INTELLIGENT ASSESSMENT OF INTRA-ORAL RADIOGRAPH QUALITY

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May, 2025

ORALOPTIX

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THIS REPORT IS SUBMITTED IN PARTIAL FULFILMENT
OF THE REQUIREMENTS FOR THE BACHELOR DEGREE
IN COMPUTER SCIENCE

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Declaration of Originality

We hereby declare that this project report is based on our original work except for citations and quotations, which had been duly acknowledged. We also declare that it has not been previously and concurrently submitted for any other degree or award at KAU or other institutions.

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Acknowledgements

We sincerely thank everyone who supported us in this project. We are especially grateful to our supervisor, Dr. Nahed Alowidi, for her invaluable guidance, and to project coordinators Dr. Nouf Abukhodair and Dr. Rania Mulla for their effective coordination. Our thanks also go to King Abdulaziz University Dental Hospital for providing access to essential radiographic data and to the dedicated professionals who assisted with data collection, as well as to the Department of Computer Science at King Abdulaziz University for their resources and supportive environment. We appreciate the constructive feedback from our mentors, which strengthened our work, and are deeply thankful to our families and friends for their unwavering support and encouragement throughout this journey.

Abstract

The Intra-Oral radiograph is a dentistry radiograph commonly used to provide diagnostic information that the dentist cannot see during a routine check. It helps in guiding the dentist to a specific treatment plan. Clinicians must justify every radiographic examination on a patient-specific basis [Aps et al., 2020] Dentists take a significant responsibility for patient care. Improving the competence in intraoral x-ray techniques and film processing are considered necessary tasks for dentists. [Mourshed, 1971] Common issues include 16 types of Radiographic errors. Radiographic inaccuracies often necessitate retaking the images, which can lead to unnecessary radiation exposure and anxiety for patients. Misidentifying the error type and repeating the mistake are key reasons for this error. Additionally, the wastage of radiographic films due to errors can be costly for the institution. [Bhatti et al., 2020] In this project, we build AI models using convolutional neural networks (CNNs). The AI classification model works in determining whether the image is non-diagnostic, diagnostic with issues or diagnostic ideal. Also, it predicts the errors that occur in the given image. The model was trained using a dataset provided by King Abdulaziz University Hospital. The models we've used to train our multimodal data was MobileNetV3-based Model, EfficientNet-based Model, Vision Transformer (ViT) Model, EfficientNet+ViT Hybrid, MobileNetV3+ViT Hybrid, and Custom ViT-style Model .the result shows that The EfficientNetB0 model emerged as the most accurate solution. while MobileNetV3 provided the best balance between efficiency and accuracy. Our AI-based system is designed for bitewing intraoral radiographic images. We have created an efficient system that automatically assess the quality of radiographic images. A significant future enhancement involves making the system adaptive and continuously learnable.

المُستخلص

الأشعة السينية داخل الفم هي تقنية تُستخدم في طب الأسنان لتوفير معلومات تشخيصية لا يمكن للطبيب رؤيتها أثناء الفحص الروتيني. تساعد هذه التقنية في توجيه الطبيب لوضع خطة علاج محددة. يجب على الأطباء التحقق كل فحص بالأشعة السينية بناءً على حالة كل مريض. هناك العديد من الأخطاء التي قد تحدث في صور الأشعة مما يجعلها غير صالحة للتشخيص. تشمل هذه الأخطا التداخل بين الصور، فقدان تيجان الأسنان، غياب السن المطلوب في مركز الصورة، وجود شوائب، تشويش الحركة، أو التعرض غير المناسب للضوء. غالبًا ما تتطلب هذه الأخطاء إعادة التقاط الصور، بالتالي يؤدي إلى تعرّض المرضى لإشعاعات غير ضرورية مما قد يسبب لهم القلق. إضافةً إلى ذلك، فإن إهدار أفلام الأشعة بسبب هذه الأخطاء قد يكون مكلفًا للمؤسسة.بدلا من ذلك من الممكن استخدام الأموال المهدرة على هذه الأفلام لتحسين مرافق المستشفى. في هذا المشروع، نخطط لتطوير نموذجين ذكاء اصطناعي باستخدام الشبكات العصبية الالتفافية (CNNs) . سيعمل النموذج الأول على تصنيف الصور لتحديد ما إذا كانت صالحة للتشخيص أم لا. وفي حال كانت الصورة غير صالحة للتشخيص، سيعمل النموذج الثاني، الذي يركز على الكشف والتحديد المكاني، على تحديد نوع الخطأ بدقة، مثل الأخطاء التشغيلية، المشكلات التقنية، أو المشكلات المتعلقة بجهاز المسح، وتحديد مكان الخطأ في الصورة. سيتم تدريب النماذج باستخدام مجموعة بيانات مقدمة من مستشفى جامعة الملك عبد العزيز. يهدف مشروعنا إلى تقديم رؤى معمقة حول جودة الصور والمشكلات المحددة التي تم العثور عليها. يعزز OralOptix عملية التقاط الصور من خلال تقديم تغذية راجعة فورية واقتراحات تصحيحية للفنيين. هذا يقلل من الحاجة إلى إعادة التصوير، ويحد من تعرض المرضى للإشعاعات، مما يعزز سلامة المرضى.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Dental X-rays are essential in clinical dentistry, providing valuable insights into various dental conditions. They are categorized into two main types: **intraoral** and **extraoral**. Intraoral X-rays are the most commonly used because they offer detailed images of individual teeth and surrounding structures, which are crucial for diagnosing specific dental issues. In contrast, extraoral X-rays provide broader views of the jaw and skull, making them useful for evaluating overall bone structure and detecting larger abnormalities.

Intraoral radiography, a fundamental diagnostic tool in dentistry, captures detailed images within the oral cavity using X-ray film, phosphor plates, or digital sensors. These radiographs help visualize dental structures necessary for accurate diagnosis and treatment planning. They enable dentists to detect cavities, bone loss, periodontal disease, and other dental issues that may not be visible during a routine clinical examination.

There are three main types of intraoral radiographs: **Bitewing**, **Periapical**, and **Occlusal**. Among these, **bitewing X-rays** are particularly valuable because they capture clear images of the crowns of premolar and molar teeth, as well as the alveolar bone crests. This makes them ideal for detecting cavities, assessing bone levels, evaluating restorations, and diagnosing periodontal disease.

Despite their importance, producing high-quality bitewing radiographs can be challenging. Errors such as improper positioning, incorrect exposure settings, and scanner-related issues often compromise the clarity and accuracy of these images, leading to potential misdiagnoses, repeated imaging, and increased radiation exposure for patients.

Currently, these challenges are mainly addressed through manual inspection, where radiologists and dental professionals visually review radiographs for errors. Some practices implement quality control measures, such as regular training programs, to improve radiographers' skills and reduce common mistakes. However, these methods remain time-consuming, rely on subjective judgment, and do not fully eliminate the need for repeated imaging due to missed errors, leading to variability in assessments and potentially inconsistent diagnostic outcomes.

To address these challenges, we introduce OralOptix, an AI-based system that automates the evaluation of bitewing radiographs using advanced algorithms. By detecting and classifying common errors, OralOptix offers real-time feedback, improving diagnostic accuracy, reducing repeat imaging, and enhancing patient safety.

In this chapter, we will outline the motivation for the OralOptix project, the problems it seeks to address, and the proposed AI-based solution. We will also cover the project's aims, objectives, scope, target users, and methodology, demonstrating how OralOptix supports more efficient and accurate dental diagnostics in line with Saudi Arabia's Vision 2030 healthcare goals.

1.2 Motivation

In modern dentistry, maintaining the quality of diagnostic tools like bitewing radiographs is essential for providing effective and accurate patient care. Despite advancements in imaging technology, dental radiographic errors remain a persistent challenge, often leading to misdiagnosis and unnecessary repeat imaging. Poor-quality radiographs not only delay treatment but also increase patient risk due to repeated radiation exposure. Our system aims to detect and address these issues by contributing to more accurate diagnoses, reducing patient exposure to radiation, and enhancing decision-making in dental care.

1.3 Problem Statement

The quality of radiographic images is a fundamental factor in ensuring diagnostic accuracy and effective clinical management, particularly in dental practices. Despite its importance, the current assessment of X-ray image quality and diagnostic value is predominantly a manual process, which is both time-consuming and prone to human error. This manual evaluation is heavily dependent on the expertise, experience, and subjective judgment of radiographers and radiologists, leading to variations in assessment outcomes and the potential for inconsistency. [Kjelle and Chilanga, 2022]

Various technique-related errors, including overlapping contacts, cone cut errors, and incorrect angulation, as well as issues related to image density and scanner artifacts, often result in unclear or distorted radiographic images. These inaccuracies, demonstrated in Figure 1.1, can significantly impair diagnostic precision, increasing the risk of misdiagnosis. Moreover, such errors frequently necessitate repeated imaging, which not only delays patient care but also exposes both patients and radiological personnel to additional ionizing radiation, raising health risks and leading to inefficient use of clinical resources.

Given these challenges, the manual approach is often inadequate in consistently identifying and correcting radiographic quality issues. This inefficiency highlights an urgent need for an automated solution capable of accurately evaluating X-ray images, identifying errors, and providing corrective feedback. Implementing such a system would enhance diagnostic accuracy, minimize unnecessary radiation exposure, and optimize the use of radiological resources, ultimately contributing to more efficient and safer patient care in clinical settings.

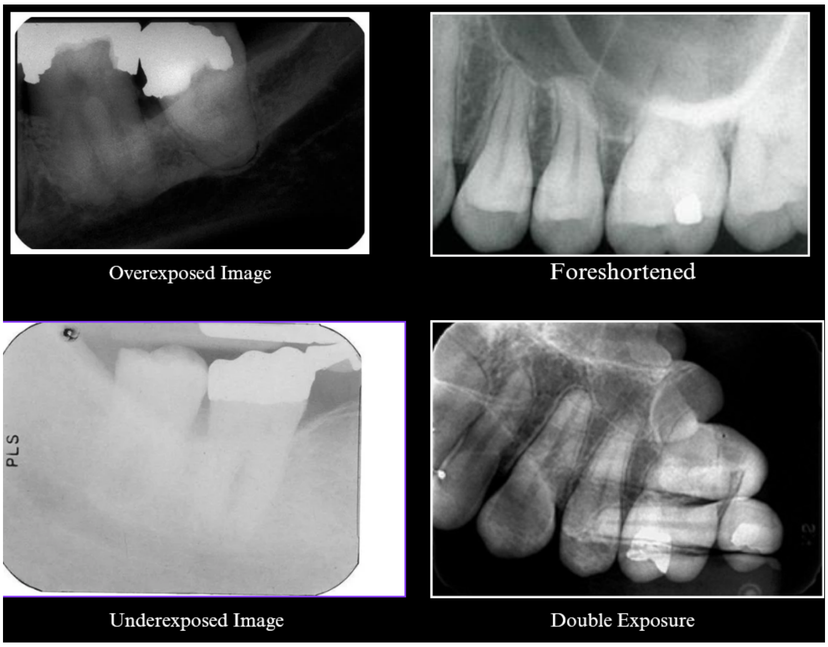


Figure 1.1: Examples of common radiographic errors: overexposure, foreshortening, underexposure, and double exposure. Source :[Rozylo-Kalinowska and Rozylo-Kalinowska, 2020]

1.4 Proposed Solution

Manual assessments of bitewing radiographs are often prone to human error and inefficiency. To address these challenges, we proposed OralOptix, an intelligent system that uses advanced Artificial Intelligence (AI) and deep learning algorithms to assess radiographic images and discover errors.

When an image is uploaded to the OralOptix website, it undergoes preprocessing. A classification model determines if the image is diagnostic or non-diagnostic , or diagnostic with issues ,then the model will print the specific quality-related attributes (errors) of the uploaded image.

The analysis results are displayed on the website, providing detailed insights into the image quality and specific errors identified. By offering feedback and corrective suggestions, OralOptix helps technicians improve the image acquisition process. This reduces the need for retakes and minimizes patient radiation exposure, enhancing patient safety.

In summary, OralOptix offers a comprehensive AI-driven solution for improving dental radiography by effectively analyzing images and discovering errors. This system supports better clinical evaluations, enhances operational efficiency, and promotes patient safety through reduced radiation exposure and streamlined diagnostic processes.The proposed solution is illustrated in Figure 1.2.

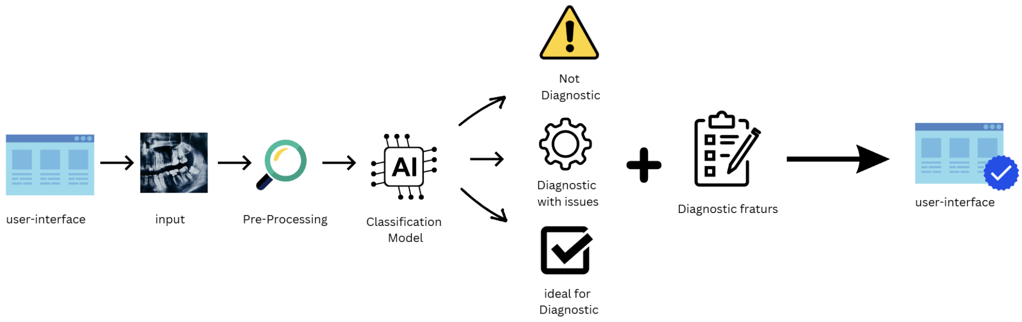


Figure 1.2: Proposed Solution

1.5 Aim and Objectives

Aim:

Our aim is to develop an AI system that automatically evaluates the diagnostic quality of bitewing radiographs,and streamline dental workflows, minimizing the risk of errors and improving diagnostic efficiency,

Objectives:

1- Gather a comprehensive dataset of bitewing X-ray images specifically for use in the project

2- Develop a reliable AI model capable of distinguishing between diagnostic and non-diagnostic, diagnostic with issues bitewing radiographs.

3- Identify and classify common radiographic errors (quality related attributes).

4-Develop a user-friendly website with a good interface that displays all the results clearly for dentists, improving usability and workflow efficiency

1.6 Scope

The goal of "OralOptix" is to improve Bitewing X-rays, a particular kind of dental X-ray that is necessary for seeing spaces in between teeth that aren't apparent during routine examinations. These X-rays are essential for tracking the health of the bones and finding cavities.

1.7 Target Users

This project's main target users are professionals like dentists, dental hygienists, and oral healthcare professionals, including those focused on intra-oral radiography processing. Moreover, the audience reached by the project is believed to be more extensive, comprising of dental scholars, specialists, and other parties that are involved in the practice of dental care and oral health.

1.8 Methodology

The Iterative Waterfall Model is the methodology selected for our project. This is much like the traditional waterfall structure, with five stages in sequence: requirement analysis, design, implementation, verification, and maintenance, shown in figure 1.3. But unlike in the standard model, here it provides flexibility to perform iterative cycles. Allowing revisits for changes and updating in earlier stages as needed. It has the ability to detect issues, giving better risk management, and that will enhance the quality assurance of the project.The waterfall model's stages do not overlap, thus each stage starts and ends before moving on to the next.[Stepanov, 2021]

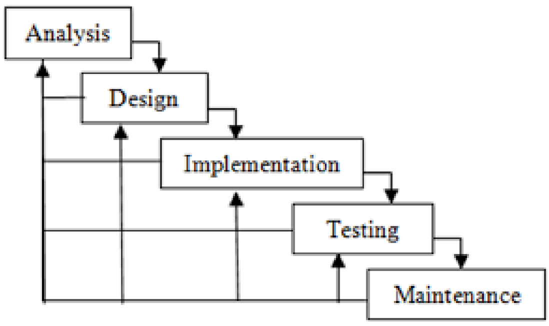


Figure 1.3: Iterative Waterfall Model

1.9 Plan and milestones

Based on the Iterative Waterfall Model methodology as mentioned in Section 1.7 above, we set the milestones of the project and the plan of the project showing the tasks, followed by the duration of each task. The following tables show the project plan and milestones in tables 1.1 and 1.2, respectively.

Table 1.1: The Project Milestones

Term	Week#	Milestone#	Milestone Description
498	8	1	Introduction (Chapter 1) Literature Review (Chapter 2)
	12	2	System Analysis and Requirements (Chapter 3) System Design (Chapter 4)
	15	3	Final Report 1
499	8	4	System Implementation (Chapter 5)
	12	5	Integration and Testing (Chapter 6) Conclusion (Chapter 7)
	15	6	Final Report 2

Table 1.2: Project Plan

Term	Task	Duration
CPCS-498	**Introduction (Chapter 1)**	**2 weeks**
	Introduction, Problem Statement, Suggested Solution	4 days
	Aim and Objectives, Scope, Motivation	5 days
	Target Users, Methodology, Plan and Milestones	5 days
	Literature Review (Chapter 2)	**3 weeks**
	Read about the related Background	7 days
	Search and Read related work Papers	9 days
	Analyze the related work	5 days
	System Analysis and Requirements (Chapter 3)	**2 weeks**
	Dataset Gathering	8 days
	Data and Requirement Specification	6 days
	System Design (Chapter 4)	**2 weeks**
	Software and Database Design	15 days
	Interface Design	6 days
CPCS-499	**System Implementation (Chapter 5)**	**5 weeks**
	Model Implementation	20 days
	Website Implementation	15 days
	Integration and Testing (Chapter 6)	**3 weeks**
	Website and Model Integration	14 days
	Testing	7days
	Conclusion (chapter 7)	**1 week**
	Define Challenges and Difficulties	3 days
	Future Work and Conclusion	4 days

1.10 Conclusion

In this chapter, we introduced the OralOptix project, an AI-driven system designed to enhance the quality of bitewing radiograph assessments in dental practices. The project's aim and objectives were clearly outlined, providing insight into how it addresses current challenges in radiograph evaluation. Furthermore, we discussed the system's scope, target users, and methodology, demonstrating how OralOptix aligns with modern healthcare goals to optimize resource usage and improve patient care in dental radiography.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Artificial intelligence (AI) has made substantial advancements in recent years, extending its reach into various industries, including healthcare. In dental medicine, the vast amounts of clinical data being generated have led to growing interest in leveraging AI to enhance diagnostic accuracy and efficiency. This research focuses on using AI to evaluate bitewing radiographs, a common dental X-ray, to determine their diagnostic value or identify errors that may hinder accurate diagnosis. By automating this process, AI has the potential to significantly reduce the time and effort required by dental professionals, allowing them to focus on more critical aspects of patient care.

The chapter begins with a literature review, providing an overview of the medical principles related to dental radiography in Section 2.2. Section 2.3 explores the technical details of how AI is applied in this context, while Section 2.4 reviews the current body of related research, examining similar efforts and the gaps this study aims to address. The chapter concludes in Section 2.5, summarizing the findings and laying the groundwork for subsequent chapters.

2.2 Medical Background

2.2.1 Dental X-Rays

Dental X-rays are quick, painless imaging techniques used to capture images of teeth and jaws by passing invisible radiation beams through the body. Dense structures like bones and teeth absorb more X-rays, appearing white on the image, while less dense tissues such as nerves and muscles absorb fewer X-rays, showing up as shades of gray. Dental X-rays are categorized into intraoral and extraoral types. Intraoral X-rays are the most common and provide detailed images, while extraoral X-rays focus on the jaw and skull. This project will specifically focus on intraoral X-rays, particularly the bitewing type.([Rozylo-Kalinowska, 2020]).

2.2.2 Types of Intraoral Radiographic Examinations

Intraoral radiography consists of three primary types of examinations, each serving a distinct diagnostic purpose, and it might be more effective to present the figures immediately after discussing each type for clarity. The **Bitewing Examination**, which is shown in **Figure 2.1**, is primarily used to evaluate the crowns of both the upper and lower teeth; it focuses on detecting dental caries, assessing existing fillings, identifying calculus deposits, and evaluating bone health. This type of examination offers a clear view and is particularly effective for detecting interproximal caries and assessing bone levels, which are crucial for comprehensive dental evaluations.

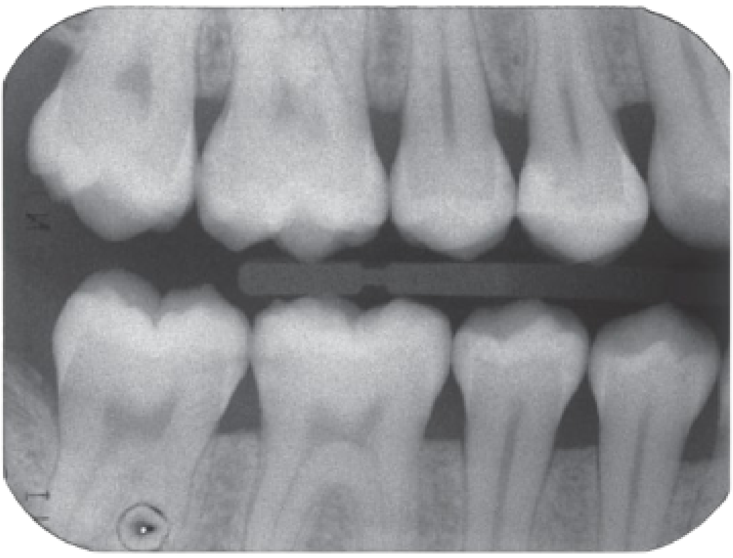


Figure 2.1: Bitewing Radiograph Source : [Rozylo-Kalinowska, 2020]

Similarly, the **Periapical Examination**, represented in **Figure 2.2**, captures the entire tooth structure, including the roots and surrounding bone; this makes it essential for diagnosing conditions such as apical pathology, fractures, and periodontal disease. This type of radiograph is indispensable for identifying deeper dental issues that may not be apparent in other imaging types.

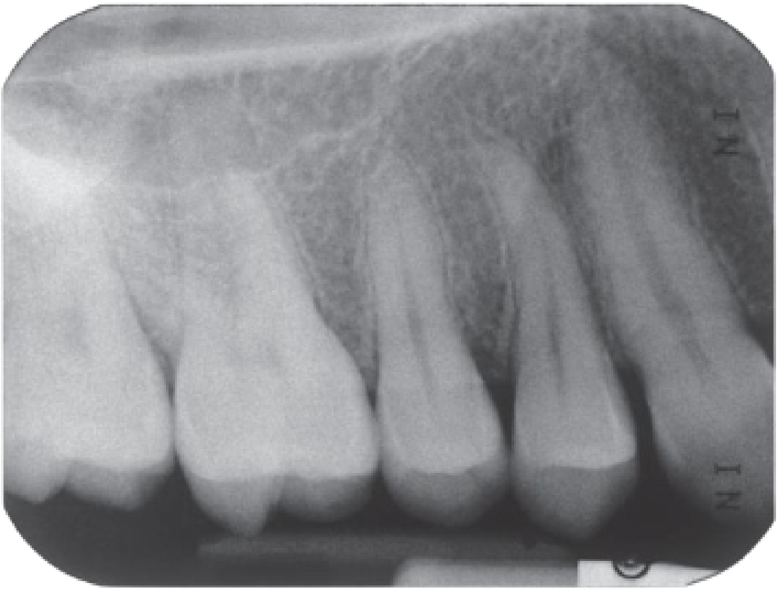


Figure 2.2: Periapical Radiograph Source : [Rozylo-Kalinowska, 2020]

Lastly, the **Occlusal Examination**, as seen in **Figure 2.3**, provides a comprehensive view of the upper or lower jaw, making it valuable for detecting jaw lesions, cysts, fractures, or salivary stones .([Rozylo-Kalinowska, 2020]).

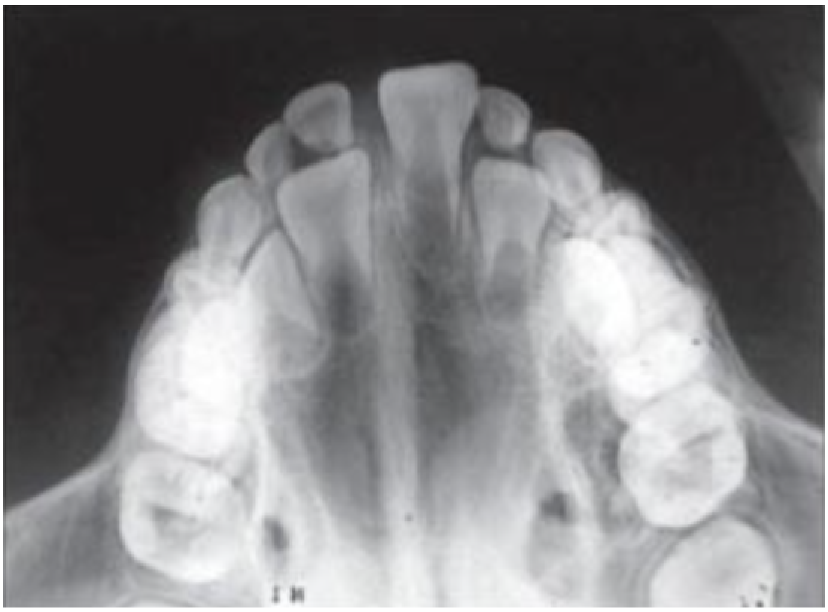


Figure 2.3: Occlusal Radiograph Source : [Rozylo-Kalinowska, 2020]

2.2.3 Importance of Intraoral Radiography in Dentistry

Intraoral radiography is a fundamental aspect of modern dentistry, acting as a crucial diagnostic tool that significantly improves the accuracy of diagnosis, treatment planning, and overall patient care. It provides detailed images that facilitate the identification of dental conditions such as caries, fractures, and periodontal disease, ensuring early detection and effective treatment. Moreover, it plays a vital role in treatment planning and monitoring, supporting precise procedures and enabling the ongoing assessment of treatment progress. Intraoral radiography is also instrumental in detecting hidden dental issues that are not visible during routine examinations, such as early-stage caries and impacted teeth. Additionally, it assists in understanding dental anatomy and development, aiding in the evaluation of tooth development, eruption patterns, and orthodontic treatment planning. Furthermore, intraoral radiography offers high-quality imaging with lower radiation exposure compared to extraoral techniques, making it a safer option for patients. Lastly, it is a cost-effective and widely accessible diagnostic method, making it a standard tool in most dental practices for routine diagnostics and treatment planning.([Rozylo-Kalinowska, 2020]).

2.2.4 The Biological Effects and Risks Associated with X-rays

The main risks associated with X-ray exposure, especially in dental radiology, include the potential for somatic deterministic effects (tissue damage, cataracts) at high doses and stochastic effects (increased risk of cancer, genetic mutations) even at low doses. Pregnant women and developing fetuses are particularly vulnerable, with risks like congenital abnormalities. Although dental X-rays use low radiation, repeated exposure can increase risks of thyroid and meningeal tumors. Therefore, minimizing exposure and following safety protocols are essential to reduce these health risks.

2.2.5 The Bitewing Examination

Bitewing radiographs, named after the original technique where patients bit on a small wing attached to an intraoral film packet, are the most commonly used intraoral radiographic tool in dental diagnostics. These radiographs capture detailed images of the crowns of premolar and molar teeth, along with the alveolar bone crests, making them ideal for early detection of caries, particularly in areas difficult to examine visually. The technique positions the image receptor close to the teeth, allowing for optimal x-ray beam angulation. While they don't capture the entire tooth, bitewing radiographs offer superior imaging of decay and bone height, making them invaluable in routine dental examinations and treatment planning.([Rozylo-Kalinowska, 2020])

Main Indications of Bite-wing images:

1. Detection of caries lesions
2. Monitoring the progression of dental caries
3. Assessment of existing restorations
4. Evaluation of periodontal status

Basic Steps of the Bitewing Radiographic Technique

1. Place the receptor in the mouth parallel to the crowns of the maxillary and mandibular posterior teeth.
2. The patient bites on the tab attached to the receptor.
3. The vertical angulation is set at +10 degrees; the horizontal angulation is directed through the contact areas of the posterior teeth.

Bitewing Devices:

There are two main devices used for bitewing X-rays: bitewing tabs and beam-alignment devices. **Figure 2.5: Bitewing tabs Source** shows the tabs, which involve sticking a tab to the receptor and aligning the circular X-ray beam manually, but this can be less accurate and doesn't allow for reducing radiation as effectively. **Figure 2.4: Beam-Alignment Device Source** shows beam-alignment devices, like the XCP® holder, which use a rectangular beam that lowers radiation and ensures the beam is automatically aligned at the right angle, making the X-ray more accurate and consistent.

Figure 2.4: Beam-Alignment Device Source : [Thomson and Johnson, 2018]

Figure 2.5: bitewing tabs Source : [Thomson and Johnson, 2018]

2.2.6 Common Errors

Common radiographic errors include overlapping contacts, cone cut, incorrect vertical angulation, double exposure, blurring, and phalangioma, all caused by improper technique or positioning. Density errors like underexposure and overexposure result from incorrect settings, while scanner errors occur when removable items like dentures or jewelry aren't taken off, causing artifacts in the image. Proper adjustments and precautions can prevent these issues and improve image quality . Figure 2.6 illustrates common radiographic errors.([Rozylo-Kalinowska, 2020])

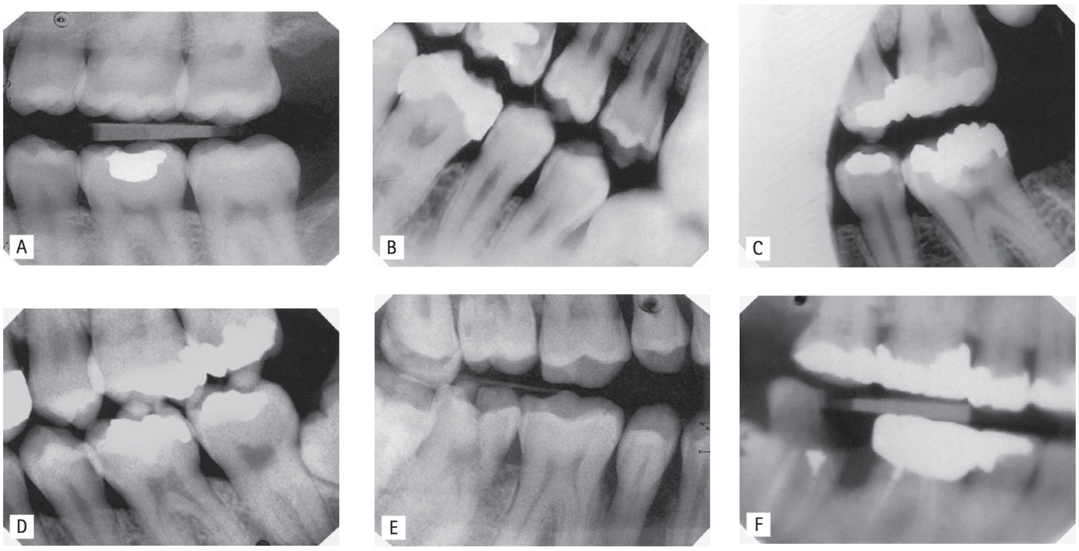


Figure 2.6:
A: Receptor too far back, missing premolars.
B: Tongue displacement, causing a tilted occlusal plane.
C: Horizontal misalignment, leading to coning off.
D: Overlapping contacts due to horizontal misalignment.
E: Vertical misalignment, causing distortion.
F: Blurring from patient movement.
Source : [Whaites and Drage, 2013]

2.3 Technical Background

Machines have taken the lead as the primary intellectual force, capable of completing tasks more quickly and efficiently than humans. As technology advances, computers and machines are becoming increasingly intelligent and human-like. These systems, which imitate human intelligence and perform similar tasks, are referred to as artificial intelligence (AI). AI has transformed technology by effectively learning from large datasets. Today's AI systems rely on machine learning, using data and algorithms to mirror human learning patterns. This enables machines to continually enhance their intelligence and accuracy as they process more information

2.3.1 Machine Learning

The rapidly evolving field of machine learning aims to develop advanced models and algorithms that empower computers to recognize patterns, predict outcomes, and continuously improve over time. By learning from data and past experiences, machine learning allows computers to make decisions autonomously, without requiring explicit programming.

Supervised Learning: is a method in which a model learns how to categorize data or make predictions by utilizing labeled datasets. In supervised learning, both the input features and the corresponding target variables are provided to the model.

Unsupervised Learning: is a method where the a model learns to recognize patterns or group datasets without using labeled data. In this situation, there are no target variables, and the machine must independently discover hidden patterns or relationships within the data.

Reinforcement Learning: is a method in which an agent inside an environment learns how to make decisions to maximize a reward signal. The agent engages with the environment by taking actions and observing the rewards that follow.

2.3.2 Deep Learning

Deep learning is a subset of machine learning (ML) that uses multilayered neural networks to learn from vast amounts of data, making it ideal for handling complex tasks that traditional algorithms often find challenging. It excels at extracting insights from complex and unstructured data by employing multiple layers of artificial neurons, which automatically learn hierarchical representations from raw data. Unlike conventional ML models, which require manual feature engineering, deep learning models can autonomously identify and learn intricate patterns through these layered structures. This capability allows them to function effectively across different learning scenarios, including supervised, semi-supervised, unsupervised, and reinforcement-based learning, making deep learning a versatile and powerful tool for a wide range of applications.([Alzubaidi et al., 2021]).

2.3.2.1 When to Apply Deep Learning

Deep learning is particularly valuable in scenarios where it outperforms traditional methods. It is ideal for tasks where human expertise is limited or unavailable, such as analyzing medical images for rare diseases. It is also highly effective in situations where human decision-making is difficult to articulate, like understanding speech or recognizing complex patterns in language. Deep learning is well-suited for dynamic problem-solving tasks that evolve over time, such as predicting stock market trends or weather patterns. Additionally, it excels in applications requiring adaptability, such as biometric identification or delivering personalized recommendations. Moreover, deep learning is highly efficient at handling large datasets, making it capable of processing massive volumes of data for tasks like sentiment analysis, image recognition, and natural language processing.([Alzubaidi et al., 2021]).

2.3.2.2 Deep Learning Network Structure:

Deep learning models consist of:

1. Input Layer: The initial layer that receives raw data.
2. Hidden Layers: Intermediate layers that process inputs through neurons, learning complex features.
3. Output Layer: The final layer that produces the model's predictions or outputs.

2.3.2.3 Classification of Deep Learning Approaches:

Deep learning can be classified into several approaches:

1. Supervised Learning: Uses labeled data to train models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks.
2. Semi-Supervised Learning: Utilizes a combination of labeled and unlabeled data, often with models like Generative Adversarial Networks (GANs).
3. Unsupervised Learning: Handles unlabeled data to find patterns and structures, often using techniques like clustering and dimensionality reduction.
4. Deep Reinforcement Learning (DRL): Involves interaction with an environment to optimize decision-making processes.

2.3.2.4 Popular Deep Learning Networks:

- *Recursive Neural Networks (RvNNs)*: Effective for handling hierarchical data structures, such as those found in natural language processing (NLP).
- *Recurrent Neural Networks (RNNs):* Suitable for sequential data processing, often used in speech and language tasks.
- *Convolutional Neural Networks (CNNs):* Widely applied in image processing tasks, such as object recognition and classification.

2.3.2.5 Applications of Deep Learning:

Deep learning is widely used in several domains:

- Classification: Identifying diseases using medical images, such as CNNs diagnosing pneumonia.
- Localization: Determining object positions within images, helpful in tasks like tumor detection in radiology.
- Detection: Recognizing multiple objects within an image, essential in areas like autonomous driving.
- Segmentation: Outlining objects, such as identifying tumor boundaries in MRI scans.
- Registration: Aligning and comparing images from different sources, such as combining MRI and PET scans.

2.3.2.6 Supervised Deep Learning Algorithms:

CNN: Artificial neural networks are called Convolutional Neural Networks (CNNs). It is a kind of feature extraction. It might be used with great accuracy in challenging fields like picture classification and object detection. These days, it's widely used, particularly for satellite image analysis and smartphone photo improvement. In essence, it selects and extracts relevant features from input data. What gives it the high efficiency is the detection-based method for the edges, translational invariance, work in decreasing the number of parameters, and the ability to capture the complex dependencies.

2.4 Key Phases in Machine Learning Deep Learning Modeling:

2.4.1 Data Gathering Phase

Acquiring real-world bitewing radiographs is essential to our project because it enables us to train the deep learning model on authentic diagnostic images, ensuring the model learns to recognize real-life diagnostic patterns and errors, The quality and diversity of the data we gather are very important, as they directly impact the model's performance in clinical applications, we formally collaborated with dental hospitals to obtain a bitewing radiograph dataset, which is crucial for training and evaluating our deep learning model. We also sought and received ethical approval to use these radiographs, ensuring that our research adheres to ethical guidelines regarding patient privacy and data protection.

2.4.2 Pre-processing phase

The goal of these steps is to ensure that the data employed for machine learning is not only accurate, but also consistent and properly structured for analysis. By systematically reviewing and adjusting the radiograph to meet quality standards, and meticulously gathering and labeling both demographic and radiographic data, the research sets a solid foundation for the machine learning model. This comprehensive approach ensures that the model can effectively learn from the data, ultimately enabling it to make reliable predictions or classifications. These predictions will pertain to assessing the overall quality and diagnostic potential of bitewing radiographs, allowing the system to differentiate between diagnostic and non-diagnostic , diagnostic with issues images with greater accuracy.

1-Labeling:

Each radiograph should be carefully evaluated by experts to determine whether it is diagnostic or non-diagnostic or diagnostic with issues. the model should further print the errors of the image or (quality related attributes) -if any , such as technique errors, density errors, or scanner errors. This detailed labeling is vital for supervised learning, as it helps the model accurately associate specific image features with diagnostic quality and errors.

2-Image Standardization:

Resolution Adjustment**:** Radiographs must be resized to a uniform resolution (e.g., 1920 × 1440 pixels) to maintain consistency and ensure that variations in image size or quality do not negatively impact the model's performance.

Resolution Adjustment**:** Images should be converted to standard, high-quality formats like webp or jpg, which preserve image details and avoid compression artifacts that could diminish diagnostic information.

3-Rotation and Alignment:

Orientation Correction**:** Radiographs need to be aligned correctly, ensuring that teeth are in their natural, upright positions. Consistent anatomical alignment aids the model in learning to detect diagnostic features more reliably.

Cropping**:** Extraneous background elements should be removed from the images, allowing the focus to remain solely on relevant dental structures. This enhances the model's training by reducing distractions and irrelevant data.

4-Normalization:

Pixel values should be normalized across all images to maintain a consistent range, providing the model with uniform input. This step is particularly important for neural networks, as it improves the model's efficiency and speeds up convergence during the training process.

4-Masking :

a technique used in machine learning to handle missing or unknown data by replacing such values with a special marker, commonly -1, to signal the model to ignore them during training. This approach helps prevent the model from misinterpreting missing values as meaningful input.

2.4.3 Dimensionality Reduction and Feature Extraction Phase

Data compression (Extraction):

The second step after pr-processing is data compression or data extraction. Identifying and extracting only the important characteristics. Data transformation involves converting raw data into a more informative representation that will improve the performance and interpretability of the model. It is often done so that critical features indicative of underlying patterns or structures can be caught. Feature extraction may be done in a manual process via edge detection, texture analysis, color histograms, or done automatically. Sometimes, feature extraction may make use of the same kind of tools as in the pre-processing step. [Ansari, 2020]

Feature selection:

The third step after pre-proccing and then data extraction is the feature selection. Work on improving the model's generalization capabilities. By selecting the relative and useful features in the training model and eliminating the unneeded features. It Reduce complexity, decrease the training time of ML algorithms, and reduce the overfitting risk. It also enhances interpretability and the model's accuracy by utilizing the well-chosen set of variables. And there are three techniques: filter method, wrapper method, and embedded method. The first one filter method, use statical measures dependently of any model in choosing feature; the second one wrapper method, select feature by regrading model performance; last kind is embedded method, select feature by integrating int model training. feature selection would ensure that a model is not only efficient but fairly accurate.[Ansari, 2020]

2.4.4 Model Training Phase:

It is an important stage in any machine learning life-cycle that consists of training, validation, and testing by data that have been already pre-processed in an earlier phase. During this phase, one selects an appropriate algorithm depending on the problem type and the nature of the dataset. The model has been trained on the training set, fine-tuned by the validation set, and finally evaluated by the test set. Pre-processing the data ensures that it effectively learns the patterns generalizes well to unseen data and provides valid and reliable predictions from the model.[Ansari, 2020]

Training set:

a subset of data used for training in the ML model. it will have the proportion in the entire data. usually from 60%-80% of the dataset. The large amount of data will help the model to learn and bring the most optimal value for the various parameters involved, the higher amount of data the more efficient model we get.[Ansari, 2020]

Validation set:

The validation set usually consider as a part of training. basically, it is taking a subset composed of 10%-20%of the training data. It works in testing the model performance during the training time. It gives an unbiased estimate of the ability of a model to generalize on temperedly unseen data. The validation set thus aids in fine-tuning model hyperparameters to prevent overfitting; hence, making sure that the model evaluation can be honest and objective at this final testing stage.[Ansari, 2020]

Test set:

The test set is a set that the model never seen it and didn't train or validate with it. usually it consists of 10%-20% of the dataset. It will only be applied to the final model after training and validation is completed. It helps in examining the model as it will be in real world. it is evaluating the model by new, unseen data. It is one of the most important measures concerning a model's true predictive capability.[Ansari, 2020]

2.5 Related Research Papers

This section reviews related studies to gain a clearer understanding of the problem and identify potential solutions. The literature is divided into two categories: the first covers studies that use AI techniques to evaluate the quality of bitewing radiographic dental images, while the second addresses studies that apply AI techniques to the diagnostic analysis of bitewing radiographs.

2.5.1 Intelligent Assessment of Bitewing Radiographs - Related Work

The study by Barayan et al. (2022) makes a substantial contribution to dental diagnostics by applying artificial intelligence (AI) to assess bitewing (BW) radiographs using a dataset obtained from King Abdulaziz University Dental Hospital. The research analyzed 864 BW radiographs from 100 patients, focusing on the diagnostic quality of contact areas between teeth. Utilizing various machine learning (ML) models, including the TensorFlow-based Efficientdet-d0, the study effectively categorized radiographs as either diagnostic or non-diagnostic, identifying specific errors like "overlap within enamel" and "overlap within restoration (clear margins)." These models demonstrated high accuracy and precision, with F1 scores reaching 0.89 and 0.76, and a low log loss value of 0.15, indicating their reliability.

The study highlights the potential of neural networks, particularly recurrent neural networks (RNN), in offering superior diagnostic capabilities compared to traditional statistical methods. It underscores the importance of integrating advanced AI tools to enhance dental diagnostic practices, suggesting that optimized AI models can reduce diagnostic errors and improve accuracy. This integration of AI presents an opportunity for more consistent, objective, and precise evaluations in dental radiography, marking a significant step forward in dental healthcare technology.([Barayan et al., 2022])

The paper "An AI-based Framework for Diagnostic Quality Assessment of Ankle Radiographs" by Mairhöfer et al. (2021) introduces a deep learning framework aimed at improving the assessment of ankle radiographs' diagnostic quality by focusing on anatomical features, rather than just technical parameters like noise and contrast used in traditional methods. This approach represents a shift towards more accurate and reliable diagnostic evaluations in radiology.

The framework was rigorously tested using a dataset of 950 ankle radiographs, which were labeled by radiologists according to their diagnostic quality. The process involves three crucial steps:

1. Recognition of the Radiographic View: This step involves identifying whether the radiograph is in the anterior-posterior (AP) or lateral (LAT) view, which is essential for accurate quality assessment.

2. Extraction of the Region of Interest (ROI): The framework extracts the most relevant portion of the radiograph, focusing on the area essential for diagnosis, ensuring that unnecessary information does not affect the assessment.

3. Quality Assessment: Using neural networks, the framework assesses the quality of the radiograph, classifying it based on a continuous scale.

The study's results are impressive, with the model achieving an average accuracy of 94.1%, which exceeds the performance of expert radiologists. This demonstrates the potential of deep learning in enhancing diagnostic quality assessment, providing more accurate and reliable outcomes.

The paper's findings have significant implications for radiology practice, as the framework offers immediate feedback to radiographers, reducing errors and improving diagnostic consistency. This AI-based system could be a valuable tool for ensuring the quality of radiographs, ultimately contributing to more efficient and accurate healthcare delivery in radiology departments.([Mairhöfer et al., 2021]).

Ma et al. (2020) address the challenge of classifying MRI diagnostic quality, focusing on the impact of motion artifacts that frequently result in non-diagnostic images and require patient rescans. The study emphasizes the need for automated systems to enhance efficiency and reduce reliance on radiologists for initial image quality evaluation. To tackle this issue, the authors compare two convolutional neural network (CNN) models: a simple 4-layer CNN and a more complex ResNet-10 architecture. These models were evaluated on two tasks: binary classification (distinguishing between diagnostic and non-diagnostic images) and three-class classification (non-diagnostic, diagnostic, and excellent). The results show that the simpler 4-layer CNN outperformed the deeper ResNet-10 model, achieving 84% accuracy in the binary classification task and 65% in the three-class classification task. The study also highlights challenges such as the subjectivity of radiologist assessments, dataset imbalance, and mislabeling of images, all of which impact the performance of the models. In conclusion, while the simpler CNN model effectively classified diagnostic quality, addressing these challenges is essential for maximizing the potential of AI in improving medical imaging.([Ma et al., 2020]).

2.5.2 Intelligent Diagnostic Analysis of Bitewing Radiographs - Related Work

The paper by Baydar et al. (2023) presents an advanced AI model utilizing Convolutional Neural Networks (CNNs), specifically the U-Net architecture, to assess the diagnostic quality of bite-wing radiographs. Using a dataset of 500 radiographs from Eskisehir Osmangazi University, the study aimed to automatically detect and evaluate dental conditions such as caries, crowns, pulp, restoration material, and root-filling material through segmentation. The U-Net model demonstrated exceptional performance, achieving sensitivity and precision scores exceeding 95%, with particular success in detecting crowns and pulp. The F1 score, a key performance metric, ranged from 0.88 to 0.97, highlighting the model's potential to enhance diagnostic accuracy and reduce the workload on radiologists. The authors conclude that AI-based tools, such as the U-Net model, offer significant promise in providing real-time, consistent, and objective diagnostic support, thus improving clinical workflows, minimizing human error, and increasing overall efficiency in dental radiology.([Baydar et al., 2023]).

The study titled "Classification of Periapical and Bitewing Radiographs as Periodontally Healthy or Diseased by Deep Learning Algorithms" by Yavuz et al. (2024) aimed to develop a deep learning algorithm for classifying dental radiographs into periodontally healthy or unhealthy categories. The researchers utilized 1120 periapical and 1498 bitewing radiographs, divided into training, validation, and test sets, and applied the YOLOv8-cls model for classification. The AI algorithm demonstrated high accuracy in detecting periodontal disease, with performance metrics—such as sensitivity, specificity, precision, and F1 scores—exceeding 75%. This study illustrates the potential of AI to assist in diagnosing periodontal health, thereby reducing human error and improving the efficiency of dental radiography interpretation. However, the authors identified limitations, including the relatively small dataset and using a single AI architecture, suggesting that future studies could benefit from larger datasets and comparisons with other AI models. In conclusion, the study supports integrating AI systems into clinical dental workflows to enhance diagnostic accuracy and speed, facilitating early detection of periodontal diseases while reducing the workload on dental professionals.([Yavuz et al., 2024]).

the study aimed to assess the effectiveness of a deep convolutional neural network (CNN), specifically the YOLOv5 model, in detecting and segmenting overhanging dental restorations in bitewing radiographs. A total of 1160 anonymized radiographs were used, with 80 percent allocated for training, 10 percent for validation, and 10 percent for testing. The model demonstrated high performance with a precision of 90.9 percent, sensitivity of 85.3 percent, an F1 score of 88.0 percent, and an AUC of 0.859, confirming its effectiveness in identifying overhanging restorations. Discussion: Bitewing radiographs are critical in diagnosing interdental caries and overhanging restorations, which can contribute to periodontal disease and secondary caries. Traditionally, such diagnoses are subjective and time-consuming. The study used the YOLOv5 model, a single-stage detection algorithm, and showed that AI could outperform less experienced dentists and rival commercial AI tools like Denti.AI and CranioCatch. Despite dataset imbalances, the model achieved high precision, correctly focusing on anatomical landmarks. Conclusion: The model's high precision, sensitivity, and overall performance indicate that AI could enhance dental diagnostic accuracy. However, more research is needed to address class imbalance, improve accuracy, and ensure generalizability across different clinical settings. Ethical considerations and regulatory standards must also be considered for real-world implementation([Magat et al., 2024]).

The paper written by J. Kühnisch et al (2022). Caries Detection on intraoral images using artificial intelligence. Automated image analysis when using artificial intelligence. This study aim is using convolutional neural networks (CNNs) as deep learning field to develop an AI diagnostic for detecting caries. It will detect, classify and compare diagnostic performance. A dataset from Ludwig-Maximilians-University has been used in this project. It consisted of 2,417 anonymized images, 1.317 was occlusal and 1.100 was smooth surfaces. It was evaluated into three categories which are caries free, nonactivated caries lesion, caries related cavitation. Model training has been applied on the to the dataset and for that the data has been divided into two groups one as a training set and the other as testing set. The validation set was part of training set by taking 25%,50%,75%, and 100% from it to validation it during training. In this study CNN was able to give the correct detection in 92.5% of the total dataset images. And for each classification it got 90.6% correctness for caries free, 85.2% for nonactivated caries lesion, and 79.5% for caries related cavitation. The author discusses the future possible improvement by displaying the excluded cases in this work. As developmental defects, fissure sealants, filling, indirect restorations these conditions need a separate training. And it was only applied to single tooth images. The author discusses the future possible improvement by displaying. AI algorithm needs more development, optimizing and documenting its quality. It still cannot be used in dental clinics there is still risk of wrong diagnosis and the diagnosis result from the AI still need to be seen by professionals. ([Kühnisch et al., 2022])

This paper by Viktor et al (2024). Validation of artificial intelligence application for dental caries diagnosis on intraoral bitewing and periapical radiographs. This study's aim is to evaluate the ability of involving AI in healthcare processes especially in diagnosis caries in intraoral radiograph. A dataset from Semmelweis University has been provided. 626 proximal surfaces were evaluated for the 323 selected. 12.7%, which is 41 out of 323 were bitewing and 87.3%, which equal 282 out of 323 were periapical radiograph. The parameters were able to change and maintain and change during the radiograph evaluation for brightness editing, contrast, and magnification. In this project humans assigned '0' to the tooth and if caries has been detected it will be assigned to '1'. The diagnostic accuracy rate is (0.86), specificity rate is (0.93), and the sensitivity rate is (0.76). There are still concerns about the reliability and it cannot be used independently. It could be used with dentist agreement for observation and CNN. The author's expectation of the future work to expand the data test and preforming interobserver reliability test to broaden the scope. ([Szabó et al., 2024])

This paper is written by Nozomi et al (2022). Development of an artificial intelligence-based algorithm to classify images acquired with an intraoral scanner of individual molar teeth into three categories. The goal is the automation of dental filing by using images obtained with intraoral scanners. In this search AI-based have been used to classify single moral teeth into three categories which is full metallic crown (FMC); partial metallic restoration (In); or (3) sound tooth, carious tooth or non-metallic restoration (CNMR). Then apply cross-validation to reduce bias. The evaluation divided into 4 types for analysis which are precision, recall, F-measure and overall accuracy. so, the individual molar teeth extracted from the scanned images for the three classifications (FMC, In, CNMR). CNN has been applied according to LeNet architecture, which is two convolution layers, max-pooling, affine layers. The results in evaluation: 0.952 for recall,0.957 for precision,0.952 for F-measure, and 0.952 for overall accuracy. It is the belief of the author that in case of a large-scale disaster, dental assessment will be more accurate and faster by the use of an intraoral scanner.([Eto et al., 2022])

Table 2.1: Summary of Intelligent Assessment of Bitewing Radiographs - Related Works Part 1

Reference	[Baydar et al., 2023]	[Yavuz et al., 2024]
Aim	To evaluate the use of AIfor detecting dental issuesin bite-wing radiographs	Develop an AI model to classify radiographs as healthy or diseased
Technique	U-Net CNN: Used for segmentation tasks.	The YOLOv8-cls model is used for classification tasks.
Pre-processing	Image augmentation techniques used: rotation, flipping, and noise.	Image resizing
Feature	Detect and segment dental conditions like caries, crowns, pulp, restorations, and root canal fillings from bitewing radiographs.	Focuses on classifying periodontal health status.
Dataset	The dataset consists of 500 anonymized bitewing radiographs.	The dataset consists of 1,120 periapical and 1,498 bitewing radiographs.
Errors	-	-
Results	The F1 scores were 0.88 for caries, 0.96 for crowns, and 0.97 for restorations.	The accuracy was 0.77 for bitewing radiographs and 0.75 for periapical radiographs.
Limitation	Limitations include a small dataset and the need for further validation.	Limitations include a limited dataset size and a lack of standardization for periapical radiographs.
Future work	Apply the model to other complex dental radiographs.	Extend to other image types and improve accuracy.

Table 2.2: Summary of Intelligent Assessment of Bitewing Radiographs - Related Works Part 2

Reference	[Kühnisch et al., 2022]	[Szabó et al., 2024]
Aim	Caries detection on intraoral images using artificial intelligence.	Validation of artificial intelligence application for dental caries diagnosis on intraoral bitewing and periapical radiographs.
Technique	CNN MopileNetV2 (Standler et al. 2018).	CNN
Pre-processing	- beast quality - remove duplicated photos - all jpg images (RGB format, resolution 1,200 x 1,200 pixel, no compression) -cropped to ratio 1:1 (Affinity photo; serif).	brightness editing, contrast, and magnification.
Feature	Detect caries from single-tooth images Both Occlusal and smooth surfaces teeth.	Classification, detection, and segmentation in image detection to get caries diagnosis.
Dataset	2,417 anonymized photograph : 1,327 Occlusal, 1.100 smooth surfaces.	626 proximal surfaces were evaluated for the 323 selected teeth: 41(12.7%) bitewing ,282 (87.3 %) periapical radiographs.
Errors	-	-
Results	The accuracy for the right detection of Caries: 0.925 overall , 0.933 for tooth surface , 0.906 for caries free , 0. 852 for nonactivated caries lesions ,0.795 for cavitated caries.	-diagnostic accuracy rate is (0.86), -specificity rate is(0.93), - sensitivity rate is (0.76).
Limitation	1- single-tooth photographs 2-exclude: developmental defects, fissure sealants, filling, indirect restorations.	data that have reflect human disagreements.
Future work	-Develop the program to include deferent tooth photograph not only single-tooth -different diagnoses and regular evaluation -optimizing and documenting its quality.	expand the scope by including additional test data and performing an interobserver reliability test.

Table 2.3: Summary of Intelligent Assessment of Bitewing Radiographs - Related Works Part 3

Reference	[Eto et al., 2022]
Aim	Development of an artificial intelligence-based algorithm to classify images acquired with an intraoral scanner of individual molar teeth into three categories.
Technique	CNN Cross-validation.
Pre-processing	remove bad quality photos.
Feature	- Classification teeth into three categories - evaluation into categories four types.
Dataset	300 images of each category
Errors	-
Results	evaluation: 0.952 for recall, 0.957 for precision, 0.952 for F-measure, and 0.952 for overall accuracy.
Limitation	Images that were unclear on visual inspection were excluded
Future work	Increase accuracy and speed of the intraoral

Table 2.4: Intelligent Diagnostic Analysis of Bitewing Radiographs - Related Works

Reference	[Barayan et al., 2022]	[Mairhöfer et al., 2021]
Aim	Assess the effectiveness of machine learning in evaluating BW radiographs for diagnostic quality.	Assess diagnostic quality of ankle radiographs using AI.
Method	864 BW radiographs from 100 patients were labeled, trained, and categorized using the EfficientDet-d0 model in TensorFlow.	Modular deep-learning framework with multiple neural networks.
Technique	EfficientDe,D0, TensorFlow	CNN (EfficientNet-B0, DeepLabV3).
Pre-processing	Radiographs were manually adjusted for rotation and contrast, exported as TIFF (1920 × 1440 pixels), then labelled using Roboflow.	1- Recognition of Radiographic View: Classifies AP or LAT views. 2- Segmentation of ROI: Extracts relevant region. 3- Augmentation: Uses rotation, flipping, noise.
Feature	the study focused on detecting overlaps in enamel, dentin, restorations (clear/unclear margins) , and DEJ (Dentino-Enamel Junction) in the bitewing radiographs.	Anatomical features of ankle radiographs.
Dataset	The dataset included 864 BW radiographs collected from a private source (King Abdulaziz University Dental Hospital records).	950 ankle radiographs labeled by radiologists.
Errors	Log loss value of 0.15 Indicates system errors.	- Misalignment - incorrect or incomplete ROIs.
Results	F1 score (Overlap within Enamel): 0.89 . F1 score (Overlap within Restoration -Clear Margins): 0.76 . Log Loss Value: 0.15.	Achieved 94.1% average accuracy, outperforming radiologists (91.4%).
Limitation	1- The model is a proof of concept. 2- Further testing is needed. 3- Not yet integrated with the web app. 4- Class imbalance affects accuracy.	Small dataset, manual labeling errors.
Future work	Optimize and balance dataset for better class representation.	Application to other body parts, improve scalability.

2.5.3 Related Works Discussion

In our literature review on the classification of X-rays and radiographs, particularly bitewings, we examined a range of recent studies that focus on the application of deep learning and machine learning methods for dental image analysis. Much of the existing work highlights the advancements in automated detection of dental pathologies,using convolutional neural networks (CNNs) and other AI models, These approaches have significantly improved diagnostic accuracy. The primary challenge that surfaced from these studies is the high variability in image quality, largely due to errors in technique, exposure, or scanner performance. Additionally, while some models have been trained to identify specific dental conditions, there is still a gap in the literature when it comes to building systems that can evaluate the diagnostic quality of radiographs themselves. Many current models focus on the detection of pathologies but lack the capacity to determine whether the radiograph is even usable for diagnosis in the first place. This is where our study aims to fill the gap by creating a model that not only identifies diagnostic issues but also classifies the type of errors in radiographs and locate it.

2.6 Conclusion

This chapter presented the background information pertinent to our research. It described the medical aspects of dental radiography, focusing specifically on intraoral radiographic examinations, particularly the bitewing type. Additionally, the technical background in Machine Learning and Deep Learning was outlined. Finally, the chapter reviewed the literature on the application of Artificial Intelligence in assessing bitewing radiographs, comparing various studies and their contributions to the field.

CHAPTER 3

SYSTEM REQUIREMENTS AND SYSTEM DESIGN

3.1 Introduction

One of the essential stages of building a software project is system analysis and requirement. Requirement is considered as the essential block and all the projects depend on it. Since it works in explain and display all the project needs toward deliver a completed project. To prevented misunderstanding of the project goal, it needs to be delivered correctly in a clear unambiguous statement. The main purpose of it is to identify the problem and feasible the study, elicit the requirements and finally analysis Models. Requirements divided into five sections functional requirements, nonfunctional requirements, Hardware requirements, software requirements and Data requirements will be discussed in section 3.4. The main purpose of it is to identify the problem and feasible the study, elicit the requirements, and finally analyze models.

3.2 Dataset

The dataset in this project was provided by King Abdulaziz University Hospital. It was collected and classified by a group of professionals' dentists who signed on a ethical approval agreement. It is labeled into the basic three error types:

1- errors in operating the machine,

2- errors in technique,

3- Scanner-related errors.

Under each one of them there are other specifications of the exact error subtypes.

3.3 Data Gathering

Basically, it is about collecting to understand the needs, goals, and constraints of a project. Gathering requirements can be done by many methods, such as questionnaires, stakeholders' interviews, workshops, brainstorming, use cases and scenarios. Using different sources ensures the delivery system's output meets the project objectives.

3.3.1 Interview

Interviews are an essential tool for gathering data in research, providing first-hand insights from experts and users that reveal practical challenges, needs, and expectations. Unlike quantitative methods, interviews enable researchers to ask detailed questions, adjust based on responses, and capture more nuanced information. This is particularly useful in areas like dental radiography, where speaking with professionals can uncover specific diagnostic issues and user requirements. Using these direct insights helps researchers develop solutions that are both applicable and impactful, effectively linking theoretical research to practical use..[Fontana and Frey, 2005].

3.3.2 Interview Results and Analysis

The interview was conducted with Dr. Najla Neamatalla Turkestani, who holds the position of Assistant Professor in the Department of Restorative and Esthetic Dentistry. During the interview, she highlighted the main problem with manually checking bitewing radiographs: it takes a lot of time to evaluate each one accurately, especially when dentists have many patients to see. Bitewing radiographs can be marked as unusable, or "non-diagnostic," for various reasons, including poor angle, incorrect density (too light or too dark), or improper positioning by the patient. These issues are especially common when images are taken by less experienced dental students who are still learning the correct techniques. With an automated system in place to evaluate these radiographs, students could receive helpful guidance on making more accurate assessments and suggestions for fixing common issues, making it easier to learn proper diagnostic practices. The system's ability to detect and classify the types of errors in these radiographs would be a big improvement in any clinic, where efficiency is essential. When radiographs need to be retaken because of quality problems, it increases the dentist's workload and can make patients less satisfied with their experience. Furthermore, poor-quality radiographs mean patients may be exposed to more X-rays than necessary, which can impact their long-term health. An automated system that checks the quality of radiographs would not only help reduce this exposure but also raise the standards of patient care and safety. Additionally, using an AI-based system could establish clear and consistent guidelines for radiograph quality, reducing disagreements among dentists about what is acceptable. This consistency would lead to better healthcare practices and improve the experience for both patients and medical staff.

3.3.3 Questionnaire

In this paper, We employed a questionnaire as a primary method for data collection, aimed at gathering insights from dental staff regarding the need for an automated system that examines the quality of bitewing radiographs. This questionnaire was designed to capture the perspectives of dental professionals on the potential benefits and challenges of implementing such a system. Questionnaires are effective tools for collecting data from a large number of participants quickly . The objectives of Our questionnaire is to ask the dental staff's about the limitations of current manual evaluation processes and to identify their requirements and expectations for an automated system. [Stone, 1993]

3.3.4 Questionnaire Results and Analysis

The questionnaire was administered via Google Forms, resulting in a sample size of 41 participants most of them were Dentists. The findings indicated that many dental professionals encounter unusable bitewing radiographs on a regular basis, with most respondents reporting quality issues on either a weekly or monthly basis. The types of errors frequently encountered include technique-related issues, and some respondents noted scanner-related errors as well. These findings highlight both human and equipment-related factors impacting the quality of radiographs. When asked about the time spent on quality-checking radiographs, Half the respondents reported dedicating between 1-3 minutes per radiograph, and 22 percent were spending 3-5 minutes. This time investment suggests that manual quality-checking could contribute significantly to their overall workload. The survey also explored the impact of poor-quality bitewing X-rays on diagnostic work. Most participants agreed that such issues lead to the need for retakes, delays in diagnosis, and, importantly, increased patient exposure to X-rays. These outcomes indicate a need for improvement in the current quality-checking processes to reduce diagnostic delays and enhance patient safety. Regarding the potential helpfulness of an automated quality-checking system, 65 percent respondents generally found it ”Extremely helpful.” While 57 percent of responses expressed that they would use the system “For every X-ray” ,others indicated they would use it “Only when unsure of quality”. This feedback highlights a demand for flexibility in the system's application to suit various professional preferences. The highest selected expected benefit of this system were “Saving time” with ratio of 95 percent , Reduces need for retakes ,and Reduces patient exposure to X-rays with ratio of 70 percent. When asking about The Most frequent challenges they currently face with checking X-ray quality manually ,the response was : Time constraints with ratio of 51%.(All the Questionnaire Questions and Results are Provided in the Appendix)

3.3.5 Difficulties

Throughout the data-gathering process, We encountered several challenges. A major obstacle was restricted access to patient data, which is often limited due to confidentiality and privacy concerns in the dental field. Additionally, We faced challenges in obtaining a sufficient response rate from dental staff across various clinics and practices.

3.4 System Requirements

Effective software project management depends on clear, explicit requirements. Research shows that systematic requirements engineering not only reduces the need for rework later but also enhances system quality in a cost-effective manner [Laplante and Kassab, 2022].System Requirements: For a project to succeed, it must have clearly defined and thoroughly documented requirements. The Requirements Analysis process includes activities aimed at identifying the needs of the target users. This section outlines the system's functional, non-functional, data, software, and hardware requirements.

3.4.1 Functional Requirements

Functional requirements are essential capabilities that the system must offer. They encompass all aspects of the system's operation relevant to the user.

FR.1: The system shall allow authorized dental staff to log in and out securely.

FR.2: The system shall allow dental staff to sign up for an account.

> **FR.2.1**: The system shall require dental staff to provide relevant information, such as name, email, and clinic Name during the sign-up process.

FR.3: The system shall detect errors .

> **FR.3.1**: The system shall categorize errors into machine operation errors (e.g., inappropriate kVp/mA settings), technique errors (e.g., positioning, receptor orientation), and scanning errors.

> **FR.3.2**: The system shall provide an immediate visual and audible alert when an error is detected.

FR.4: The system shall generate detailed analysis reports for each radiograph image.

> **FR.4.1**: The report shall include detected errors, the image classification, and relevant technical parameters.

> **FR.4.2**: The system shall allow dental staff to download the report in PDF format.

FR.5: The system shall store all captured images and their analysis results in a secure database.

> **FR.5.1**: The system shall allow users to retrieve and view stored images and their corresponding analysis reports.

FR.6: The system shall support manual override during imaging.

FR.7: The system shall allow users to input and manage patient data.

FR.8: The system shall allow users to input and manage radiograph details

FR.9: The system shall enable staff to upload X-ray images for quality assessment.

FR.10: The system shall allow authorized users to share X-ray images and corresponding quality assessment reports securely.

FR.11: The system shall enable authorized users to delete X-ray images and associated data if needed.

> **FR.11.1**: The system shall prompt for confirmation before finalizing deletion to prevent accidental data loss.

FR.12: The system shall allow users to print X-ray images and quality assessment reports.

FR.13: The system shall allow users to upload an X-ray image for analysis.

3.4.2 Non-functional Requirements

Non-functional requirements (NFRs) set the performance and operational standards for a system, covering aspects like responsiveness, availability, usability, and security. This document outlines the essential NFRs to ensure the system is robust, secure, and user-friendly.

NFR.1: The system should respond within an acceptable timeframe.

> **NFR.1.1:** All stored images and reports shall be retrievable within 2 seconds.

NFR.2: The system should be available to all users 24/7.

NFR.3: The system must provide a user-friendly interface.

> **NFR.3.1**: The interface shall be intuitive and easy to navigate, minimizing the need for user training.

> **NFR.3.2**: The interface should include visual and auditory alerts for errors detected during imaging.

NFR.4: The system should support the English language.

NFR.5: The system shall ensure data security and privacy.

3.4.3 Hardware Requirements

To guarantee optimal user experience, users must meet the following hardware specifications to effectively use the system:

HR.1: A desktop computer or laptop capable of connecting to the internet and running modern web browsers (e.g., Google Chrome, Firefox).

HR.2: A reliable internet connection for efficient data transmission and real-time feedback.

3.4.4 Software Requirements

For the Intelligent Assessment of Intra-Oral Radiograph Quality project, the following software requirements are essential:

- **Python** for backend development and implementing AI models.
- **TensorFlow** for building and training the machine learning models to assess radiograph quality.
- **OpenCV** for real-time image processing and manipulation.
- **MySQL** for managing and storing patient records, radiographs, and analysis results in a secure and structured database.
- **HTML, CSS, JavaScript** for designing the user interface and front-end development to ensure a responsive and user-friendly application.
- Flask for back-end implementation.

3.4.5 Data Requirements

1. **Patient Data**

- Patient ID: Unique identifier for each patient.
- Full Name: Patient's full name, including first, middle, and last names.
- Patient Age .
- Gender: Specifies gender (e.g., Male, Female).

- Phone Number
- Medical History: A brief summary of relevant medical history.

2. Radiograph Data

- Radiograph ID: Unique identifier for each radiograph.
- Radiograph Type: Type of radiograph taken (e.g., Bitewing, Periapical).
- Date and Time: Timestamp indicating when the radiograph was created (either uploaded or captured) (Format: YYYY-MM-DD HH).
- Image Path: File path or storage reference to the digital radiograph file.
- Source Type: Indicates the origin of the radiograph (e.g., Upload, Captured).
- Technical Settings:

- Exposure Time (s): Duration of the exposure measured in seconds.

- kVp: Kilovolt peak used during radiograph capture.

- mA: Milliampere used during radiograph capture.

3. User Data

- User ID: Unique identifier for each user.
- Password: Securely stored and encrypted password for user authentication.
- Email Address: User's email for notifications and account recovery.

4. Evaluation Data

- Evaluation ID: Unique identifier for each evaluation instance.
- Errors Detected: Description of errors identified in the radiograph, such as improper positioning, exposure issues, or artifacts.

- Classification: Indicates whether the image is classified as ”diagnostic quality” or ”needs retake.”

5. Report Data

Report Data formalizes the results into official, downloadable documents for patient records and clinical use.

- Report ID: Primary Key, unique identifier for each generated report.
- Report Path: File path or location where the generated report is stored.
- Analysis Data
- User ID
- Technical Settings
- Patient Data

3.5 Conclusion

The findings in this chapter highlight the need for an automated X-ray analysis system to improve the accuracy and consistency of diagnostic evaluations. By assessing system requirements, we have defined the necessary functional and non-functional needs, along with the data, hardware, and software requirements essential for the system’s success in dental diagnostics.

CHAPTER 4

SYSTEM DESIGN

4.1 Introduction

It is the process of expressing the system requirements in an architecture, components, interface modules, and data of the system. This chapter outlines the high-level design as initial design in section 4.2. using Use case diagram, and its description, class diagram, sequence diagram, and activity diagram. Also, the low-level design as database design in section 4.3 containing the database design and the database schema diagram. In addition to the prototype of the system in section 4.4.

4.2 Initial Design

This phase focuses on determining the core structure. Work in visualizing the aspect of the system depends on given requirements. Display the major elements and layout of the interface also data exchanging in diagrams form. It is considered as a primary outline for detailing the future design and development.

4.2.1 Use Case Diagram

A use case explains a particular sequence of actions,a user takes to accomplish a goal within a system It focuses on the user-system interaction, with an emphasis on the value or benefits delivered by the system,Common in software development,use cases help outline the system delivers to the user Use cases are extensively employed in outline a system's functional needs, clarify its intended goals, and demonstrate how these are achieved through user interactions A use case diagram serves as a visual tool, mapping out how different user roles relate to system functionalities. For this project, the dental professional and administrator are the primary actors, as depicted in Figure 4.1.[Mule et al., 2015]

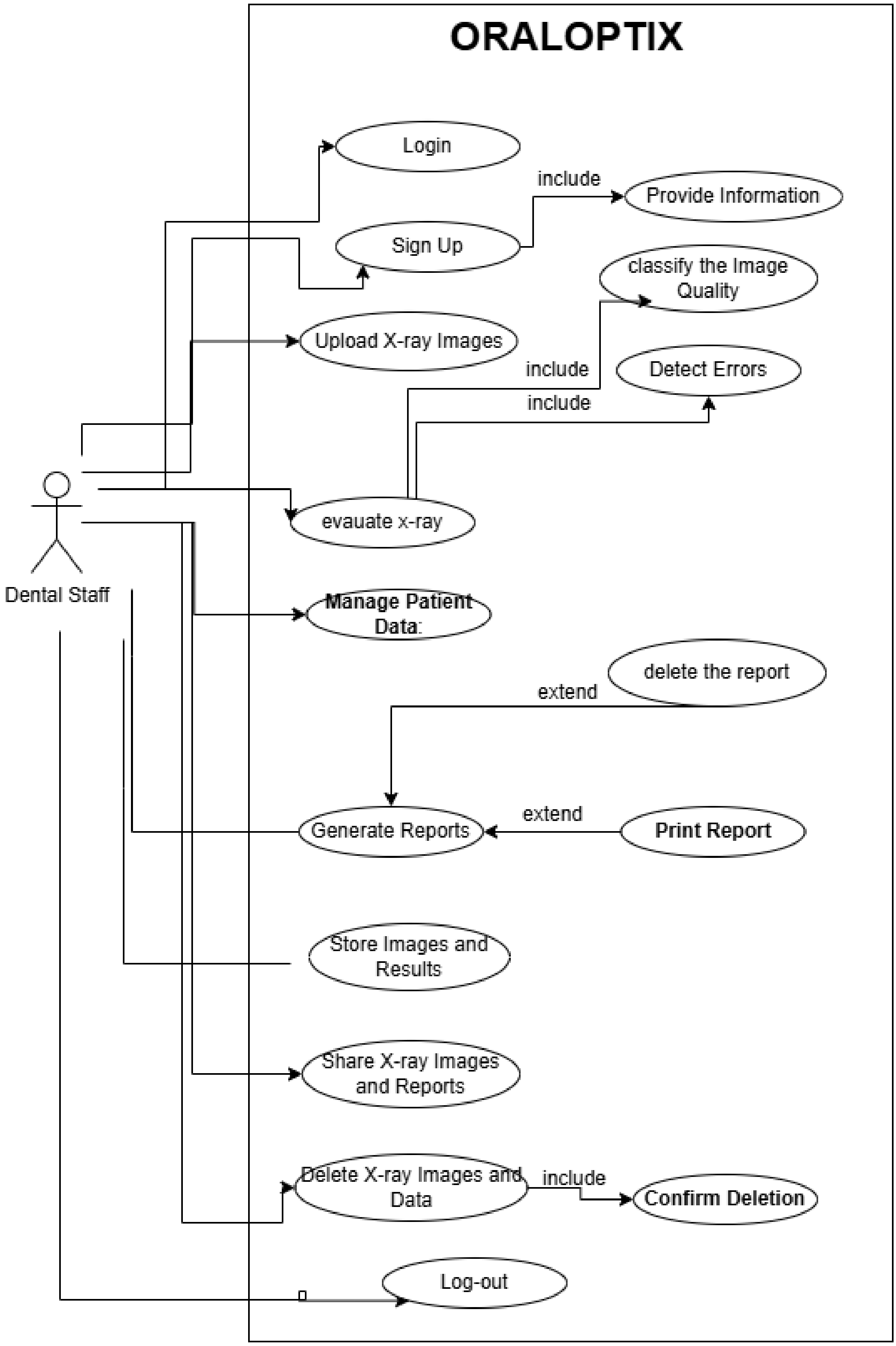


Figure 4.1: Use Case Diagram for OralOptix System

4.2.2 Use Case Description

Each use case from the previous section will be described in this section.

Table 4.1: Use Case Description for log-in

Use Case	Login
Goal	Allow authorized dental staff and administrators to log in securely.
Actor	Dental Staff
Pre-condition	The user has an existing account.
Post-condition	The user is logged into the system.
Flow of Activities	The user enters their username and password.
	The system validates the credentials.
	If the credentials are valid, the system grants access to the user dashboard.
	If the credentials are invalid, the system displays an error message.

Table 4.2: Use Case Description for Sign Up

Use Case	Sign Up
Goal	Allow new dental staff to create an account.
Actor	Dental Staff
Pre-condition	The dental staff member does not have an existing account.
Post-condition	The dental staff member has a new account in the system.
Flow of Activities	The dental staff selects the "Sign Up" option.
	The system prompts for necessary information (name, email, role, clinic info).
	The dental staff enters the required information.
	The system validates the information.
	Upon successful validation, the system creates a new account and sends a confirmation email.

Table 4.3: Use Case Description for Monitor and Analyze Images

Use Case	Monitor and Analyze Images
Goal	Enable real-time monitoring and analysis of dental X-ray images.
Actor	System
Pre-condition	The dental X-ray machine is connected to the system.
Post-condition	The system has analyzed the X-ray images and provided feedback.
Flow of Activities	The dental technician initiates the image capture process.
	The system monitors the X-ray machine's operation.
	The system analyzes the captured images in real-time.
	The system provides feedback on image quality.

Table 4.4: Use Case Description for print Errors

Use Case	print Errors
Goal	print the detected errors into the interface.
Actor	System
Pre-condition	The system has detected an error.
Post-condition	The system prints the detected error
Flow of Activities	The system analyses the image.
	The system detects the error..
	The system prints the detected error.

Table 4.5: Use Case Description for Store Images and Results

Use Case	Store Images and Results
Goal	Securely store captured X-ray images and their analysis results.
Actor	System
Pre-condition	An X-ray image has been captured and analyzed.
Post-condition	The images and results are stored in the database.
Flow of Activities	The system receives the analyzed image and results.
	The system encrypts the data for security.
	The system saves the images and results to the database.
	The system confirms successful storage.

Table 4.6: Use Case Description for Delete X-ray Images and Data

Use Case	Delete X-ray Images and Data
Goal	Allow authorized users to delete X-ray images and associated data.
Actor	Dental Staff
Pre-condition	The dental staff is logged into the system and has the right permissions.
Post-condition	The selected X-ray images and data are deleted from the system.
Flow of Activities	The dental staff selects the images and data to delete.
	The system prompts for confirmation of deletion.
	The dental staff confirms the deletion.
	The system removes the selected images and data.

Table 4.7: Use Case Description for Include Error Details

Use Case	Include Error Details
Goal	Provide detailed information about detected errors in reports.
Actor	System
Pre-condition	A report is being generated.
Post-condition	Error details are included in the report.
Flow of Activities	The system collects all relevant error details for the report.
	The system formats the error details for inclusion in the report.
	The system finalizes the report with the included error details.

Table 4.8: Use Case Description for Share X-ray Images and Reports

Use Case	Share X-ray Images and Reports
Goal	Enable authorized users to securely share X-ray images and corresponding assessment report
Actor	Dental Staff
Pre-condition	The images and reports are available in the system.
Post-condition	The selected images and reports are shared with the specified recipients.
Flow of Activities	The dental staff selects the images and reports to share.
	The system prompts for recipient information (e.g., email).
	The dental staff enters the recipient's details and confirms sharing.
	The system sends the selected images and reports to the specified recipients.

Table 4.9: Use Case Description for Print Images and Reports

Use Case	Print Images and Reports
Goal	Enable users to print X-ray images and assessment reports.
Actor	Dental Staff
Pre-condition	The dental staff is logged into the system and has selected an image or report to print.
Post-condition	The selected image or report is printed.
Flow of Activities	The dental staff selects the image or report to print.
	The system prepares the selected document for printing.
	The dental staff confirms the print command.
	The system sends the document to the printer.

4.2.3 Activity Diagram

Activity diagrams serve as visual representations of the sequence of activities and actions occurring within a system ,hey display how activities relate to one another (interconnections) including decision points, simultaneous activities, and loops,effectively modeling the system's dynamic behavior. These diagrams are useful for visualizing and understanding the workflow within a system and are often used in the field of software development, the Figure 4.2 shows an activity diagram for the proposed application to illustrate the flow within the system. [Dumas and Ter Hofstede, 2001]

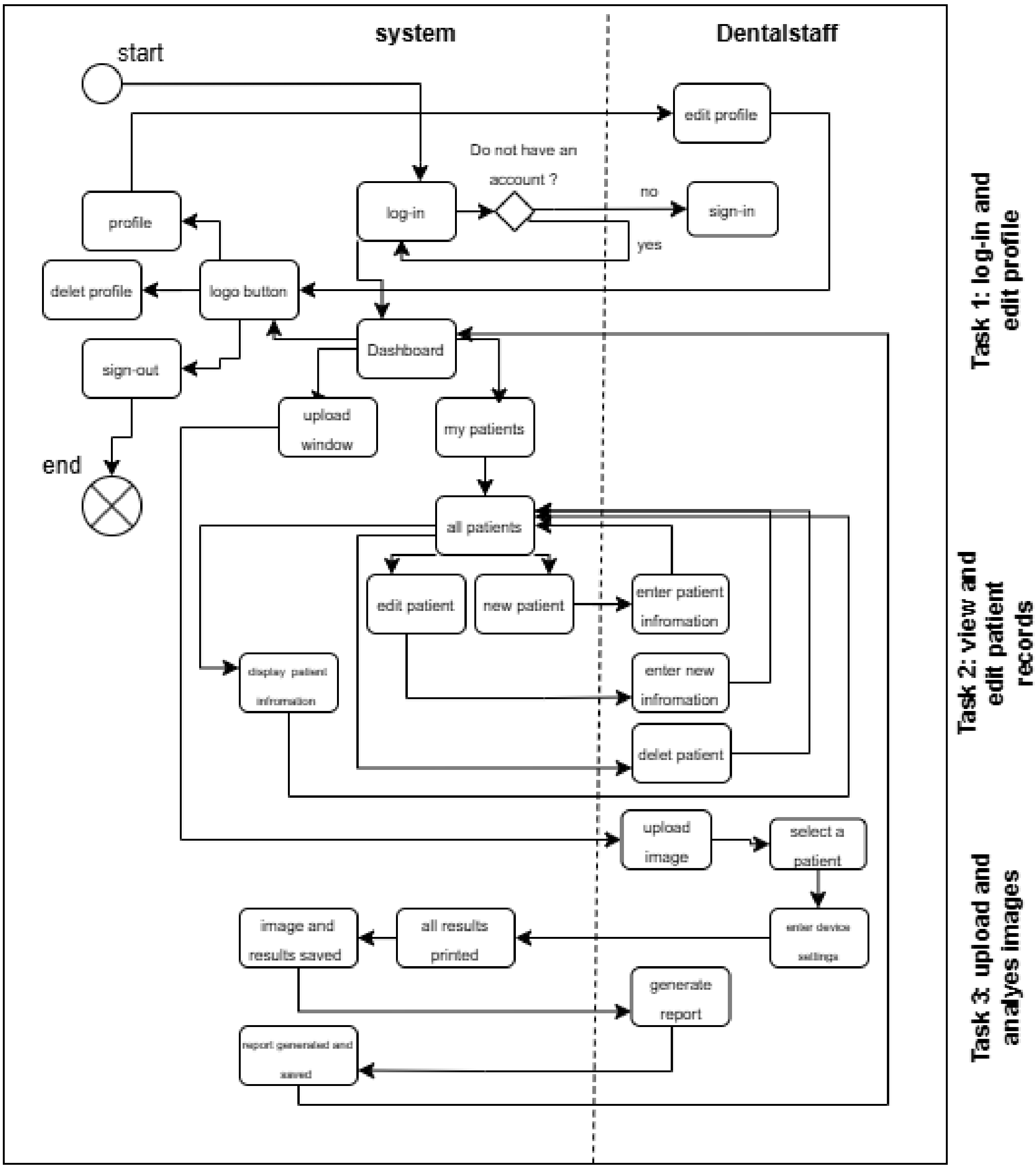


Figure 4.2: Activity Diagram for OralOptix System

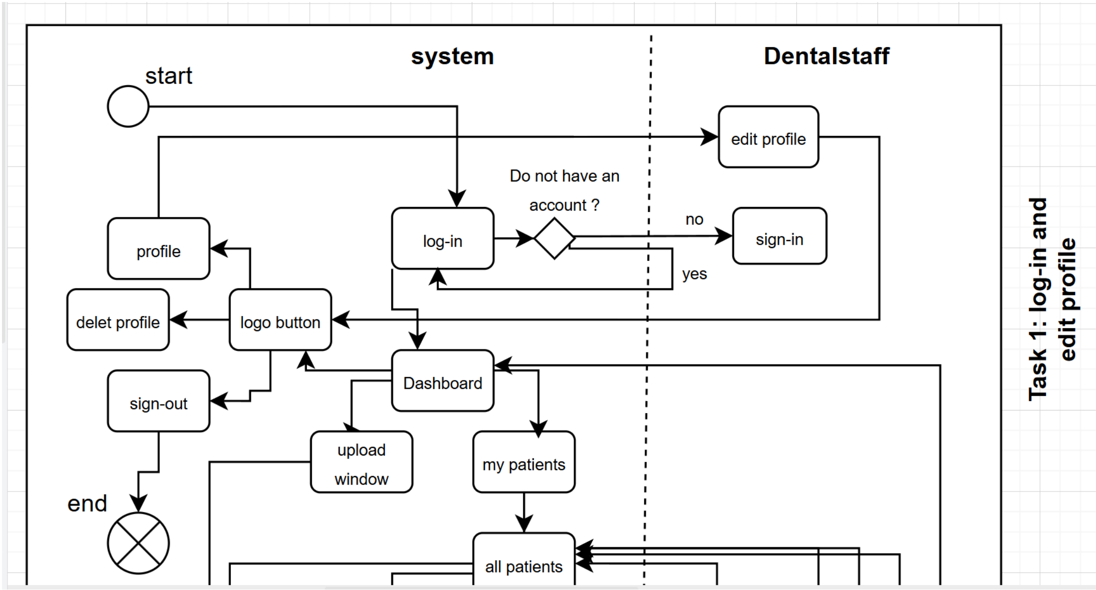


Figure 4.3: Task 1 : Activity Diagram for logging -in and edit user profile

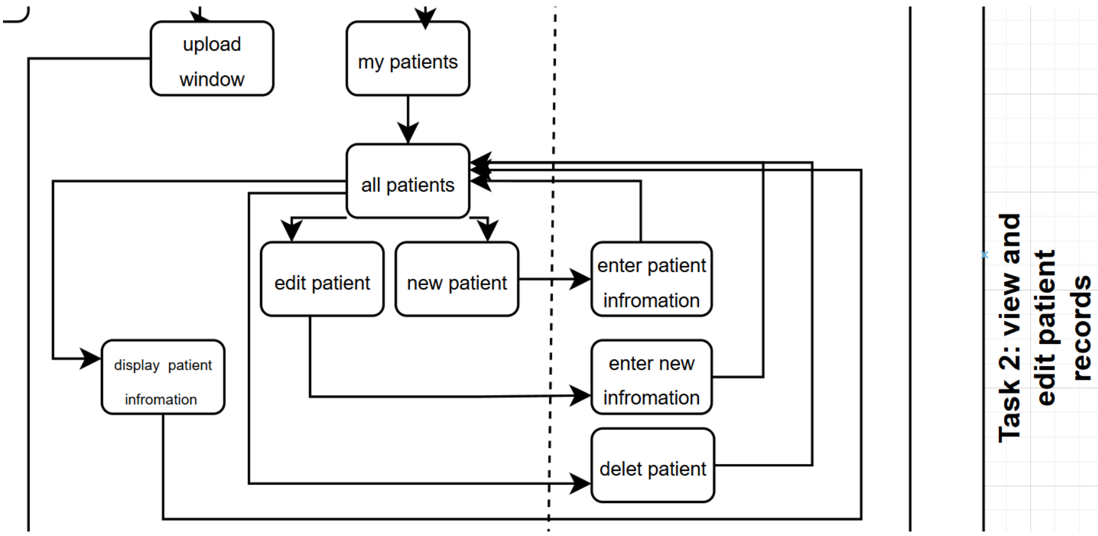


Figure 4.4: Task 2 : Activity Diagram for view and edit patients records

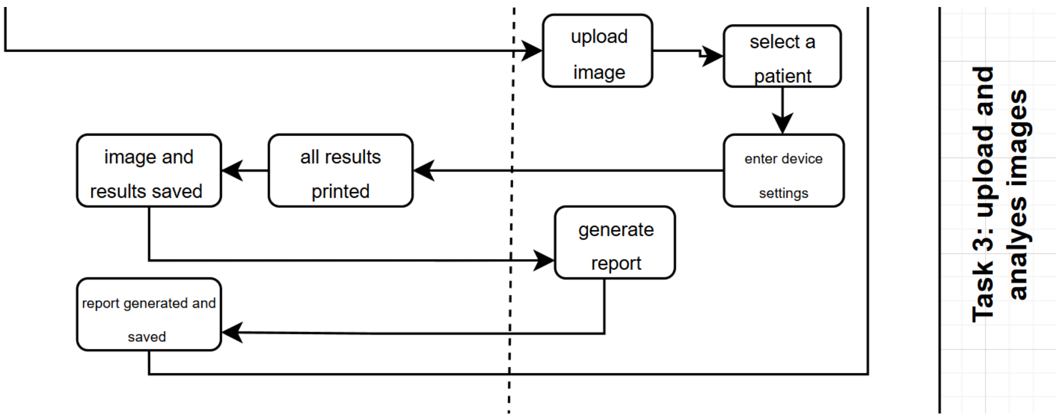


Figure 4.5: Task 3 : Activity Diagram for upload and analyzes images

4.2.4 Sequence Diagram

It is a diagram shows the main objects and its interaction with the system over a time. It shows when the system is activeness of each object and the elimination.That done by sequence of rows tagged by the method that will be used for it or the messages. The following figure 4.3 we used five objects GUI, User login system, detect, Monitor, Summary, Store; to display the system's mechanism from uploading to storing the data at the Store object. The next sequence diagram shows the mechanism of retrieving information from the Store object in figure 4.4.

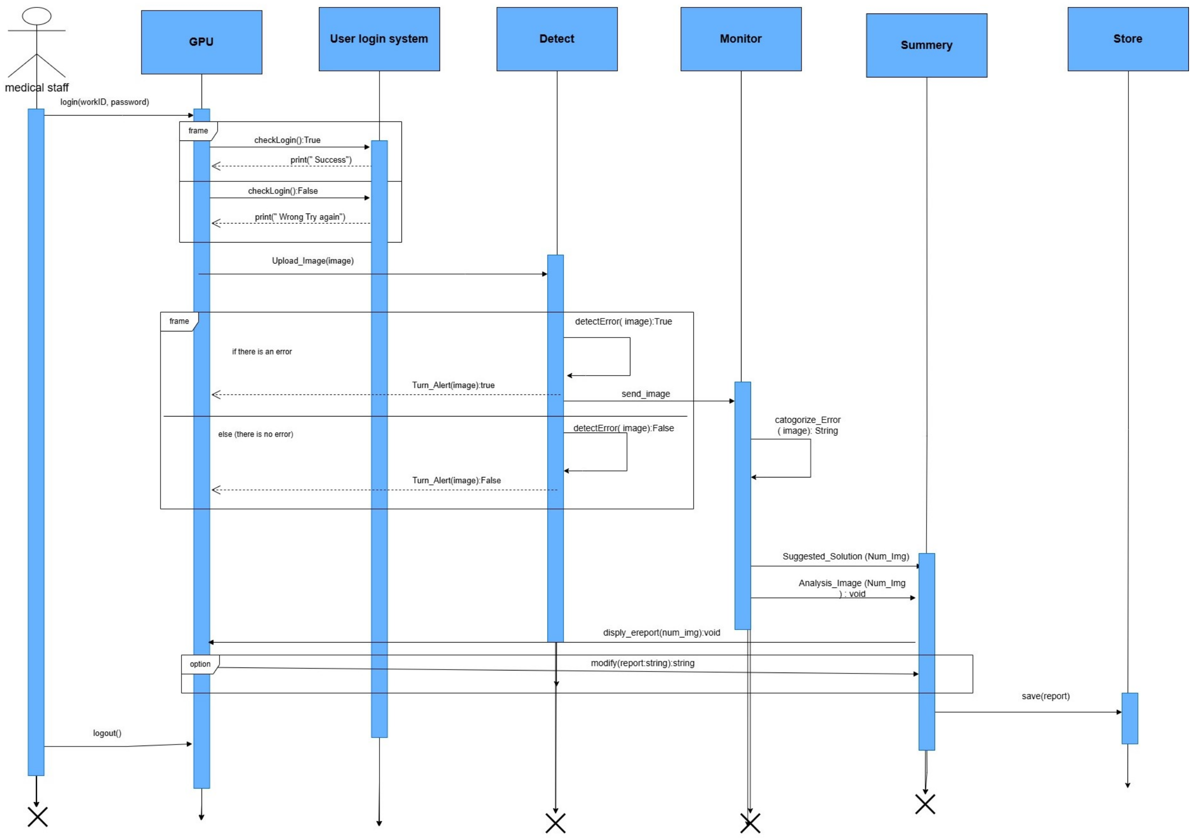


Figure 4.6: Sequence Diagram of medical Staff

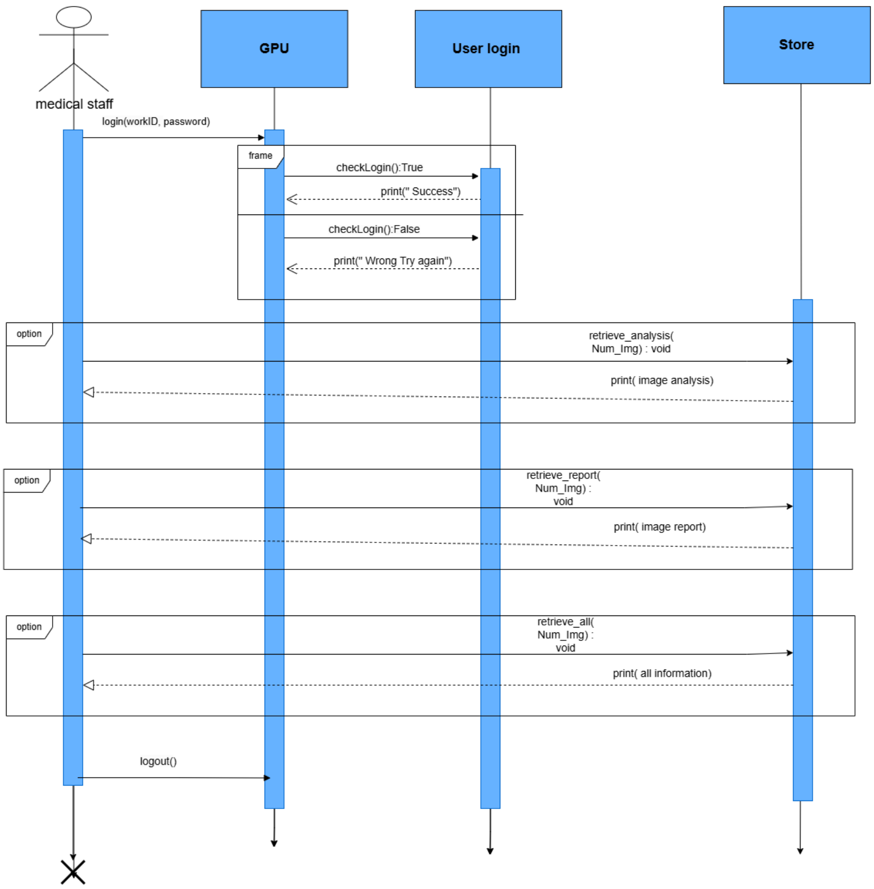


Figure 4.7: Sequence Diagram of retrieve stored information

4.2.5 Class Diagram

Software engineering is a subject that uses Unified Modeling Language (UML) diagrams to represent object-oriented design models, which are widely acknowledged as a standard. UML diagrams help to establish the needs and scopes of systems and applications by offering visual models.[Koç et al., 2021]. As shown in the following diagram figure 4.5, there are 8 classes: The main class to run the program OralOptex, The detector class detects whether there is an error or not and determines whether the alert will be on or off. and the monitor class's main job is to categorize the error type. The three following classes are to know the exact type of error: operation errors could be inappropriate kVp/mA settings; technique errors could be positioning or receptor orientation; and scanning errors. Then in the summary class to disply report and image information, a report will be created and saved in the store class to be retrieved anytime.

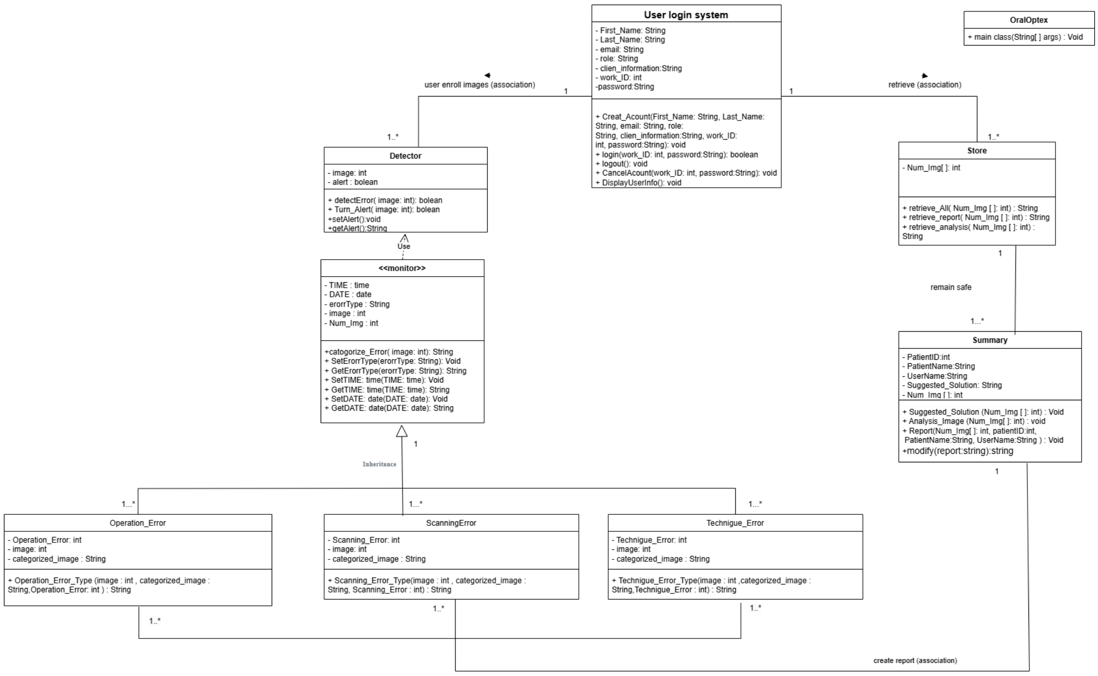


Figure 4.8: UML Class Diagram of OralOptix

4.3 Database Design

4.3.1 The Entity Relationship Model (ERM)

Database design involves various techniques, with the Entity Relationship Diagram (ERD) being one of the most essential. ERD is a key visual tool in database design, representing the conceptual data model and addressing the data needs of users. As the first step in database design, the ERD defines entities, their relationships, and key attributes. Important considerations in creating an ERD include ensuring that entities are connected by relationships and that each entity has attributes, including a primary key and other descriptive details [Azzahra et al., 2022]. The Entity Relationship Model (ERM) for this project comprises six main entities: Patient, Radiograph, User, Evaluation, TechnicalSettings, and Report, as illustrated in Figure 4.6 . The relationships between these entities are described below:

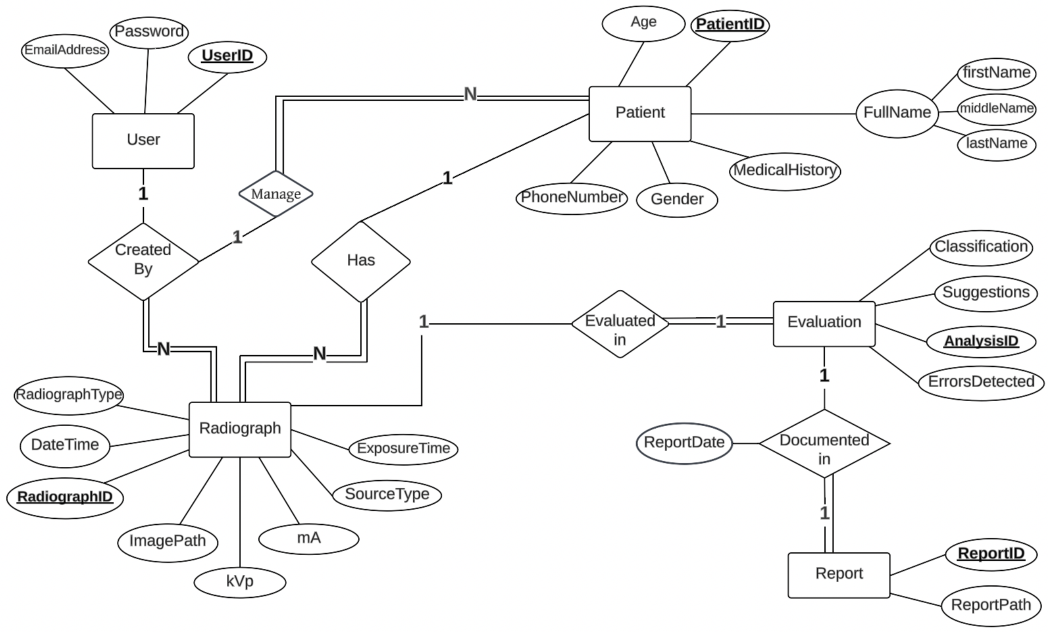


Figure 4.9: The Entity Relationship Diagram

4.3.1.1 Business Rules for the ER Diagram:

- Each user can create multiple radiographs, but each radiograph is created by only one user.
- Each patient can have multiple radiographs, but each radiograph belongs to only one patient.
- Each radiograph is associated with exactly one evaluation.
- Each evaluation results in exactly one report.
- Each report is based on one evaluation.
- A radiograph must have a timestamp indicating when it was created (captured or uploaded).
- Each radiograph must have a defined source type (e.g., 'Upload' or 'Captured').

4.3.2 Database Schema Diagram

The database schema defines the logical structure of the OralOptix System, showing the relationships between data elements and how they are connected. It provides a clear overview of how the database is organized, demonstrating how the data is structured and related. Figure 4.7 shows the schema of the OralOptix System after the normalization process, ensuring a well-organized data structure.

The schema is essential for efficient data storage, faster query processing, and maintaining data accuracy. These aspects are crucial for the smooth operation and effectiveness of the OralOptix System, helping it perform real-time error detection and assessment of bitewing radiographs.

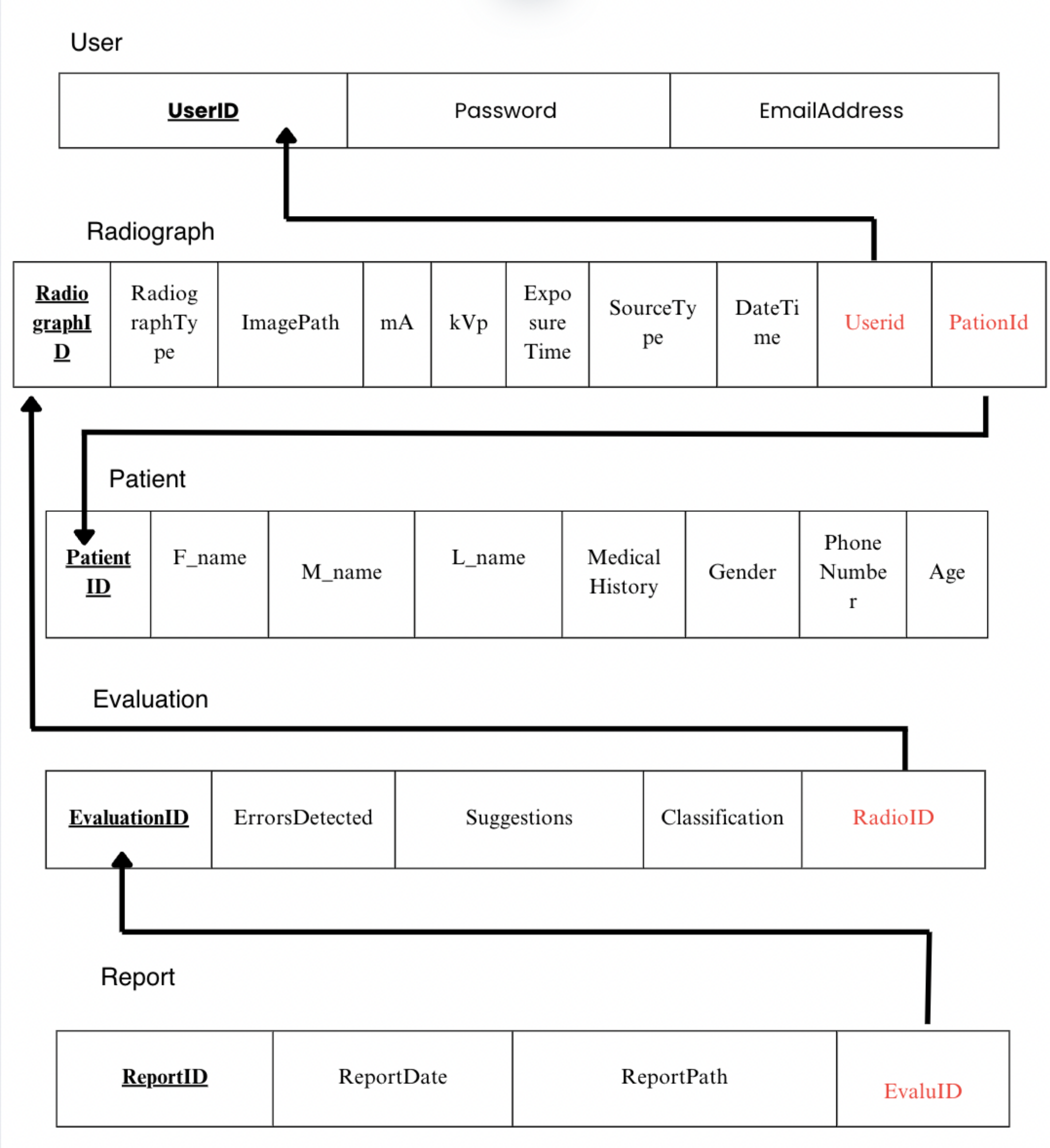


Figure 4.10: Database Schema Diagram

4.4 Prototype

4.4.1 Interface Type

The system's interface will follow a graphical user interface (GUI) model, focusing on ease of use and accessibility. This GUI will be web-based, allowing dental professionals, including dentists, radiologists, and dental students, to access it from various devices, such as desktops, tablets, and possibly even mobile devices in future iterations. The goal is to create an interface that minimizes the learning curve, enabling users to leverage the automated features with minimal training. [Hoggenmüller et al., 2021]

4.4.2 Interface Description

The interface of the automated bitewing radiograph evaluation system is designed for ease of use and efficiency, providing dental professionals, including dentists, radiologists, and dental students with a streamlined workflow for assessing radiograph quality. After logging in through a secure authentication screen, the system displays patients records , reports, The system allows users to upload radiographs, which are then analyzed automatically. The results include a quality assessment, and errors detected. The interface also features a report generation tool, allowing users to save and download detailed analysis summaries for each patient. the system links each radiograph to the patient profile, storing a history of evaluations. Overall, the interface ensures that users can efficiently evaluate radiographs, reduce retakes, and improve patient care and diagnostic consistency.[Carter and Hundhausen, 2010]

Figure 4.11: OralOptix Log-in page

The Log-In Screen allows users to access their accounts by entering their credentials. It includes: User Name Field: For entering the registered username. Password Field: For entering the associated password, with secure text masking. Log-In Button: To submit the credentials and access the account. Sign-Up Redirect Link: For new users to navigate to the sign-up page. The screen is simple, secure, and user-friendly, ensuring quick access to the website

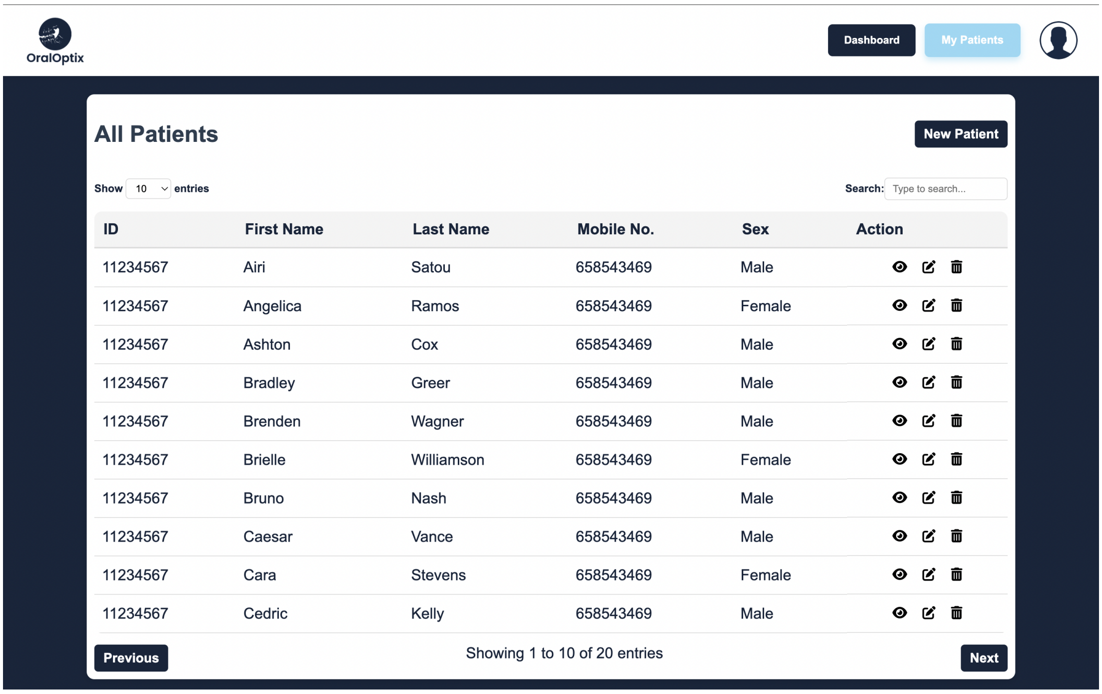


Figure 4.12: OralOptix Patient Management Page

The Patient Management Interface allows dental professionals to efficiently organize and manage patient records through a structured and interactive table. Each entry in the table displays key patient details, including the ID, first name, last name, mobile number, and gender. Users can easily search for specific patients using the integrated search bar, while pagination controls enable smooth navigation through large datasets. Action buttons next to each record provide quick options to view, edit, or delete patient information. Additionally, a prominent "New Patient" button allows users to register new patients by opening a dedicated form. This interface ensures that managing patient data is both seamless and organized within the OralOptix system

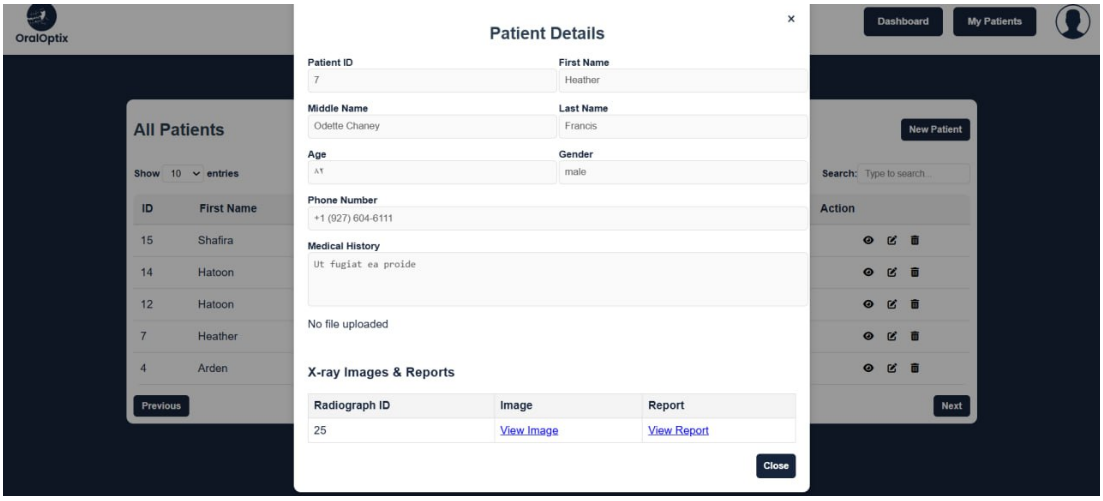


Figure 4.13: OralOptix patient details display

The Display Patient Info Interface provides a clear and organized view of a selected patient's full details. When a user clicks the "View" button next to a patient's entry in the management table, a dedicated window appears showing all recorded information for that patient. This includes their ID, full name, gender, age, mobile number, and any additional medical notes. Uploaded files or past radiographs, if available, are also displayed for reference. The layout is clean and readable, allowing dental professionals to quickly review important information before proceeding with diagnosis or analysis. This interface supports efficient access to patient data, enhancing clinical workflow and record accuracy

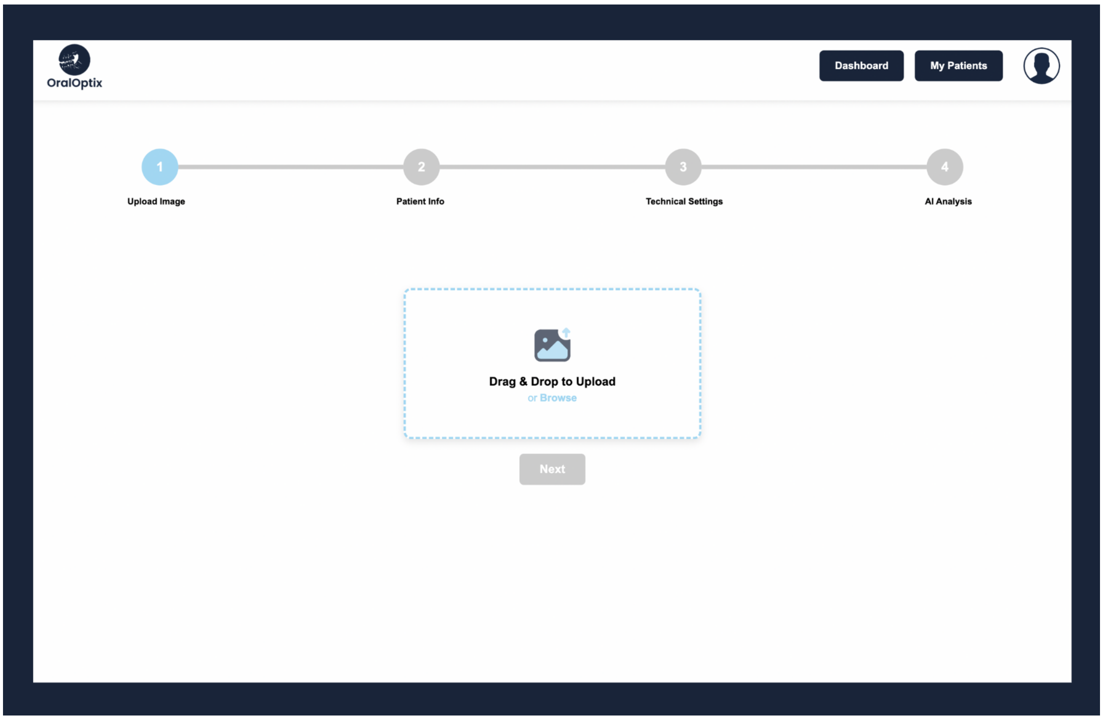


Figure 4.14: OralOptix dashboard Page

The Dashboard page serves as the starting point for users to begin the diagnostic process. It features a clean and user-friendly interface where dental professionals can easily upload intra-oral X-ray images using a drag-and-drop area or file selection button. Once the image is uploaded, the user can proceed by clicking the "Next" button, which navigates them to the analysis page. The dashboard is designed to streamline the workflow, guiding users step-by-step through the process of image evaluation, making it both efficient and accessible for clinical use.

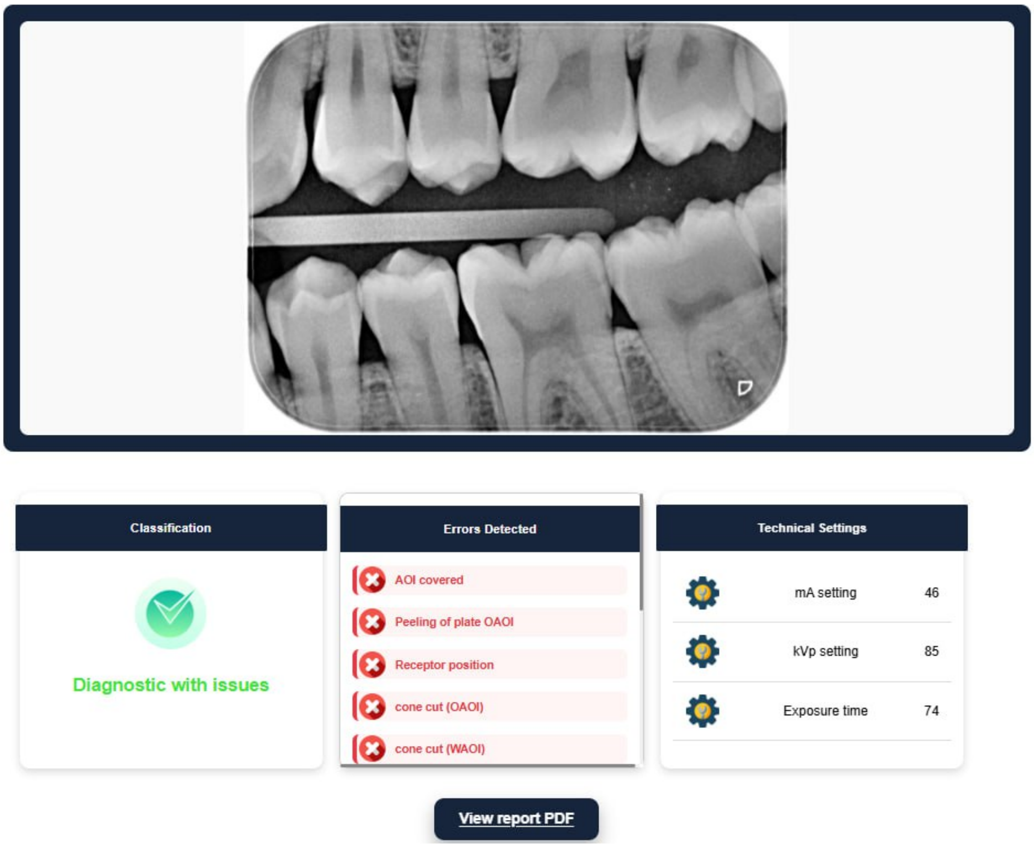


Figure 4.15: OralOptix results display

After uploading the dental X-ray image and pressing the "Next" button, the user is taken to a detailed results page where the system presents a comprehensive diagnostic report. This page displays the uploaded X-ray image along with its classification result (e.g., Diagnostic with issues), a list of detected errors (such as "AOI covered" or "cone cut"), and the corresponding technical settings used (including mA, kVp, and exposure time). The interface is visually organized into three sections for clarity: Classification, Errors Detected, and Technical Settings. Additionally, a button labeled "View report PDF" allows the user to download or print a professional report summarizing all findings for record-keeping or further clinical use.

Medical Imaging Center

Department of Radiology

Radiograph Quality Assessment Report

Report ID: REP-22 | Date: 2025-04-28 09:38 AM

1. Patient Information

Attribute	Details
Patient Name	Miriam Basia Mccray Dejesus
Patient ID	P-5
Radiograph ID	RAD-22
Radiograph Type	Bitewing
Examined by	rafa balkhdhar

2. Radiograph Classification

Classification Status	Result
Diagnostic Status	Diagnostic with issues

3. Technical Imaging Parameters

Parameter	Value
Exposure Time (ms)	74 ms
Milliampere (mA)	46 mA
Kilovolt Peak (kVp)	85 kVp
Error Detected	Yes

4. AI-Bitewing Errors detector

Detected Errors
AOI covered

Figure 4.16: OralOptix report display

When the "View report PDF" button is pressed, the system generates a comprehensive diagnostic report in PDF format summarizing the analysis of the selected dental X-ray. The report includes the X-ray image, the overall diagnostic classification (e.g., "Diagnostic with issues"), a detailed list of detected errors such as AOI coverage or cone cut, and the associated technical parameters used during the image capture (mA setting, kVp setting, and exposure time). This report provides a clear and organized overview that can be printed or shared with dental professionals for documentation, consultation, or training purposes, ensuring transparency and traceability in radiographic evaluation.

4.5 Conclusion

This chapter explores the foundational design of the automated dental X-ray evaluation system, highlighting essential modeling components critical for its functionality and accuracy. Key design elements include the use case diagram, which maps user interactions within the system; the class diagram, which defines the system's structure and relationships among key components; and sequence diagrams, capturing the interactions between objects over time. Additionally, an activity diagram is provided to outline the workflow, alongside an entity-relationship model that structures the system's database. A system prototype is also presented to showcase its intended functionalities. Together, these design components informed the development of a solution tailored to user needs.

CHAPTER 5

IMPLEMENTATION

5.1 Introduction

This chapter overview the detailes of developments stages for the web-based system. Starting with an overview of the system. The tools and technologies will be mentioned in Section 5.3. In Section 5.4 we show the dataset processing techniques and data-splitting methodology. and Section 5.5 is about AI model by explaining the Multiclass classification model, model performance evaluation I, results analysis of the first experiment, result analysis of the second experiment, Comparison of top performance models,and results analysis of the third experiment. In section 5.6 the ranking will be discussed along with the similarity of cosine, jaccard,and HLA similarity. finally review the implementation of Front end and back-end in sections 5.6 and 5.7 respectively.

5.2 The System's Overview

The proposed web-based system, OralOptix, is designed to assess the quality of intra-oral radiographs, particularly Bitewing images, using artificial intelligence. The system is structured into three main layers: the front-end layer, the intelligent model layer, and the back-end layer.

The front-end layer provides an interactive interface for dentists, radiologists, and dental students to upload radiographs for assessment. Through this interface, users can view analysis results, receive feedback on detected errors, and access generated reports to improve radiographic quality and reduce diagnostic errors.

The intelligent model layer forms the core of the system. It employs deep learn-

ing techniques to analyze radiographs in real time, determining their diagnostic quality. If an image contains errors, such as improper positioning, incorrect exposure, or scanning artifacts, the system detects and classifies these issues while providing corrective recommendations to minimize the need for retakes.
The back-end layer manages the system's database, storing patient records, radiograph details, evaluation results, and reports. This ensures data security, allows historical tracking of assessments, and facilitates better diagnostic consistency over time.

5.3 Tools and Technologies

The development of OralOptix required various tools and technologies to create an efficient and user-friendly system for assessing dental radiographs. These technologies are categorized into three main parts: front-end development, back-end development, and AI model implementation.

1. Front-End Development

The front-end of OralOptix was developed using HTML, CSS, and JavaScript to create a structured, visually appealing, and interactive interface.

- HTML organizes content.
- CSS enhances design and improves user experience.
- JavaScript adds interactivity and dynamic functionality.

Development was done using Visual Studio Code (VS Code), a free, cross-platform code editor developed by Microsoft. It offers essential features like debugging, syntax highlighting, IntelliSense, and Git integration. VS Code was chosen for its lightweight yet powerful environment, supporting multiple programming languages and customization through extensions. Features like Live Share for collaboration and SSH support for remote development make it highly flexible. With frequent updates, a large developer community, and seamless GitHub integration, VS Code provides an efficient and modern coding experience, making it an ideal choice for software development [bin Uzayr, 2022].

2. Back-End Development

The back-end is responsible for data processing, user authentication, and database management. The following technologies were used:

- PHP – A server-side programming language that processes user requests and ensures smooth communication with the database.
- XAMPP – A local web server that includes Apache, MySQL, and PHP, allowing developers to test and run applications locally before deployment.
- phpMyAdmin – A user-friendly database management tool that enables easy handling of MySQL databases without complex SQL commands. It provides comprehensive administration tools, supports multiple MySQL servers, and allows efficient data import/export across various formats, making it a powerful and flexible choice for database management.

3. AI Model Implementation

The AI model in OralOptix was developed using Python on Google Colaboratory (Colab), a cloud-based Jupyter notebook environment. Colab provides free access to GPUs and TPUs, which enhances deep learning computations and speeds up model training and testing [Bisong et al., 2019].

Colab integrates with Google Drive, allowing users to store, share, and access notebooks from any device. It also supports saving to GitHub or downloading files locally, making collaboration and version control easier. As a widely used and free tool, Colab is ideal for AI model prototyping and data science applications [Bisong et al., 2019].

These technologies were selected for their efficiency, flexibility, and ease of use, ensuring that OralOptix delivers accurate and reliable radiograph assessments.

5.4 Dataset

A structured dataset in healthcare that combines tabular data and medical images represents a critical advancement in modern medicine, enabling a more holistic approach to patient care and research. These datasets bring together structured information—such as Diagnostic Status, Region of Diagnostic, proximal contact,and overlaps,records—with unstructured or semi-structured imaging data, including X-rays, MRIs, CT scans, ultrasounds, and pathology slides. By linking these two types of data through unique identifiers like patient IDs, healthcare professionals can correlate clinical findings with visual evidence, leading to more accurate diagnoses, personalized treatment plans, and improved patient outcomes.[Tayeb et al., 2020] The key label in the dataset is Diagnostic Status, which has three classes: 0 (X-ray not captured correctly, unusable , non-diagnostic), 1 (X-ray captured correctly but with minor issues, still usable for diagnosis , diagnostic with issues), and 2 (X-ray captured correctly with ideal quality , diagnostic). This classification helps assess the usability of dental X-rays for diagnosis.

Table 5.1: Sample of Tabular Data

BW-Xrays	Diagnostic Status	Region	AOI covered	proximal contact	number of proximal overlap	occlusal plane centered
1	0	1	1	0	1	1
2	1	1	1	0	1	1
3	2	1	1	1	1	1

For example, in this table, the row corresponding to BW-Xray Number 3 indicates that Image 3 has its Area of Interest (AOI) fully covered. Additionally, no technical errors were observed either inside or outside the AOI. This includes the absence of cone cuts, scratches, scanner errors, incorrect exposure, improper receptor positioning, or plate peeling.

5.4.1 Pre-Processing

Preprocessing is a crucial step in data analysis and machine learning, ensuring that raw data is cleaned and transformed into a structured format suitable for model training. It involves handling missing values by filling gaps with appropriate replacements, removing duplicates to avoid bias, and encoding categorical data into numerical values using techniques like label encoding or one-hot encoding. Additionally, preprocessing includes normalizing or scaling numerical data to a common range, improving model performance. For images, preprocessing steps such as resizing, normalizing pixel values, and applying augmentations enhance training quality. In the case of the dental X-ray dataset, effective preprocessing ensures that both tabular data and images are clean, consistent, and ready for training, In this process, missing and invalid values in the tabular data were handled by replacing entries such as "-", "s", " ", "", and NaN with -1, and converting all numerical columns to the proper format. The target variable, which includes three classes (0, 1, 2), was encoded using LabelEncoder to facilitate model training. For image data, each X-ray was loaded from a specified folder, resized to (224, 224), and normalized by scaling pixel values between [0,1]. Missing images were identified and removed to ensure dataset consistency. The dataset was then split into 80 Percent training and 20 percent testing using train-test split, ensuring a balanced distribution. Additionally, class weights were computed to address potential class imbalance, improving model performance.[Cai-Ming and Hao-Nan, 2020]

5.5 AI Model

The use of an AI model in dental X-ray classification offers a significant improvement in the evaluation process, particularly in determining the Diagnostic Status of X-ray images. The model, such as the Vision Transformer (ViT), can be trained to classify X-rays into three distinct categories:

- (2) X-rays suitable for diagnosis.
- (1) X-rays with minor issues but still usable.
- (0) Poorly captured X-rays that are unsuitable for diagnosis.

This automated classification reduces human error and speeds up the assessment process, ensuring that only high-quality images are used for dental diagnoses. The AI model not only streamlines workflows but also enhances the overall diagnostic accuracy, providing consistent and reliable results across large datasets.

5.5.1 Multimodal AI

Incorporating multimodal data—combining both image data and tabular data—further strengthens the AI model's ability to classify dental X-rays with greater precision. The image data allows the model to analyze visual features of the X-rays, while the tabular data, which includes technical details such as the region of the X-ray, AOI coverage, and proximal contact, provides additional context to support decision-making. By integrating both data types, the model can learn complex relationships and correlations, improving its robustness and accuracy. This multimodal approach allows the AI to make more informed predictions by considering both the image quality and technical factors, ultimately providing a more comprehensive and reliable classification system for dental X-rays.

- **MobileNetV3-based Model**: A lightweight CNN architecture that combines MobileNetV3Small for image feature extraction with dense layers for tabular data processing. The model uses global average pooling on image features, processes tabular data through two fully-connected layers, then concatenates both modalities before final classification. Includes dropout layers for regularization.

- **EfficientNet-based Model**: Similar in structure to the MobileNet version but utilizes the more powerful EfficientNetB0 backbone for image processing. Features a learning rate scheduler to optimize training. Processes tabular data through reduced dimension dense layers before combining with image features for classification..

- **Vision Transformer (ViT) Model**:A pure transformer implementation using standard patch embedding and positional encoding. Processes images through multiple transformer encoder blocks while separately handling tabular data with dense layers. Combines both modalities through concatenation before final classification

- **EfficientNet+ViT Hybrid**:Attempts to merge CNN and transformer advantages by combining EfficientNetB0 image features with ViT-extracted features. Both feature sets are concatenated and processed through additional dense layers. The architecture struggles with effectively fusing the different feature types.

- **MobileNetV3+ViT Hybrid**:Similar hybrid approach as Code4 but substitutes MobileNetV3Small for EfficientNetB0. Maintains the same fusion challenges between CNN and transformer features through simple concatenation.

- **Custom ViT-style Model**:A simplified transformer-inspired architecture that replaces standard patch embedding with convolutional layers and global average pooling. Processes tabular data with L2-regularized dense layers. Uses a more efficient feature combination approach than the pure ViT implementations

Each of these models handles multimodal data (images and tabular) differently, using different architectures for image feature extraction (EfficientNet or Vision Transformer) and integrating them with tabular data through concatenation. [Roumeliotis and Tselikas, 2023]

5.5.2 Model Performance Evaluation:

- **Accuracy**: Measures the overall correctness of the model by calculating the ratio of correctly predicted instances to the total instances. However, it can be misleading in imbalanced datasets. equation: Accuracy = (TP + TN) / (TP + TN + FP + FN)

- **Precision (Positive Predictive Value)**: Indicates how many of the predicted positive cases are actually positive. It is important in scenarios where false positives are costly, such as spam detection. equation: Precision = TP / (TP + FP)

- **Recall (Sensitivity)**: Measures how well the model identifies actual positive cases. This is crucial when missing a positive instance has serious consequences, like in medical diagnoses. equation: Recall = TP / (TP + FN)

- **F1-score**: The harmonic mean of precision and recall, providing a balanced measure when there is an uneven class distribution. While accuracy is useful in balanced datasets, the F1-score is often preferred in imbalanced datasets to ensure both precision and recall are considered. equation: F1 = 2 * (Precision * Recall) / (Precision + Recall) were: TP = True Positives results from confusion matrix

TN = True Negatives results from confusion matrix

FP = False Positives results from confusion matrix

FN = False Negatives results from confusion matrix

[Willmott, 1982]

Table 5.2: Model's Performance

Model	Accuracys	Precision	Recall	F1 Score
MobileNetV3 Small	97.26%	97.28%	97.26%	97.21%
EfficientNetB0	98.63%	98.83%	98.63%	98.63%
Vision Transformer (ViT)	84.93%	92.67%	84.93%	87.09%
EfficientNet +ViT Hybrid	82.19%	67.55%	82.19%	74.16%
MobileNetV3 +ViT Hybrid	82.19%	67.55%	82.19%	74.16%
Custom ViT-style	89.04%	93.07%	89.04%	90.09%

Table 5.3: Hyperparameter Settings

Model	Learning rate	Optimizer	Batch size	Epochs	Dropout
MobileNetV3 Small	0.001	adam	16	20	0.5 (image) 0.3 (tabular)
EfficientNetB0	0.001	adam	16	20	0.5 (image) 0.3 (tabular)
Vision Transformer (ViT)	0.001	adam	8	20	0.5(image)
EfficientNet +ViT Hybrid	0.001	adam	16	20	0.3 (both branches)
MobileNetV3 +ViT Hybrid	0.001	adam	16	20	0.3 (both branches)
Custom ViT-style	0.001	adam	32	20	0.5 (image) 0.3 (tabular)

5.5.3 Result and Analysis

The comparative evaluation of the six multimodal architectures revealed significant performance variations based on their design choices. The EfficientNet-based model emerged as the top performer, demonstrating how robust CNN feature extraction combined with tabular data processing can achieve superior classification accuracy. In contrast, the Vision Transformer (ViT) and hybrid CNN-Transformer models underperformed substantially, highlighting the challenges of transformer-based approaches with limited training data and the difficulties in effectively fusing CNN and ViT features through simple concatenation.

Interestingly, the lightweight MobileNetV3 model delivered competitive accuracy with significantly faster training times, making it ideal for resource-constrained applications. The custom ViT-style architecture proved to be the most efficient transformer variant, outperforming standard ViT implementations by adopting convolutional preprocessing while maintaining low computational demands.. Here's an analysis of their performance based on the provided metrics:

- **Training Accuracy:**
  - MobileNetV3Small-based Model: Achieved strong performance (97.26% accuracy, 97.21% F1) with excellent efficiency (22s/epoch). It demonstrated reliable convergence and minimal overfitting, making it suitable for deployment in production environments.
  - EfficientNetB0-based Model: Delivered the best overall performance (98.63% accuracy, 98.63% F1) at the cost of higher computational requirements (100s/epoch). Validation metrics confirmed its robustness for applications where accuracy is critical.
  - Standard Vision Transformer (ViT) : Underperformed (84.93% accuracy) despite its theoretical advantages, indicating the need for larger datasets. The testing revealed unstable training patterns and suboptimal feature extraction
  - EfficientNet+ViT Hybrid: Performed poorly (82.19% accuracy) with significant class imbalance issues (67.55% precision). Testing highlighted difficulties in feature fusion between the two architectures

  - MobileNetV3+ViT Hybrid: Showed similar poor results (82.19% accuracy). The testing confirmed that combining architectures without careful design led to compromised performance
  - Custom ViT-style Model: Achieved promising results (89.04% accuracy) with exceptional efficiency (28ms/epoch). Testing validated its balanced precision-recall tradeoff (93.07% precision, 90.09% F1) and stable convergence.

- **Test Accuracy, Precision, Recall, and F1 Score:**
  - To ensure result reliability, all models were evaluated using the same test sets and standardized metrics (accuracy, precision, recall, F1). The validation process included multiple training runs to verify consistency and learning curve analysis to detect overfitting.

- **Conclusion:**
  - These comprehensive tests confirmed that architectural choices have a significant impact on performance, beyond just parameter counts. The EfficientNetB0 model emerged as the most accurate solution, while MobileNetV3 provided the best balance between efficiency and accuracy. The results also showed that transformer-based models require careful adaptation to outperform traditional CNNs in this particular multimodal task.

5.6 Front-end Implementation

The front-end of a web application is essential for providing a smooth and efficient user experience. In the OralOptix project, the front-end is designed to be simple, interactive, and easy to use, allowing dental professionals to assess intra-oral radiographs efficiently. It is built using HTML, CSS, and JavaScript, which work together to create a well-structured, visually appealing, and responsive interface.

HTML provides the basic structure of the web pages, organizing elements such as forms, buttons, and image uploads. CSS improves the appearance by applying styles that enhance readability and create a professional look. JavaScript adds interactive features, such as real-time validation, smooth navigation, and user feedback, making the system more dynamic and user-friendly.

The system follows a clear step-by-step process, guiding users through the necessary actions. It starts with the sign-up page (Figure 5.1), where users can create an account or navigate to the login page (Figure 5.2) to access the system.

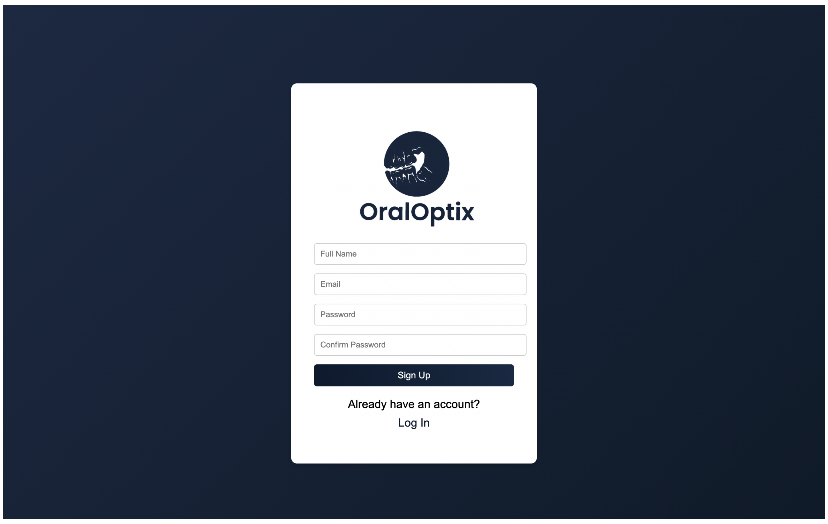


Figure 5.1: OralOptix's Sign up Pag

Figure 5.2: OralOptix's Log In Page

Once logged in, they are directed to the dashboard (Figure 5.3), which provides access to key features such as managing patient records and analyzing radiographs. From there, users follow a structured workflow that includes the following steps:

1.Uploading an image (Figure 5.4) 2.Entering patient details (Figure 5.5) 3.Adjusting technical settings (Figure 5.6) 4.Analyzing the radiograph using AI (Figure 5.7)

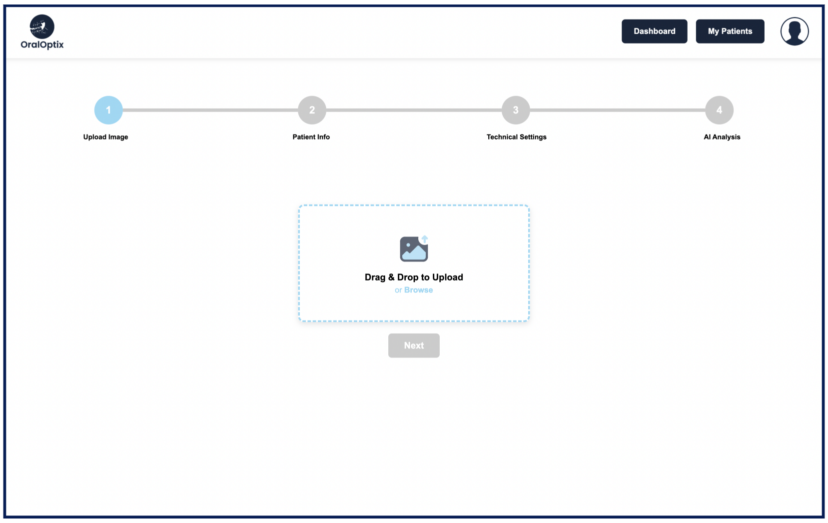


Figure 5.3: dashboard Page

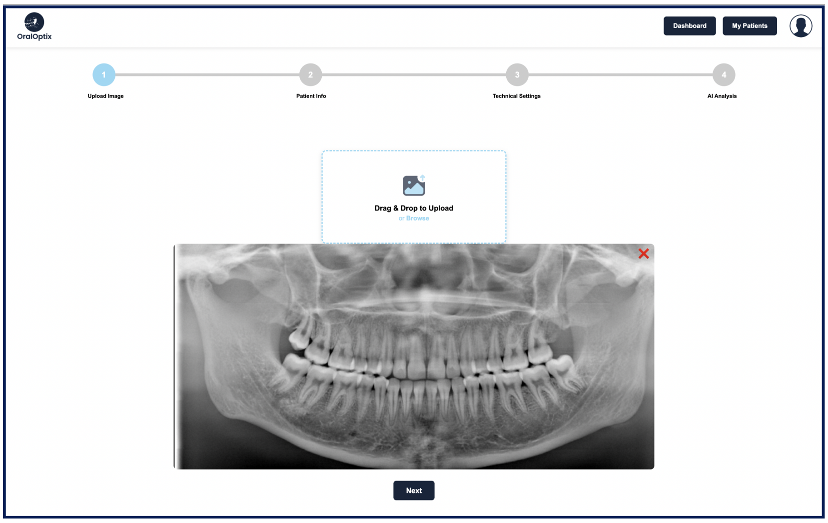


Figure 5.4: Uploading an image through the drag-and-drop option in OralOptix

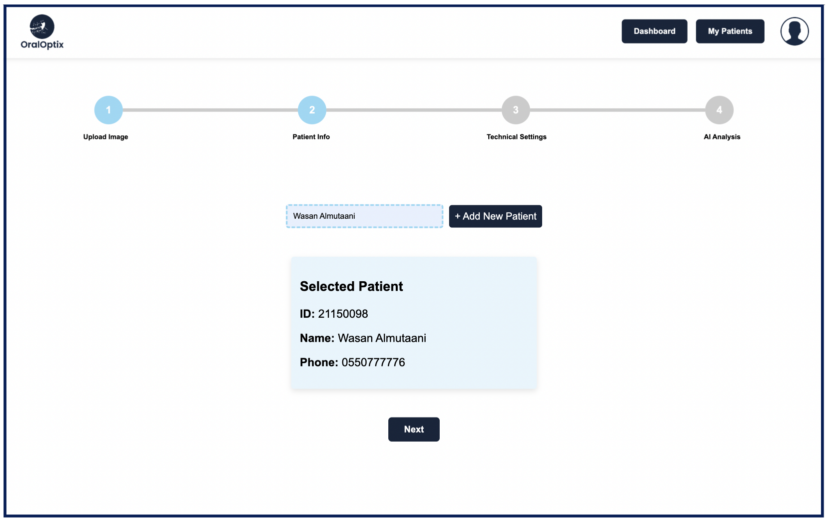


Figure 5.5: Selecting or adding a new patient in the Patient Information page of OralOptix.

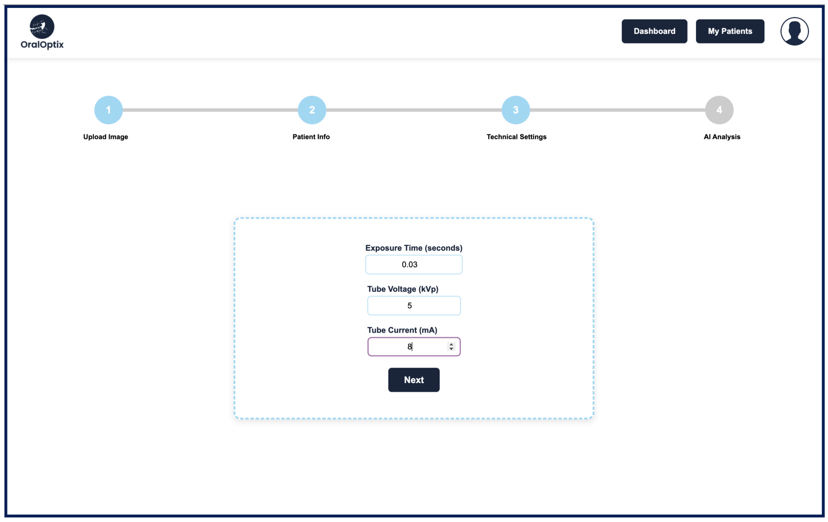


Figure 5.6: Configuring technical settings, including exposure time, tube voltage, and tube current, for radiograph analysis in OralOptix

Figure 5.7: The Results Page

After the AI processes the radiograph, the Results Page (Figure 5.7) displays the uploaded image and classifies it as either diagnostic or non-diagnostic. It also presents detected errors, technical settings, and suggested corrections. At the final stage, users can generate a detailed PDF report (Figure 5.8), which summarizes the findings, classification results, identified errors, and necessary corrections. This report includes patient details, technical imaging parameters, and AI-suggested improvements to ensure optimal radiograph quality.

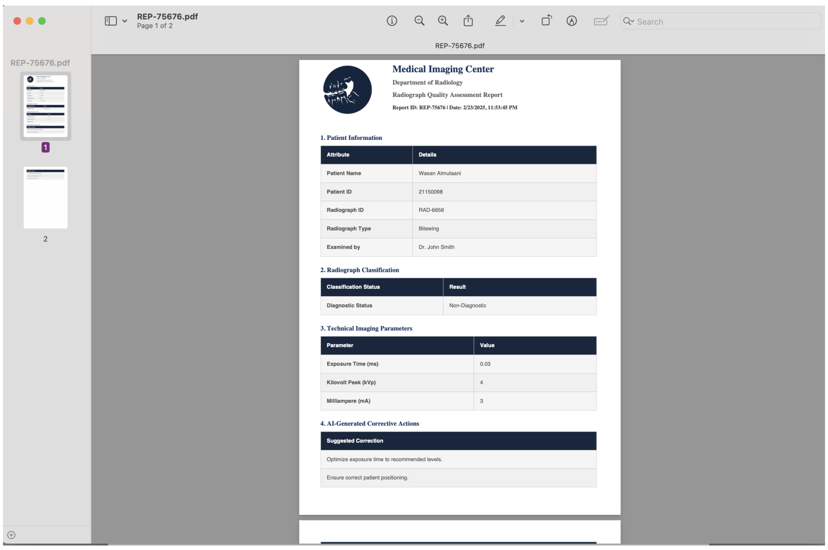


Figure 5.8: PDF Radiograph Quality Assessment Report

Figure 5.9 shows the Patient Management Page in OralOptix, which helps dental professionals efficiently manage patient records. The page displays a structured table containing essential patient details, such as ID, first name, last name, mobile number, and gender. A search bar allows users to quickly find specific patients, while pagination buttons help navigate through multiple entries. Additionally, action buttons enable users to view, edit, or delete patient records.

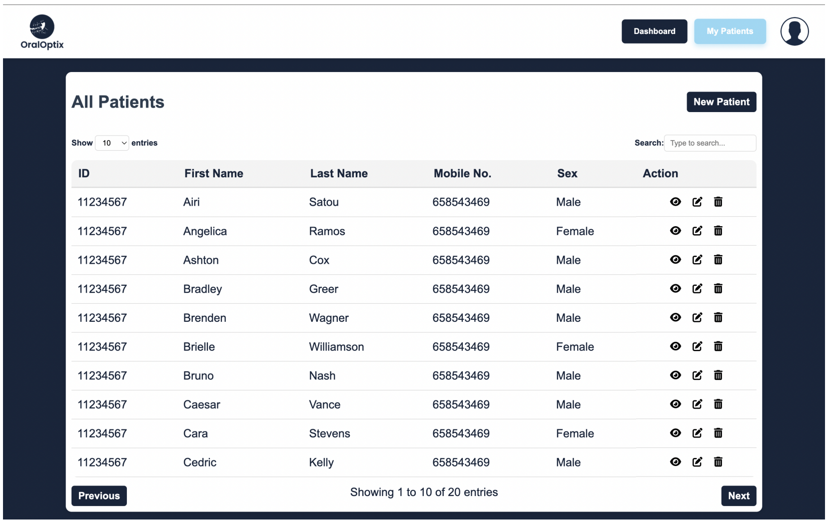


Figure 5.9: The Patient Management Page.

Figure 5.10 presents the New Patient Window, which appears when users click the "New Patient" button on the Patient Management Page. This window allows users to enter a new patient's details, including ID, name, gender, age, phone number, and additional medical information. Users can also upload relevant files before saving the new patient record.

These features enhance the efficiency of patient management, ensuring that dental professionals can easily organize, update, and access patient information in a structured and user-friendly manner.

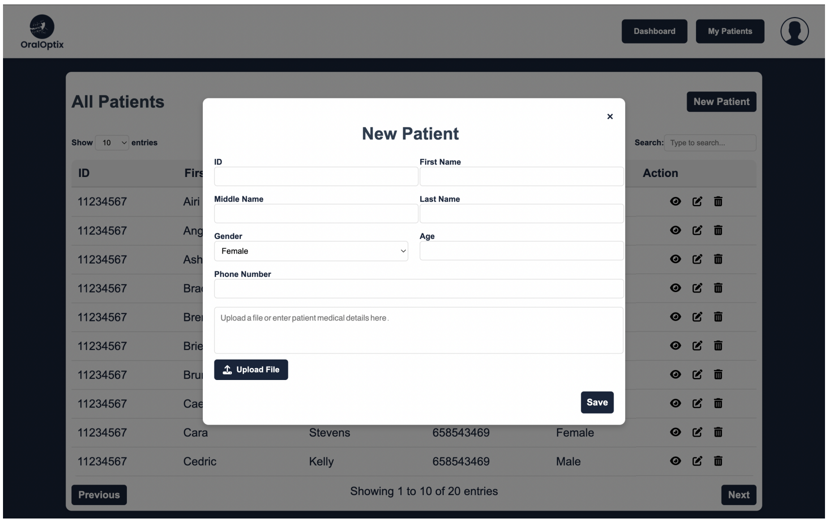


Figure 5.10: New Patient Window for adding patient details.

Figure 5.11 shows the User Profile Page in OralOptix, where users can manage their personal information. The form includes fields for ID, first name, last name, middle name, email address, and password. Users can update their details and securely save the changes by clicking the "Save" button, ensuring their profile information remains accurate and up to date.

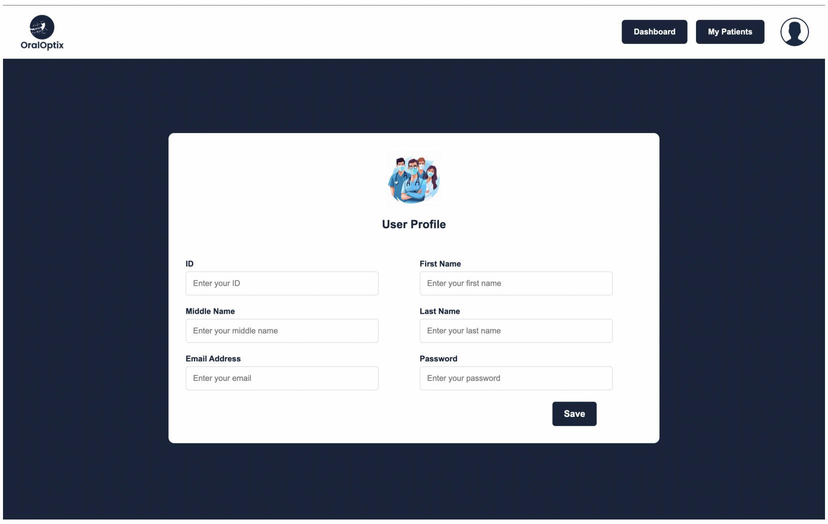


Figure 5.11: User Profile Page .

All pages in OralOptix have a top bar (Figure 5.12) that helps users navigate the system easily. It includes the platform logo, a Dashboard button to access the main page, and a My Patients button to manage patient records. On the right side, there is a profile icon that opens a menu with options to view and edit the profile, delete the account, or log out.

Figure 5.12: OralOptix Top Bar for Efficient Navigation and User Access.

5.7 Back-end Implementation

Most users think the result and the quick responses deliver from the websites as a one level structure without knowing that performance depends on server-side or backend programming. Nowadays many different backend frameworks and scripting technologies exist but which is the best? The answer to this question needs a look at factors such as performance, scalability, and architecture. [Odeniran et al., 2023]

The chosen back-end language for this project is Hypertext Pre-processor (PHP), which is considered as the world most popular scripting language and because of its high flexibility and ease of use. monotonous and difficult to maintain occur a lot while structuring the code. By simplifying web development, providing structured coding, and offering built-in APIs, libraries, and extensions for faster development PHP solve these issues. In addition to helping ensure successful connection to the database, reduce spending time in creating the actual application which causes increasing productivity. [Tenzin, 2022]

5.7.1 Database Implementation

The database within the oraloptix system is essential for storing and retrieving important information. The database was implemented using myadmainphp along with XAMPP control panel. Myadmainphp basically is a free software tool written in PHP; it works in handling the MySQL administration over the web. It offers a huge amount of operation on MySQL and MariaDB. The main advantage of it is that the user can perform all the following through the user interface (managing databases, tables, columns, relations, indexes, etc.) in addition to the ability to execute any SQL statement.[Kofler, 2005] The following figures; figure 5.13 shows an overview of all tables that have been used in the system. Figures 5.14 and 5.15 show two of the tables.

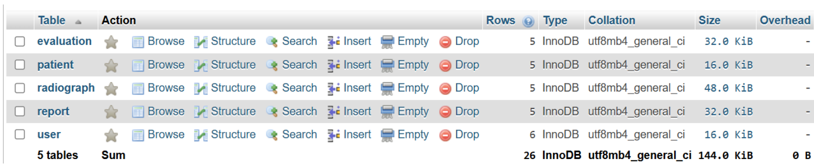
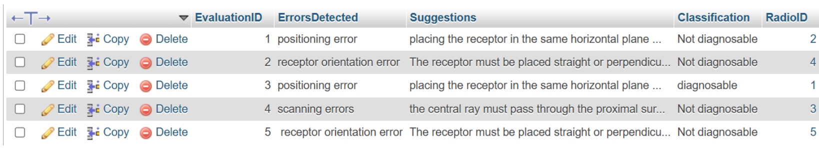


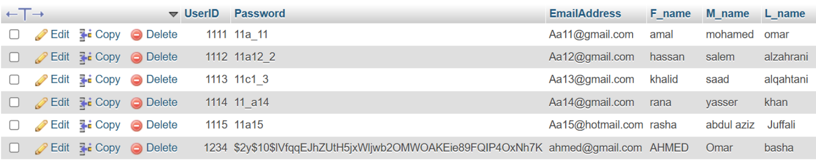
Table	Action	Rows	Type	Collation	Size	Overhead
evaluation	Browse Structure Search Insert Empty Drop	5	InnoDB	utf8mb4_general_ci	32.0 KiB	-
patient	Browse Structure Search Insert Empty Drop	5	InnoDB	utf8mb4_general_ci	16.0 KiB	-
radiograph	Browse Structure Search Insert Empty Drop	5	InnoDB	utf8mb4_general_ci	48.0 KiB	-
report	Browse Structure Search Insert Empty Drop	5	InnoDB	utf8mb4_general_ci	32.0 KiB	-
user	Browse Structure Search Insert Empty Drop	6	InnoDB	utf8mb4_general_ci	16.0 KiB	-
5 tables	Sum	26	InnoDB	utf8mb4_general_ci	144.0 KiB	0 B

Figure 5.13: database tables



←T→	EvaluationID	ErrorsDetected	Suggestions	Classification	RadioID
Edit Copy Delete	1	positioning error	placing the receptor in the same horizontal plane ...	Not diagnosable	2
Edit Copy Delete	2	receptor orientation error	The receptor must be placed straight or perpendicu...	Not diagnosable	4
Edit Copy Delete	3	positioning error	placing the receptor in the same horizontal plane ...	diagnosable	1
Edit Copy Delete	4	scanning errors	the central ray must pass through the proximal sur...	Not diagnosable	3
Edit Copy Delete	5	receptor orientation error	The receptor must be placed straight or perpendicu...	Not diagnosable	5

Figure 5.14: The evaluation table



←T→	UserID	Password	EmailAddress	F_name	M_name	L_name
Edit Copy Delete	1111	11a_11	Aa11@gmail.com	amal	mohamed	omar
Edit Copy Delete	1112	11a12_2	Aa12@gmail.com	hassan	salem	alzahrani
Edit Copy Delete	1113	11c1_3	Aa13@gmail.com	khalid	saad	alqahtani
Edit Copy Delete	1114	11_a14	Aa14@gmail.com	rana	yasser	khan
Edit Copy Delete	1115	11a15	Aa15@hotmail.com	rasha	abdul aziz	Juffali
Edit Copy Delete	1234	$2y$10$lVfqqEJhZUtH5jxWljwb2OMWOAKEie89FQIP4OxNh7K	ahmed@gmail.com	AHMED	Omar	basha

Figure 5.15: The user table

5.8 Conclusion

In conclusion, in this chapter of implementation we have represented AI-model for multi-class classification, in addition to the full-stack development of a web-based system. An overview of OralOptix system, tools and technologies used, the preprocessing techniques for the dataset, multimodal AI (EfficientNet-based Model, Vision Transformer, MobileNet-based Model) ,Model Performance Evaluation.

CHAPTER 6

TESTING

6.1 Introduction

The main role of testing phase is to ensure that the software operates correctly without errors and meets the user's needs. And it is a central part of the software development cycle. There are different types of testing techniques. Each technique focuses on a different point such as: designing, coding. This chapter overviews the testing phase through the following sections system testing in section 6.2. then System Components Testing in section 6.3. then in section 6.4 shows the Types of Software Testing. After that, Unit Testing in section 6.5. and finally, the usability testing in section 6.6. [Tuteja et al., 2012]

6.2 System Testing

System testing represents a comprehensive validation phase aimed at ensuring that the OralOptix system operates without defects or unintended behavior. This stage follows the complete integration of all system components, including the image processing module, error detection algorithms, and reporting interface. It verifies that the system performs as intended in realistic operational conditions.

This testing phase is critical in confirming that OralOptix fulfills its functional and clinical goals, particularly in the accurate detection and classification of errors in Bitewing radiographs. It ensures adherence to both technical and user-driven requirements, thereby validating the reliability and effectiveness of the AI-based analysis.

The primary objectives of system testing in OralOptix are:

- To ensure the system satisfies all specified functional and non-functional requirements.
- To detect and address logic, semantic, and computational errors within the system.
- To confirm alignment between the system's design, features, and performance and the established project specifications.

Following the integration phase, a sequence of detailed system tests was conducted. The anticipated outcomes for each scenario are presented in Table 6.1.

6.3 System Components Testing

The OralOptix system is made up of three main parts: the user interface (UI), the AI-powered image analysis module, and the database system. System testing checks that these parts work well together and that data moves between them correctly, without any loss or mistakes.

During testing, it was confirmed that the user interface displays the analysis results from the AI module clearly and retrieves data from the database accurately and quickly. The AI module was also tested to make sure it correctly analyzes radiographic images and sends the results back to the interface without any delays or errors.

This testing step is important because it makes sure that OralOptix works as expected and gives dental professionals a smooth, accurate, and reliable experience. It also helps confirm that the system meets both clinical and technical requirements.

6.4 Types of Software Testing

Testing is a crucial phase in the development of the OralOptix system, designed to ensure the accuracy, reliability, and clinical effectiveness of the platform. Various testing methods were employed to confirm that the system performs as intended in both technical and practical use cases. Two essential testing approaches used in this project are unit testing and usability testing.[Basili and Selby, 1987]

Unit testing was conducted to assess the functionality of individual components, such as the AI-based radiographic error detection module, image input handling, and data flow processes. Each module was tested in isolation to ensure it functions correctly before integration.

Usability testing focused on evaluating how effectively dental professionals can interact with the system. This included testing the clarity of the user interface, the accuracy of displayed diagnostic results, and the overall ease of navigation within the platform.

These testing methods address different but equally important aspects of the system and are discussed in detail in this chapter to provide a comprehensive overview of the testing procedures implemented in OralOptix.

Table 6.1: System Testing Results

Test Name	End-User Input	Expected Output	Actual
Sign Up	User ID, name, email, password	Show log in page	As Expected
Log In	User email or user ID and password	Show home page	As Expected
Add New Patient	Patient ID, name, gender, age,phone number, medical file upload	Display success message and list patient in the table	As Expected
Edit Patient	Patient ID, name, gender, age,phone number, medical file upload	Show success message and reflect updates in table	As Expected
Delete Patient	Click Delete icon, confirm deletion	Remove patient and show success message	As Expected
Upload Radiograph	Upload Bitewing image via drag-and-drop or browse	Show radiograph preview and enable Next button	As Expected
Select Patient	Choose patient or click Add New Patient	Show patient info under Selected Patient section	As Expected
Enter Technical Settings	Input exposure time, kVp, mA values	Save settings and enable Next button then proceed to AI analysis step	As Expected
AI Analysis	Wait for auto-analysis	Show classification, errors, Technical Settings,and AI suggestions	As Expected
Generate Report	Click Generate Report	Generate downloadable PDF report with analysis	As Expected
Search Patient	Type keyword in Search bar	Filter and display matching patient records	As Expected

6.5 Unit Testing

Unit testing plays a crucial role in the machine learning development lifecycle, ensuring that each model performs as expected and meets system requirements. In this context, unit testing was conducted to evaluate the individual model architectures, checking their internal structures, design, and performance metrics. The goal was to identify strengths, weaknesses, and potential optimization opportunities for each model. Unit testing ensures that the models are reliable, capable of making accurate predictions, and maintainable over time.[Daka and Fraser, 2014] For this multimodal classification system, unit testing was conducted on six distinct model architectures to validate their functionality and compare performance. Detailed procedures and results for each model are provided in the following subsections

6.5.1 AI Model Unit Testing

AI testing, a crucial part of the system validation process, focused on evaluating the performance and accuracy of the implemented deep learning models through the web-based platform. The goal was to confirm the models' ability to analyze dental X-ray images and deliver accurate diagnostic predictions.

As outlined in Section 5.5, six different architectures were implemented and rigorously tested. Among these, the EfficientNetB0 model delivered the highest accuracy, while MobileNetV3Small achieved a strong balance between performance and computational efficiency. Although Vision Transformer (ViT)-based models showed promise, they still require further optimization to outperform traditional convolutional networks in this task.

To evaluate the system in a practical setting, testing was conducted with computer science students using the website interface. This real-world interaction confirmed that the models function reliably and efficiently when accessed through the web application, successfully processing uploaded X-ray images and generating diagnostic outputs.

These results confirm the system's readiness for further clinical testing, pending the arrival of additional data from hospital collaborators. Future evaluations will focus on expanding the dataset and verifying performance in real healthcare environments.

6.5.2 Back-end Unit Testing

To begin, an additional test was performed to validate the overall system functionality before proceeding with more focused tests. The back-end testing for this project was then manually executed by interacting with the graphical user interface (GUI) and cross-checking that the corresponding database tables reflected the correct implementation. A detailed account of these tests, along with test scenarios, expected outcomes, and actual results, can be found in Table 6.2 [Tsai et al., 2001]

6.6 Usability Testing

Spotting the light on the user's experience and his feedback after using OralOptix website or in a scenario-based environment. The usability test should be started before publishing the website. It applied for small groups of people. The researcher can see how the user navigates through the Oralptix website finding the point of confusion facing the user. Recording the behavior of the user and what he feels about the keystrokes and the duration.[Aziz et al., 2021]. The following table 6.2 shows the eleven task that have been testing in the usability testing for the back-end of OralOptix system. All the tasks have been applied the participants.

Table 6.2: Usability Testing Tasks For the Back-end of OralOptix System.

Test name	Expected output	Actual
Sign up	Successfully adding a new user	As Expected
Log in	Successfully log in for an authorized account	
Add patient	Successfully adding and storing new patients into the database	
Edit patient	Successfully modifying patients from the back-end database	
Delete patient	Successfully deleting patients from the back-end database	
Uploading images	Successfully uploading image in the website to the AI model	
Select Patient	Selecting patient from whom already exists in the database	
Enter Technical Settings	Successfully setting the technical settings in the back-end database	
AI Analysis	Store the AI Analysis result for each image	
Generate Report	Storing patient's report	
View patient	easy reviewing patients	

6.6.1 Participants

The suitable participants for the usability test are students. Toward obtaining priceless information from their knowledge and to provide feedback, optimize the website user interface, user expectance and functionalities, and enhance the effectiveness of the OralOptix website. To ensure involving OralOptix goes along with their needs without difficulties. 6 participants have been joined in the usability test. All the tasks have been applied to them.

6.6.2 Environment of the Test

The usability testing of OralOptix system has been in king Abdulaziz university. The system has been open as the pre- usability testing for the participants and each one had a set of tasks scenario about their roles as dentists who want to check for the diagnosability of a given intra-oral radiography image. This would allow them to approach the testing from a professional perspective and assess the way that the website would assist them in their existing job responsibilities.

6.6.3 Evaluation Tasks

Eleven tasks have been assigned to our participants to ensure the usability of the OralOptix system.

1- Sign up: The user must click the" don't have an account? Sign up" button and fill his information correctly then click on "sign up" button.

2- Log in: The user must log in using his correct email address or his id and the password, then clicking in the "Log in "button.

3- Add a new patient: to add a new patient to the system, the user clicks" add patient" button, fill the information of the patient then click "Save" button.

4- Edit patient: To edit the patient's information the user must click on" my patient" button. Then click on the edit icon's button next to the patient's name in the patients list.

5- Delete patient: To delete the patient's information the user must click on" my patient" button. Then click on the delete icon's button next to the patient's name in the patients list.

6- Uploading radiograph: uploading radiograph image by clicking in "Browse "button browse or via drag-and-drop inside the box.

7- Select Patient: The user can select a patient from the list or searching by the name or adding a new patient by clicking in "Adding new patient" button.

8-Enter Technical Settings: the user can insert an input of the technical settings exposure time, kVp, mA values by writing in the text boxes.

9- AI Analysis: after uploading the image, choosing the patient's name and entering technical settings. And after clicking "next" button, a dashboard with AI analysis of the image will appears to the user.

10- Generate Report: downloadable PDF report with AI analysis result can be generated when the user click on "Generate Report" button.

11-View patient: To view the patient's information the user must click on" my patient" button. Then click on the view icon's button next to the patient's name in the patients list.

6.6.4 Object Measure Analysis

The objective measure is dependent on the number of user messages received by a component. Is mainly to measure the success rate of the OralOptix system, expected time and number of clicks required for the compilation of each task have been set. This technique will help assess the performance of the task. The following table 6.3 shows the expected measures for the compilation of each task.[Brinkman et al., 2008]

Table 6.3: Expected Measures for the Compilation of Each Task

Task	Expected Clicks	Expected Duration
1	2	1 minute
2	1	30 seconds
3	3	2 minutes
4	3	1 minute
5	1	30 seconds
6	2	1 minutes
7	2	30 seconds
8	1	1 minute
9	3	30 seconds
10	1	15 seconds
11	2	1 minute

6.6.4.1 Number of Clicks

The first measure used for the assessment is the number of clicks for each task. The following table 6.4 shows the minimum and maximum number of clicks for each task for the 6 participants.

Table 6.4: The Minimum and Maximum Number of Clicks for Each Task

Task	Participants Number of Clicks	
	Minimum number of clicks	Maximum number of clicks
1	2	2
2	1	1
3	3	4
4	3	3
5	2	1
6	2	6
7	2	2
8	1	1
9	3	5
10	1	1
11	4	5

6.6.4.2 Task Duration

The second measure used for assessment is the duration for each task. The following table 6.5, shows the minimum and maximum duration of each task for the 6 participants.

Table 6.5: The Minimum and Maximum Duration for Each Task

Task	Participants Number of Clicks	
	Minimum duration	Maximum duration
1	47 seconds	1 minute
2	15 seconds	1 minutes
3	47 second	1 minutes 20 seconds
4	15 second	20 seconds
5	15 seconds	40 seconds
6	15 seconds	1 minute 5 seconds
7	7 seconds	15 seconds
8	15 seconds	50 seconds
9	2 seconds	45 seconds
10	10 seconds	15 seconds
11	20 seconds	1 minute

6.6.5 Subjective Measure Analysis

The subjective measures are obtained through a questionnaire. How users feel about the use of the products. And the Post-Test consists of group questions have been provided to the 6 participants by the questionnaire to gather feedback toward enhancing the website before publishing. In the following tables 6.6 and 6.7 show the answer of the post-Test for both yes/ No questions and rating questions respectively.[Brinkman et al., 2008]

Table 6.6: Post-Test Summary for Yes and No Questions.

Question	**Answer**	
	Yes	**No**
# Are all website functions clear to you?	6	
# Does this website save time in determining the diagnosability of radiograph images?	6	

Table 6.7: Post-Test Summary for Rating Questions.

Question (1-5)	**1**	**2**	**3**	**4**	**5**
# What do you think of the website in general?					6
# How often would you use it?				1	5
# How much the website solves the diagnosability problem?					6

according to the previous table 6.6, The website's overall impression is primarily favorable. Many respondents shows satisfaction with the website, suggesting that they were satisfied about their overall experience.On of them said that "The website was very easy to use. It is straightforward and simple which I appreciate." None of the participants expressed dissatisfaction with the website. Furthermore, all respondents expressed satisfaction with both visual design and user interface of the system.

6.7 Conclusion

In the conclusion of testing chapter. We have applied two types of testing techniques which are software testing and usability testing. Software testing for ensuring both technical and user-driven requirements adherence of OralOptix system. And usability testing for groups of participants to examine user's point of view about the system.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Introduction

The OralOptix project report shows the success of our AI-based system designed to bitewing intra oral radiographic images. We have created efficient system that automatically assess the quality of radiographic images. We have created a web-based platform with a user-friendly interface. This project significantly reduces the use of non-diagnostic images. reliable solution that addresses key challenges in dental radiography by reducing the waste of dentist time in checking the correct (able to be diagnostic from it) from the incorrect images (unable to be diagnostic from it). The project development process began with the problem definition and project description, followed by a literature review, requirements gathering, system design, implementation, and testing.

7.2 Challenges and Difficulties

During the development of the OralOptix system, several challenges were encountered across different phases of the project. These challenges are categorized and discussed as follows:

7.2.1 Dataset Challenges

7.2.1.1 Data Availability and Access

One major difficulty was securing a sufficiently large and annotated dataset for training and testing the AI models. Initially, the dataset provided by

King Abdulaziz University Dental Hospital was delayed, which limited early experimentation and model optimization. Additionally, ensuring consistent and high-quality annotations for radiographic errors required extensive expert involvement, making data preparation time-consuming and complex. This delay significantly impacted the overall project timeline.

7.2.1.2 Data Imbalance

Radiographic errors were not equally distributed across the dataset. Certain types of errors, such as motion artifacts and scanner-related issues, were underrepresented. This class imbalance affected the model's ability to accurately detect rare errors and necessitated the use of data augmentation techniques and advanced training strategies to improve model robustness.

7.2.2 System Integration and Technical Challenges

7.2.2.1 Integration of Components

Integrating the AI model outputs with the web-based system while maintaining real-time analysis and user-friendly display posed significant technical challenges. Synchronizing processes such as image uploading, AI-based analysis, error detection, and result visualization required meticulous coordination between the back-end and front-end components to ensure system stability and responsiveness.

7.2.2.2 Unexpected Technical Issues

During development, unexpected technical problems occasionally arose, such as errors in dataset preprocessing, fluctuations in model performance, and bugs during system integration. These issues disrupted the planned timeline and required dynamic replanning and reallocation of resources to maintain project progress.

7.2.3 Time Management Challenges

Because the project involved many tasks such as developing, training, integrating, and testing a complete AI-based system managing time effectively was very important. Balancing university responsibilities with the heavy workload of the project sometimes caused pressure on available resources. To deal with unexpected delays and stay on track, flexible project management methods were needed.

7.3 Learned Skills and Lessons

Since the beganing of our programming project, we have gained a huge amount of knowledge and information about different branches of computers since starting with programming project management to software engineering then full stack development and AI model. It also improved our soft skills such as teamworking and taking decisions. Even thouge we faced many challenges it enhance our problem-solving skills. Mentioning skills that what reason for improving us throughout delivering OralOptix system are:

7.3.1 Technical Skills

Technical skills, or "hard skills," are often associated with the use of tools and equipment related to work properly and efficiently. Technical skills are skills that require a combination of specific knowledge and skills of the work done using the body.[Nasir et al., 2011]

- being introduced to new tools and languages.
- Experience in full-stack developing and building both front and back end.
- experience In building a website, take care of both UI (user interface) and UX (user experience), ensuring it is interactive and user-friendly.
- Expanding our knowledge of programming paradigms and data structures.
- Debugging and optimizing for the module
- Building a database and storing the data successfully.

7.3.2 Project Management Skills

It is a concept that has been used by both engineering and business colleagues to manage each of construction, product launches, and computer program development projects. The phase of project management is public and reachable by anyone dealing with the task required to manage implementation like in our case new programs.[Childre and Perce, 1998]

- Planning from the early beginning and setting a plan that we can dispel.
- Setting a meeting every one or two weeks.
- Preparing for every presentation that has been present in an online meeting.

7.4 Future Work

To enhance the practical application and effectiveness of the AI models developed in this project, several directions for future work are proposed. First, instead of maintaining separate multimodal models for different tasks, we aim to integrate both diagnostic classification and feature prediction into a unified multiclass and multilabel classification model. This approach will streamline the inference process and potentially improve overall performance through shared learning representations. Additionally, a key step in improving the accuracy and generalizability of the AI model is to expand the dataset by collecting a larger number of annotated dental X-ray records. A more diverse and extensive dataset would allow the model to learn richer patterns and reduce bias, especially for underrepresented classes.

Another significant future enhancement involves making the system adaptive and continuously learnable. We plan to implement a feedback-driven mechanism that allows the AI model to update itself based on new data entered by users (e.g., dentists or radiologists) through the platform. This could be achieved through online learning or periodic re-training, thereby keeping the model current with evolving diagnostic standards and practices. Additionally, transforming the web-based interface into a fully functional mobile application will make the solution more accessible and practical for real-time clinical environments. The mobile version could support functionalities such as image capture from mobile cameras, immediate AI-based feedback, and offline access with limited resources.

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APPENDIX 1

Stakeholder Survey Questions

Table 1.1: OralOptix Stakeholder Survey Questions

Survey Question	Answer	Percentage (%)
What is your professional title?	Dentist	76
	Radiologist	5
	Dental student	19
What types of errors do you most frequently find in bitewing radiographs?	Errors in operating the machine	12.5
	Errors in technique	75
	Scanner related errors	12.5
How much time do you spend on average checking bitewing radiographs for quality before diagnosing?	Less than a minute	17.5
	1-3 minutes	55
	3-5 minutes	22.5
	More than 5 minutes	5
How does poor quality in bitewing X-rays affect your diagnostic work? (Select all that apply)	Causes delays in diagnosis	65
	Leads to more retakes and higher patient exposure to X-rays	85
	Reduces confidence in diagnosis	42.5
	Increases overall workload	62.5
	The patient will not prefer our clinic	2.5
How helpful would an automated system be in identifying unusable radiographs?	Extremely helpful	65
	Somewhat helpful	30
	Not very helpful	5
	Not helpful at all	0
How often would you use an automated quality-checking system if available?	For every X-ray	75.5
	Only when unsure of quality	30
	Rarely	12.5
	Never	0
What do you think are the biggest benefits of using an automated system to check X-ray quality? (Select all that apply)	Saves time	95
	Reduces need for retakes	70
	Improves diagnostic accuracy	60
	Reduces patient exposure to X-rays	70
What are the biggest challenges you currently face with checking X-ray quality manually?	Time constraints	50
	Lack of clear criteria for errors	22.5
	Inconsistent image quality	28.2