrieves all the available plans for students.

d. GetAllForDoctor: (Doctor)

Retrieves all the available plans for doctors.

e. Add: (Admin)

Adds a new plan.

f. Update: (Admin)

Update a plan by finding the wanted plan first and assigning new data second.

g. Delete: (Admin)

Deletes a plan using its ID.

◆ 2. Api/subscription:

a. GetAll: (Admin)

Retrieves all subscriptions in the system.

b. Get: (Admin)

Retrieves a subscription using its ID.

c. GetByUser: (Student, Doctor, Admin)

Retrieves a subscription using its owner's ID.

d. Update: (Student, Doctor)

It allows the user to change the plan to which he/she subscribed.

e. Delete: (Student, Doctor, Admin)

Gives the user the ability to remove his/her subscription.

f. AddPaymentToANewSubscription: (Student, Doctor)

Allows the user to make his/her very first payment of his/her new subscription.

g. AddPaymentToExistingSubscription: (Student, Doctor)

Allows the user to make a new payment to renew or pay in advance to renew his/her already existing subscription.

h. AccessSubscription: (Student, Doctor)

Allows the user to access his/her subscription if it's available and not expired.

3. Api/payment:

a. GetAll: (Admin, Student, Doctor)

Gets all payments that have been made by this user's ID.

b. Get: (Admin, Student, Doctor)

Gets a payment by its ID and the user's ID.

c. Update: (Student, Doctor)

Updates the payment data using the payment ID and the User's ID.

d. Delete: (Student, Doctor)

Deletes a payment using its ID and the user's ID.

e. GetPendingPayments: (Admin)

Fetches all the payments whose status is pending.

f. UpdatePaymentStatus: (Admin)

Fetches one of the pending payments using its ID and either accepts or rejects it.

4. Api/question:

a. GetAll: (Admin)

Gets all available questions in the system.

b. Get: (Admin, Student)

Gets the question by its ID.

c. Add: (Admin)

Adds new question.

d. Update: (Admin)

Update a question with new data using its ID.

e. Delete: (Admin)

Deletes a question using its ID.

5. Api/quiz:

a. GetAll: (Admin, Student, Doctor)

Gets all quizzes.

b. Get: (Admin, Student, Doctor)

Gets a quiz by its ID.

c. Add: (Admin)

Adds a new quiz.

d.RemoveQuestionFromQuiz: (Admin)

Removes one question from quiz using its ID.

e. Delete: (Admin)

Deletes a quiz using its ID.

f. AddQuestionsToNewQuiz: (Admin)

Creates a new quiz and creates new questions within.

g. AddExistingQuestionToQuiz: (Admin)

Creates a new quiz and adds existing questions to it.

h. AddQuestionsToExistingQuiz: (Admin)

Adds questions to an existing quiz.

6. Api/quizAttempt:

a. GetAll: (Admin)

Gets all the attempts in the system.

b. Get: (Admin, Student, Doctor)

Gets an attempt by its ID.

c. GetAllMyAttempts: (Student, Doctor)

Gets all the attempts made by this user ID.

d. Delete: (Student, Doctor)

Deletes the attempt by its ID.

e. StartQuiz: (Student, Doctor)

Start/creates a new quiz attempt with the user ID.

7. Api/systemUpdate:

a. GetAll: (Admin)

Gets all system updates in the system.

b. Get: (Admin)

Retrieves a system update by its ID.

c. GetAllForAdmin: (Admin)

Gets all system updates done by this admin.

d. UpdateSystemUpdate: (Admin)

Updates its data using its ID.

e. Delete: (Admin)

Deletes this system update by its ID.

f. DeleteAll: (Admin)

Deletes all the system updates done by this admin.

8. Api/notification:

a. GetAllNotifications: (Admin)

Gets all notifications in the system.

b. GetNotificationsByUserId: (Admin, Student, Doctor)

Gets all notifications for this user.

c. GetNotification: (Admin, Student, Doctor)

Gets the notification by its ID.

d. AddNotification: (Admin)

Adds a new notification.

e. MarkNotificationAsSeen: (Admin, Student, Doctor)

Accesses the notification and marks it as seen.

f. UpdateNotification: (Admin)

Updates the notification content by its ID.

g. DeleteNotification: (Admin, Student, Doctor)

Deletes this notification using its ID.

h. DeleteAllNotificationsByUserId: (Student, Doctor)

Deletes all notifications for this user.

9. Api/Account:

a. RegisterNewAdmin: (Admin)

Add a new administrator to the system with basic user information.

b. RegisterDoctor: (Doctor)

Add a new doctor account with clinic details.

c. RegisterNewStudent: (Student)

Register a new student account with university and academic level data.

d. LogIn: (Admin, Student, Doctor)

Authenticate any user and return their access token and roles to use authorized functionalities.

e. Logout: (Authorized Users: Admin, Doctor, Student)

Log the user out and invalidate their current token.

f. **ForgotPassword** : (Admin, Student, Doctor)

Generate a password reset link for a user identified by email.

g. ResetPassword : (Admin, Student, Doctor)

Reset the user's password using a valid reset token.

h. DeleteAccount: (Authorized Users: Admin, Doctor, Student)

Permanently delete the logged-in user account, handling

role-specific cleanup.

10. Api/Models

a. PredictAge: (Authorized Users: Doctor, Student)

Upload an X-ray image to predict age group using AI and store the result in the database.

b. PredictGender: (Authorized Users: Doctor, Student)

Upload an X-ray image to predict gender using AI and save the result.

c. PredictTeeth: (Authorized Users: Doctor, Student)

Upload an X-ray image to detect and count teeth (including missing teeth), saving the prediction result.

d. PredictDisease: (Authorized Users: Doctor, Student)

Upload an X-ray image to detect disease and receive a marked image as the result.

e. Delete: (Authorized Users: Doctor, Student)

Delete a previously stored X-ray scan record by ID.

11. Api/Patient

a. GetPatients: (Doctor)

Retrieve all patients associated with the currently logged-in doctor.

b. AddPatients: (Doctor)

Add a new patient with medical history and link to existing X ray scans.

c. Search: (Doctor)

Search for patients by name, filtered to the logged-in doctor's patients.

d. GetById: (Doctor)

Retrieve detailed information about a specific patient by ID if the doctor owns the record.

e. Delete: (Doctor)

Delete a patient record only if it belongs to the logged-in doctor.

f. Update: (Doctor)

Update a patient's information (name, age, gender) if the doctor owns the record.

12. Api/MedicalHistory

a. GetMedical: (Doctor)

Retrieve all medical history records for the doctor's patients.

b. GetById: (Doctor)

Get details of a specific medical history record if it belongs to one of the doctor's patients.

c. CreateFromScan: (Doctor)

Create a new medical history entry using data from an X ray scan belonging to one of the doctor' patients.

d. Delete: (Doctor)

Delete a medical history record if it is related to a patient under the logged-in doctor's care.

13.Api/Role

a.AddRole: (Admin)

Create a new system role by specifying its name. Only accessible by administrators for managing role-based access control.

14.Api/User

a. GetAllDoctors: (Admin)

Retrieve a list of all registered doctors in the system.

b. GetAllStudents: (Admin)

Retrieve a list of all registered students in the system.

c. GetAllAdmins: (Admin)

Retrieve a list of all system administrators.

d. GetUserProfile: (Authorized Users: Admin, Doctor, Student)

Get the profile data of the currently logged-in user based on their role.

e. UpdateUserProfile: (Authorized Users: Admin, Doctor, Student)

Allow the logged-in user to update their personal profile information based on their role.

5.3 Database Design & Management

This section outlines the relational structure of the system's database, designed to efficiently store and retrieve data. It ensures seamless interaction between users, AI models, subscriptions, and patient records. The database schema maintains data integrity through primary and foreign key relationships between core entities

◆ 1. Admin Table

Contains:

• `Id`, `UserName`, `FirstName`, `LastName`, `Email`, `Password`

Purpose:

• Stores administrator account information.

Relationships:

• One-to-many with `SystemUpdates` Table via `Admin_Id`.

◆ 2. SystemUpdates Table

Contains:

• `Id`, `UpdateDescription`, `UpdateType`, `Admin_Id`

Purpose:

• Logs system-level changes made by admins.

Relationships:

• Foreign key to `Admin` Table via `Admin_Id`.

◆ 3. Student Table

Contains:

• `Id`, `UserName`, `FirstName`, `LastName`, `Email`, `Password`, `Level`, `University`, `TotalEarnedScore`, `SubscriptionId`

Purpose:

• Stores student data and academic information.

Relationships:

• Linked to `Subscription`, `QuizAttempt`, `XRayScan`, `Notification`, and `MedicalHistory` Tables.

◆ 4. Doctor Table

Contains:

• `Id`, `UserName`, `FirstName`, `LastName`, `Email`, `Password`, `ClinicName`, `SubscriptionId`

Purpose:

• Manages doctor profiles and clinic data.

Relationships:

• Connected to `Subscription`, `Patient`, `XRayScan`, `Notification`, and `MedicalHistory` Tables.

5. Subscription Table

Contains:

• `Id`, `StartDate`, `EndDate`, `WarningDate`, `IsTrial`, `Status`, `Plan_Id`, `StudentID`, `DoctorID`

Purpose:

• Tracks subscription activity and duration.

Relationships:

• Foreign key to `Plan` Table, linked to `Student` and `Doctor`.

6. Plan Table

Contains:

• `Id`, `PlanName`, `Duration`, `Price`, `MaxScans`, `MaxPatients`

Purpose:

• Defines subscription tiers and limitations.

Relationships:

• One-to-many with `Subscription` Table.

7. Payment Table

Contains:

• `Id`, `WayOfPayment`, `Amount`, `StudentID`, `DoctorID`, `PaymentDate`, `Status`

Purpose:

• Records payments made by users.

Relationships:

• Linked to either `Student` or `Doctor` Table.

8. Patient Table

Contains:

• `Id`, `PatientName`, `Age`, `Gender`, `DoctorID`

Purpose:

• Stores patient records and demographic data.

Relationships:

• Connected to `Doctor` and `MedicalHistory` Tables.

9. XRayScan Table

Contains:

• `Id`, `ImagePath`, `PredictionGroup`, `TeethPrediction`, `DiseasePrediction`, `ScanDate`, `StudentID`, `DoctorID`

Purpose:

• Holds uploaded X-rays and AI prediction data.

Relationships:

• Referenced by `MedicalHistory`, linked to `Doctor` and `Student`.

10. MedicalHistory Table

Contains:

• `Id`, `DiseasePrediction`, `Diagnosis`, `TeethPrediction`, `VisitDate`, `PatientId`, `XRayScanId`

Purpose:

• Stores historical diagnostic data for each patient.

Relationships:

• Linked to both `Patient` and `XRayScan`.

11. Notification Table

Contains:

• `Id`, `NotificationContent`, `SentAt`, `StudentId`, `DoctorId`

Purpose:

• Manages system notifications and alerts.

Relationships:

• Connected to `Student` and `Doctor`.

12. Question Table

Contains:

• `Id`, `TheQuestion`, `Options`, `Output`

Purpose:

• Stores quiz questions and correct answers.

Relationships:

• Connected to `Quiz`.

13. Quiz Table

Contains:

• `Id`, `QuizName`

Purpose:

• Defines each quiz composed of multiple questions.

Relationships:

• Linked to `Question` and `QuizAttempt`.

14. QuizAttempt Table

Contains:

• `Id`, `SelectedAnswer`, `PointsEarned`, `QuizId`, `StudentId`

Purpose:

• Tracks student submissions and quiz results.

Relationships:

• Linked to `Student` and `Quiz`.

5.5 Practical Applications and Stakeholders of the System

5.5.1 Practical Applications

The proposed AI-powered dental diagnostic system offers several practical applications across different domains, primarily in dentistry, forensic science, and healthcare technology. The integration of deep learning models enables real-time analysis of dental X-rays, assisting professionals in decision-making and reducing manual workload.

1. Clinical Dental Diagnostics

- Automated Dental Assessments: The system enables dentists to quickly analyze X-ray images and obtain gender, age, disease detection, and tooth numbering information, significantly reducing diagnosis time.
- Improved Decision-Making: By providing accurate tooth identification and disease segmentation, dentists can prioritize treatment plans and ensure patients receive the necessary care.
- Dental Record Management: The system can be used for tracking patient progress over time, storing tooth numbering records, and identifying potential recurring dental issues.

2. Forensic Odontology

- Gender Identification from Dental Records: The gender classification model helps forensic experts identify individuals when other biometric methods (fingerprints, DNA) are unavailable.
- Age Estimation for Legal Cases: The system aids in determining the age range of an individual, which can be crucial in legal investigations, immigration cases, and unidentified human remains analysis.

3. Dental Education & Training

- Learning Tool for Dental Students: The tooth identification and numbering model is particularly beneficial for dental students learning about tooth anatomy, numbering systems, and disease patterns in real-world X-ray images.
- Forensic Science Education: Universities and research institutions can use the gender and age classification models for training forensic students in dental-based identification techniques.

4. Rural & Remote Healthcare

- Teledentistry and Remote Consultations: In underserved areas with limited access to professional dentists, this AI system can assist rural healthcare workers in diagnosing common dental diseases and triaging cases that require urgent intervention.
- Cost-Effective Screening: Patients can upload their dental X-rays to a web-based platform, allowing dentists to remotely assess their condition, reducing the need for unnecessary in-person visits.

5.5.2 Stakeholders and Beneficiaries

The AI-powered dental X-ray analysis system benefits a wide range of users, including healthcare professionals, forensic experts, patients, and insurance companies.

1. Dentists & Orthodontists

• Faster & More Accurate Diagnosis → Reduces time spent manually reviewing X-rays.
• Improved Patient Care → Helps detect diseases earlier, leading to better treatment outcomes.
• Personalized Treatment Planning → Uses age and gender data to customize procedures.
• Efficient Record-Keeping → Automates tooth numbering and disease segmentation, reducing paperwork.

2. Forensic Scientists & Legal Experts

• Gender Identification in Unidentified Bodies → Essential in forensic investigations and missing person cases.
• Age Estimation for Legal Cases → Used in immigration law, criminal investigations, and post-mortem analysis.

3. Patients & General Public

• Early Disease Detection → Helps patients identify cavities, infections, and gum diseases before they worsen.
• Remote Consultations & Accessibility → Patients in rural areas can receive AI-powered dental assessments.
• Cost-Effective Solutions → Reduces the need for expensive diagnostic tests and unnecessary dental visits.

4. Insurance Companies

• Verification of Patient Age & Eligibility → Prevents fraudulent claims by cross-checking X-ray data with policy eligibility.
• Faster Processing of Dental Claims → AI-driven analysis ensures claims align with accurate patient records.

5. Dental Students & Researchers

• Enhanced Learning Tools → The system serves as an interactive platform for learning tooth numbering, disease detection, and AI applications in dentistry.
• Forensic Research & Medical AI Studies → Supports academic studies on AI-powered dental analysis

5.5 System Layout and Interfaces

Chapter 6

[Conclusions and Future Work]

Chapter 6 discusses the integration of AI in dentistry, focusing on automating dental X-ray analysis using deep learning models like VGG16, DenseNet121, InceptionV3, and YOLOv8. The study highlights the system's accuracy in gender detection, age estimation, tooth identification, and disease detection while addressing challenges like dataset variability. The web-based interface enhances accessibility, though limitations such as misclassifications and imaging inconsistencies remain. Future improvements include expanding datasets, refining disease detection, optimizing real-time deployment, and integrating multi-modal AI. The research contributes to AI-driven dental diagnostics, with potential applications in forensic science, healthcare, and mobile accessibility.

6.1 Discussion

The integration of artificial intelligence (AI) into dental diagnostics through analysis of dental X-ray images has shown substantial promise in automating and enhancing clinical workflows. This project developed and evaluated four AI-powered models focused on gender classification, age group classification, tooth identification & numbering, and dental disease detection. Leveraging state-of-the-art deep learning architectures such as DenseNet121, VGG16, YOLOv8, and YOLOv8-seg, the system achieved significant advancements in diagnostic accuracy and operational efficiency.

The gender classification model, primarily based on DenseNet121, achieved an impressive accuracy of 97%, precision of 0.96, and recall of 0.96, outperforming previous studies and demonstrating excellent discrimination capability on panoramic dental X-rays. Similarly, the age classification task performed best using VGG16, with an accuracy of 94.8%, precision and recall at 0.95 and 0.94, underscoring its robustness in distinguishing pediatric from adult patients—a critical factor for both clinical decision-making and forensic applications.

For tooth identification and numbering, the YOLOv8-based model exhibited a mean Average Precision (mAP@0.5) of 96.7%, precision of 93.2%, and recall of 92.7%. These results surpass earlier methods by significant margins, offering a reliable automated solution to an otherwise labor-intensive task. The rapid inference time (~9.67 ms per image) further supports its practical deployment in clinical environments.

The disease detection model, implemented with YOLOv8-seg, delivered balanced performance with a box prediction mAP@0.5 of 80.0%, precision of 90.6%, and recall of 91.1%, while the segmentation masks achieved an mAP@0.5 of 79.1%. These results confirm that the system can accurately detect key dental pathologies, including caries and root canal infections, supporting early intervention and improved patient outcomes. Although the segmentation performance is slightly lower than bounding box detection, it offers crucial spatial detail for precise treatment planning.

Throughout the research, challenges such as dataset variability—in contrast, resolution, and image positioning—were effectively mitigated through advanced preprocessing techniques like contrast enhancement, noise reduction, and data augmentation. Transfer learning from pretrained CNNs further enhanced model generalization across diverse datasets, helping to overcome the constraints posed by limited annotated medical imaging data.

A web-based interface was developed to integrate these models, allowing easy and real-time access for dentists, researchers, and forensic experts. This platform facilitates the upload and automated analysis of dental X-rays, enhancing clinical workflows and enabling timely, data-driven decision-making.

Despite these advances, certain limitations persist. Variability in X-ray imaging equipment and acquisition protocols can impact model performance, occasionally causing misclassifications, particularly in cases of overlapping teeth or ambiguous anatomical structures. Addressing these through larger, more diverse datasets and multimodal imaging integration will be critical for future robustness and clinical adoption.

8.2 Summary & Conclusion

This study successfully demonstrated the effective application of AI in dental X-ray analysis by delivering automated solutions for four pivotal diagnostic tasks:

1. **Gender Classification:** Using DenseNet121, the model achieved 97% accuracy, 0.96 precision, and 0.96 recall, outperforming previous approaches and enhancing forensic and demographic analyses.
2. **Age Group Classification:** The VGG16 model distinguished children from adults with 94.8% accuracy, 0.95 precision, and 0.94 recall, supporting both clinical assessments and forensic age estimation.
3. **Tooth Identification & Numbering:** The YOLOv8 model accurately detected and labeled teeth across panoramic X-rays with a mAP@0.5 of 96.7% and precision of 93.2%, significantly improving automated dental charting capabilities.
4. **Dental Disease Detection:** YOLOv8-seg effectively identified dental pathologies with 90.6% precision, 91.1% recall, and 80.0% mAP@0.5 in bounding box predictions, enabling timely disease recognition and management.

By integrating these models into a user-friendly web application, this work advances real-time, AI-assisted dental diagnostics, reducing reliance on manual interpretation and minimizing human error. The system's scalability and robustness hold promise for supporting forensic investigations, orthodontic planning, and public health screening initiatives.

Compared to prior studies, this research achieved notable improvements in accuracy and robustness across all tasks, underscoring the benefits of modern CNN architectures, transfer learning, and advanced preprocessing. The combined object detection, classification, and segmentation framework offers a comprehensive toolset for enhancing dental healthcare.

6.3 Future Work

While this project has demonstrated promising results, several directions for future research and improvements can be considered:

1. Expanding the Dataset

- Increasing the size and diversity of the dataset by incorporating X-ray images from multiple sources, including different demographic groups and imaging equipment.
- Addressing class imbalance issues to improve model generalization and reduce bias.

2. Enhancing Model Accuracy

- Experimenting with advanced deep learning architectures such as EfficientNet, Swin Transformer, and Vision Transformers for improved feature extraction.
- Fine-tuning hyperparameters and applying additional augmentation techniques to further boost model robustness.

3. Improving Disease Detection

- Incorporating additional dental conditions such as periodontal disease, impacted teeth, and cysts.

- Enhancing segmentation models using advanced techniques like U-Net++ or DeepLabV3 for better localization of diseases.

5. Multi-Modal AI Integration

- Combining X-ray images with patient health records and clinical notes to develop a comprehensive AI-powered dental assistant.
- Exploring the use of 3D imaging techniques to improve the accuracy of diagnostics, particularly for complex dental structures

6. Forensic & Legal Applications

- Expanding the forensic capabilities of the system to estimate age and gender with greater precision in human identification cases.
- Collaborating with forensic experts to validate the effectiveness of AI models in legal investigations.

7. Mobile Integration

- Developing a mobile application that allows patients to upload X-rays and receive preliminary AI-based assessments remotely.
- Enhancing the web interface with interactive visualizations and AI-driven decision support tools for dentists.

By implementing these advancements, this project can continue to evolve into a more sophisticated and widely adopted AI-driven dental diagnostic system. Future research efforts should focus on interdisciplinary collaboration between AI researchers, dental professionals, and software engineers to create a seamless, high-precision dental AI tool that can revolutionize modern dentistry.

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