Periodontal Diagnosis and Prognostication Detection Using Medical Image Processing

Jarupat Jundaeng

A Thesis Submitted in Partial Fulfillment of Requirements for

degree of Doctor of Philosophy in Health Science

November 2024

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The examining committee has unanimously approved this Thesis, submitted by Mr. Jarupat Jundaeng , as a partial fulfillment of the requirements for the Doctor of Philosophy Health Science at Mahasarakham University

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ABSTRACT

Background: The elderly population faces a growing burden of various diseases, with dental issues—especially periodontal disease—often overlooked due to their asymptomatic nature. Periodontitis, however, is linked to numerous systemic conditions, leading to serious complications and negatively impacting quality of life. Affecting over a billion people globally, periodontal diseases pose a significant public health challenge due to their potential for severe oral complications. Early and accurate diagnosis is crucial, yet current methods, which rely on clinical exams and radiographs, have limitations. This study aims to develop and validate AI-driven models to enhance diagnostic accuracy and consistency in detecting periodontal disease. Methods: We analyzed 2,000 panoramic radiographs using image processing techniques. The YOLOv8 model segmented teeth, identified the cemento-enamel junction (CEJ), and quantified alveolar bone loss to assess stages of periodontitis. Results: The teeth segmentation model achieved an accuracy of 97%, while the CEJ and alveolar bone level segmentation models reached 98%. Our AI model demonstrated a remarkable performance with 94.4% accuracy and perfect sensitivity (100%). In comparison, periodontists achieved 91.1% accuracy with a sensitivity of 90.6%. General practitioners (GPs) also benefited from AI assistance, achieving 86.7% accuracy and 85.9% sensitivity, with AI enhancing diagnostic outcomes further. Conclusions: This research underscores the transformative potential of AI in dental diagnostics, highlighting its crucial role in reducing diagnostic errors, saving time, enhancing patient care, and optimizing healthcare efficiency. The implications are profound, suggesting that AI integration in periodontal diagnostics may become standard practice, significantly improving patient outcomes and streamlining dental care processes.

Keyword : Artificial Intelligence, Periodontal Disease, Periodontitis Diagnosis, Panoramic Radiographs, Convolutional Neural Networks (CNNs)

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Jarupat Jundaeng

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CHAPTER 1

Introduction

According to the World Health Organization (WHO) on November 18, 2022 [1, 2], the elderly population is increasingly burdened by various chronic diseases, significantly impacting healthcare systems globally. The top ten diseases affecting the elderly include cardiovascular diseases, chronic respiratory diseases, cancers, diabetes, Alzheimer's disease and other dementias, osteoarthritis, chronic kidney disease, stroke, depression, and dental diseases such as periodontitis (Fig. 1).

1. Cardiovascular Diseases: Cardiovascular diseases (CVD) affect approximately 60% of older adults and remain the leading cause of morbidity and mortality among the elderly. Conditions such as coronary artery disease, hypertension, and heart failure are prevalent, largely due to prolonged exposure to risk factors and the natural aging of the cardiovascular system.

2. Chronic Respiratory Diseases: Chronic respiratory diseases, particularly chronic obstructive pulmonary disease (COPD) and asthma, are common among older adults, affecting about 15-20% of this population. These diseases are often exacerbated by long-term exposure to tobacco smoke, environmental pollutants, and other respiratory irritants.

3. Cancers: The incidence of various cancers, including lung, colorectal, prostate, and breast cancer, increases with age, affecting around 20-30% of the elderly population. Early detection and treatment are crucial; however, the overall burden of cancer remains high in the elderly population.

4. Diabetes: Type 2 diabetes affects approximately 25-30% of older adults. Factors such as obesity, sedentary lifestyle, and genetic predisposition drive its prevalence. Managing diabetes in older adults is complicated by the presence of comorbidities and the risk of complications like neuropathy and cardiovascular disease.

5. Alzheimer's Disease and Other Dementias: Neurodegenerative diseases, including Alzheimer's disease, are major causes of disability and dependency among older individuals. The prevalence of dementia doubles every five years after the age of 65, affecting nearly 10-15% of the elderly population, significantly impacting patients' quality of life and placing a burden on caregivers.

6. Osteoarthritis: Osteoarthritis affects about 30-40% of older adults and is a leading cause of pain and disability in the elderly. It affects joints such as the knees, hips, and hands, resulting from cartilage degeneration and is exacerbated by factors like obesity and joint injuries.

7. Chronic Kidney Disease: Chronic kidney disease (CKD) affects around 20-25% of the elderly due to factors like hypertension, diabetes, and the natural decline in kidney function with age. CKD often progresses to end-stage renal disease, requiring dialysis or transplantation.

8. Stroke: The incidence of stroke increases significantly with age, with risk factors including hypertension, atrial fibrillation, and diabetes. Around 10-15% of older adults experience strokes, leading to severe long-term disabilities affecting mobility, speech, and cognitive functions.

9. Depression: Depression affects approximately 10-20% of older adults and is often linked to chronic diseases, loss of independence, and social isolation. It significantly affects the quality of life and can exacerbate other medical conditions.

10. Dental diseases: While dental caries is the most prevalent condition in the oral cavity, periodontitis is often overlooked due to its asymptomatic nature, affecting approximately 20-30% of the elderly population [3]. This condition can lead to tooth loss, adversely impacting nutrition and overall health. Additionally, poor oral health is linked to systemic conditions such as diabetes and cardiovascular diseases, which can result in severe complications and diminish quality of life.

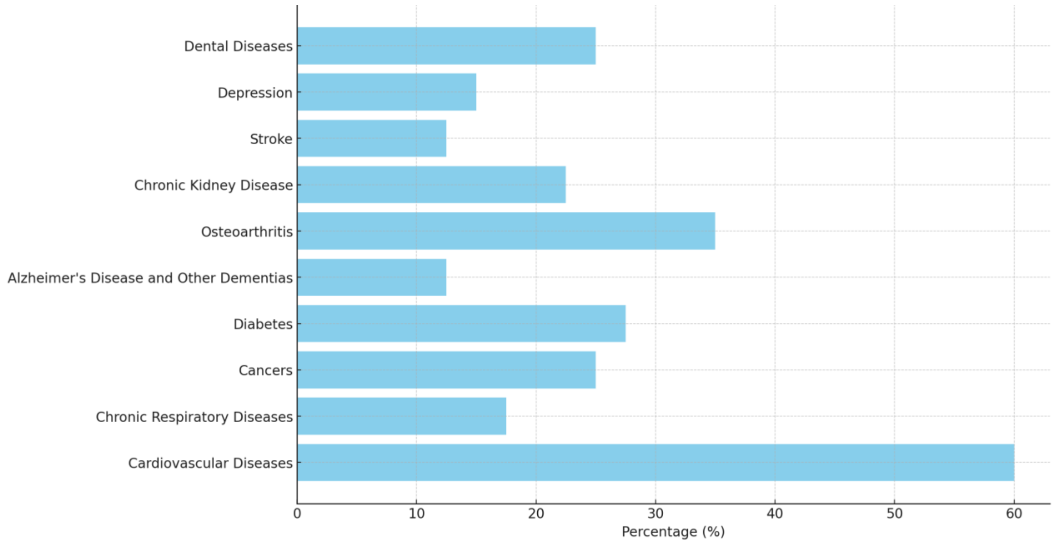


Figure 1: The prevalence of the top ten diseases in the elderly in 2024 [2].

Following the above data, aging is a universal phenomenon that has profound implications for health systems, economies, and societies worldwide. The global demographic shift towards an older population presents numerous challenges, particularly concerning chronic diseases prevalent in the elderly. Among these, periodontal disease stands out due to its high prevalence and significant impact on overall health, quality of life, and economic burden. This introduction explores the multifaceted impact of diseases in the elderly, with a specific focus on periodontal disease, from economic, social, and health perspectives.

1. Economic Impact of Elderly Diseases

1.1 Healthcare Costs:

The aging population drives an increase in healthcare expenditures, primarily due to the rising prevalence of chronic conditions that require long-term management. Elderly individuals often suffer from multiple comorbidities such as cardiovascular diseases, diabetes, arthritis, and respiratory disorders, alongside periodontal disease. Treating these conditions involves significant direct costs, including hospital admissions, medication, routine medical consultations, and specialized care [4].

Periodontal disease, in particular, necessitates ongoing dental care, including professional cleanings, periodontal surgeries, and maintenance therapy. These treatments are costly and often not fully covered by insurance, leading to substantial out-of-pocket expenses for the elderly. The indirect costs, such as loss of productivity and long-term disability, further compound the economic burden [5-7].

1.2 Impact on National Economies:

The economic impact extends beyond individual healthcare costs to affect national economies. The increase in healthcare spending can strain public health systems and divert resources from other essential services. Additionally, the economic contributions of the elderly, although significant, may be offset by their healthcare needs. The cost of caregiving, both formal and informal, adds another layer of financial strain. Family members who act as caregivers often face reduced work hours or even job loss, affecting household income and national productivity [4].

1.3 Insurance and Policy Implications:

The rising prevalence of elderly diseases necessitates changes in health insurance policies and public health strategies. There is a growing need for comprehensive insurance plans that cover the broad spectrum of elderly care, including dental health. Policymakers must address the sustainability of healthcare financing systems to ensure that the increasing demands do not compromise the quality of care [8].

2. Social Impact of Elderly Diseases

2.1 Quality of Life:

Chronic diseases significantly impact the quality of life of elderly individuals. Periodontal disease, characterized by symptoms such as gum bleeding, pain, and tooth loss, can severely affect daily functioning. Difficulty in chewing and eating due to periodontal issues can lead to nutritional deficiencies, exacerbating other health conditions. Moreover, the aesthetic impact of tooth loss can affect self-esteem and social interactions. Elderly individuals may experience social isolation due to embarrassment over their dental appearance or physical limitations imposed by other chronic diseases. This isolation can lead to mental health issues such as depression and anxiety, further diminishing quality of life [9].

2.2 Family Dynamics:

The need for long-term care for elderly individuals with chronic diseases can alter family dynamics. Family members often assume the role of primary caregivers, which can lead to emotional and physical stress. Balancing caregiving responsibilities with other family and work commitments can strain relationships and lead to caregiver burnout [10].

2.3 Community and Social Services:

Communities must adapt to the increasing needs of the elderly population. Social services, including transportation, meal programs, and community health centers, play a critical role in supporting elderly individuals. Ensuring access to these services requires coordinated efforts and adequate funding. Additionally, public health initiatives focusing on preventive care can help mitigate the impact of chronic diseases, including periodontal disease, within the community [11].

3. Health Impact of Periodontal Disease in the Elderly

3.1 Systemic Health Connections:

Periodontal disease is not merely a local oral health issue but has significant systemic health implications. Studies have shown strong associations between periodontal disease and systemic conditions such as diabetes, cardiovascular disease, respiratory infections, and adverse pregnancy outcomes. The chronic inflammation associated with periodontal disease can exacerbate these conditions, leading to a vicious cycle of deteriorating health. For instance, periodontal pathogens can enter the bloodstream, contributing to systemic inflammation and increasing the risk of atherosclerosis and cardiovascular events. Diabetic patients with periodontal disease may experience more difficulty in controlling blood glucose levels, highlighting the bidirectional relationship between these conditions [12].

3.2 Nutritional and Functional Impact:

The functional impact of periodontal disease on eating and nutrition is profound. Elderly individuals with severe periodontal disease may find it challenging to consume a balanced diet, leading to malnutrition. Malnutrition, in turn, weakens the immune system, making the elderly more susceptible to infections and slowing the healing process [13].

3.3 Mental Health:

The psychological impact of periodontal disease should not be underestimated. The visible symptoms and functional limitations can lead to self-consciousness and social withdrawal. The chronic pain and discomfort associated with advanced periodontal disease can also contribute to mental health issues such as depression and anxiety, which are already prevalent in the elderly population [14].

4. Addressing the Challenges

4.1 Integrated Care Approaches:

Addressing the multifaceted impact of elderly diseases, including periodontal disease, requires integrated care approaches. Health systems should promote coordinated care models that integrate dental and medical care to manage chronic diseases effectively. This integration can ensure that the systemic implications of periodontal disease are addressed alongside other health conditions [15].

4.2 Preventive Measures:

Emphasizing preventive care is crucial in reducing the prevalence and impact of periodontal disease. Public health campaigns should focus on educating the elderly and their caregivers about the importance of oral hygiene and regular dental check-ups. Fluoride treatments, professional cleanings, and early intervention can help manage periodontal disease more effectively and prevent severe complications [12].

4.3 Policy and Funding:

Policymakers must recognize the growing healthcare needs of the aging population and allocate appropriate resources. Funding for research into the connections between periodontal disease and systemic health conditions can lead to better prevention and treatment strategies. Additionally, expanding access to dental care through public health insurance and community health programs can help reduce the economic and social burden of periodontal disease [16].

4.4 Identification of Diseases Using Advanced Technology:

At present, both medicine and dentistry are entering a new era due to the rapid advancement and integration of technologies in these fields. This growth is expected to assist human labor and emphasize new trends in disease diagnosis, prognostication, treatment planning, and the selection of treatment modalities.

Moreover, elderly diseases, including periodontal disease, pose significant challenges across economic, social, and health domains. The economic burden of managing chronic conditions in the elderly can strain healthcare systems and national economies. Socially, these diseases impact quality of life, family dynamics, and community services. Healthwise, the systemic implications of periodontal disease underscore the need for integrated care approaches. Addressing these challenges requires a coordinated effort from policymakers, healthcare providers, and communities to ensure that the elderly receive comprehensive and compassionate care.

In an epidemiological study, the highest prevalence of chronic periodontitis was observed in the elderly population at 82%, followed by adults at 73% and adolescents at 59% [17]. Notably, 100% of older individuals in China, India, and Croatia were found to have periodontal disease, with the highest rates in Germany (88%), Croatia (83%), Nepal (73%), and

Taiwan (73%) [18] (Fig. 2). The elevated prevalence of periodontal disease among older adults can be linked to inadequate oral hygiene, insufficient government funding for oral health services, and a lack of targeted health promotion programs [19]. Additionally, low income serves as a barrier to accessing oral healthcare, with individuals lacking dental insurance less likely to seek routine care [20]. Many low-income individuals may underestimate the importance of oral health and be unaware of their dental care needs, contributing to lower expectations regarding their health [21]. Consequently, those from higher-income backgrounds are more likely to have dental insurance, facilitating both preventive and curative dental care, which aids in the retention of natural teeth [22].

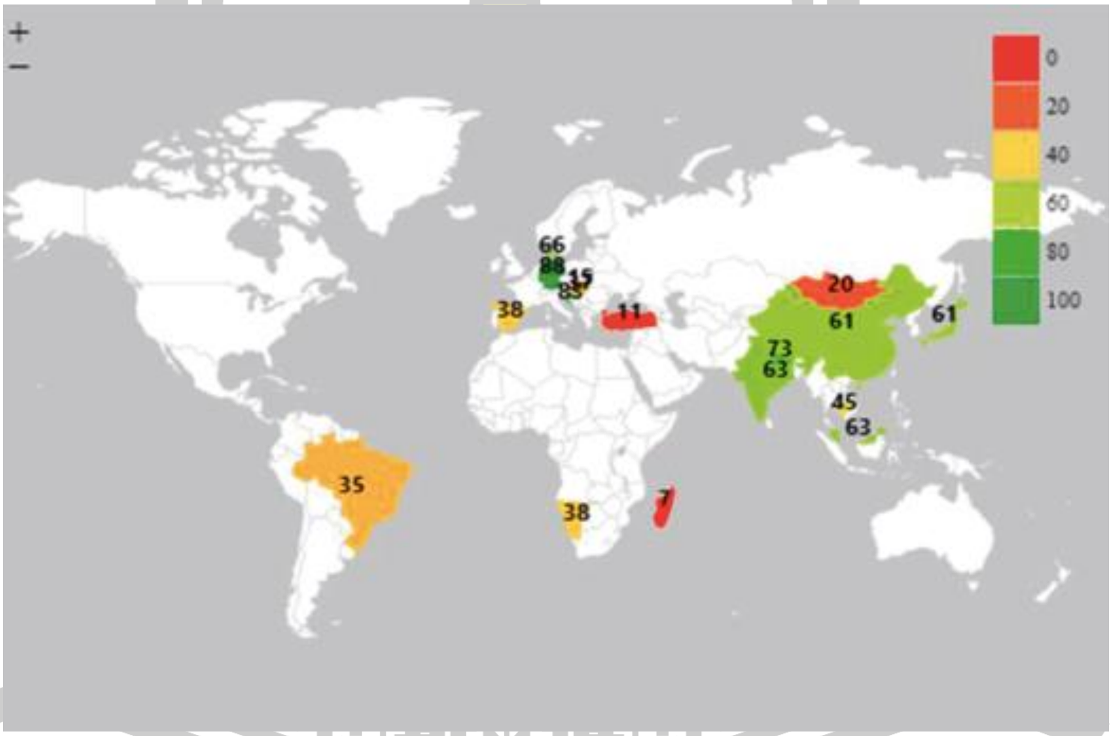


Figure 2: Global prevalence of periodontitis among the elderly [18].

According to the Bureau of Dental Health, Department of Health in Thailand, the National Oral Health Survey is conducted every five years. The 9th National Oral Health Survey (2022-2023) assessed the oral health status, behaviors, and key factors related to oral health among the Thai population [23]. It was found that the prevalence of periodontitis in Thailand is higher than the global data reported by the WHO. The Global Burden of Disease Study reported that severe periodontal disease affects 19% of adults worldwide, over 1 billion people, making it the 11th most prevalent disease [24-26] (Fig. 3). However, the latest survey in 2023 showed that 48.7% of older patients in Thailand suffer from periodontitis, an increase from 36.3% in the previous survey (Fig. 4). The highest prevalence was found in the Northern Region at 58.4%, followed by the Southern Region at 56.7%, the North-Eastern Region at 47.1%, and the Central Region at 42.3% (Fig. 5). Additionally, at Fang Hospital in Chiangmai Province, 35.65% of patients (2,391 out of 6,706) were found to have periodontitis from June 2023 to May 2024.

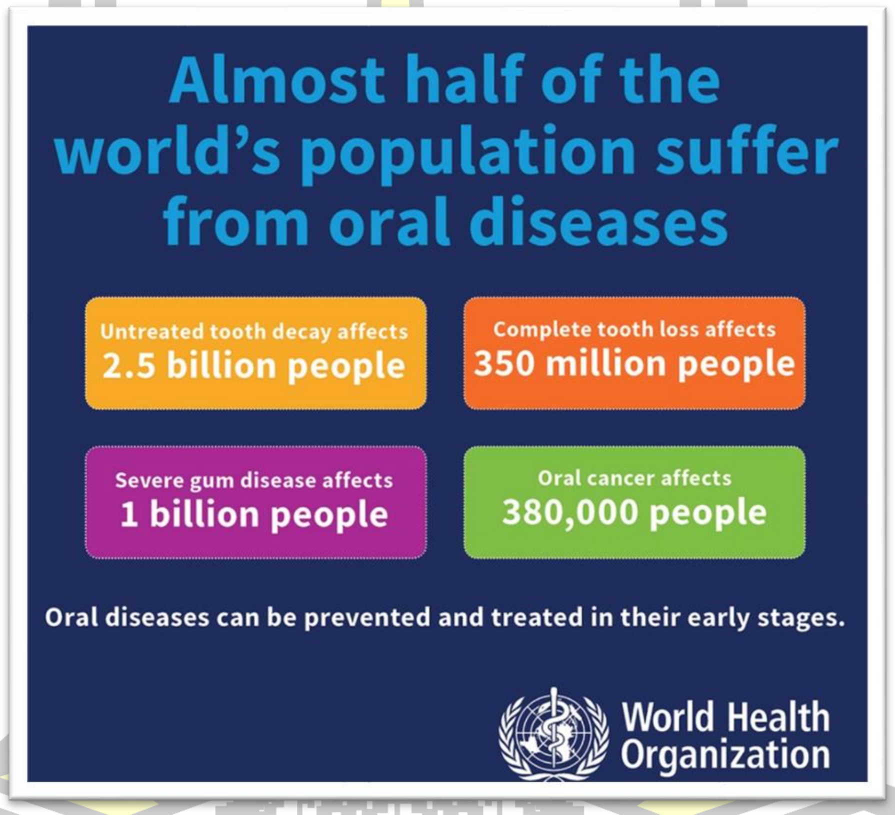
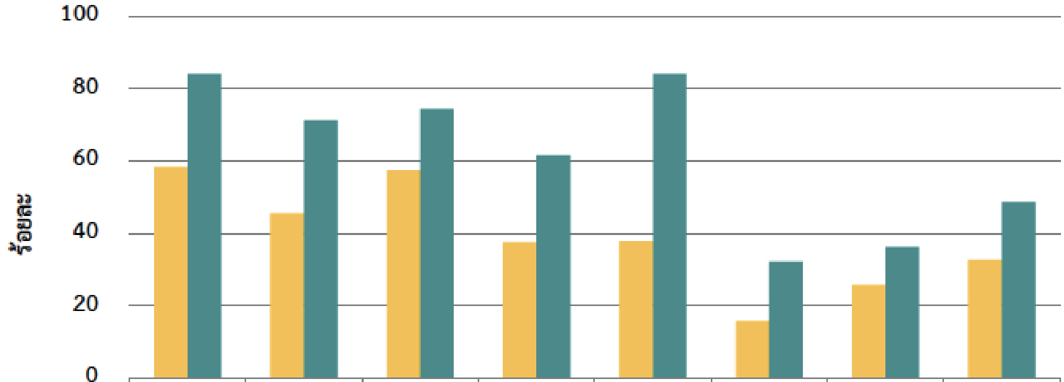
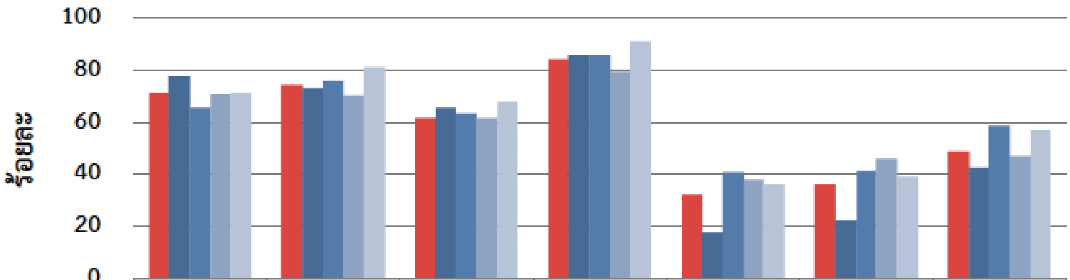


Figure 3: Global Impact of Oral Diseases. This infographic from the World Health Organization, dated December 16, 2022, illustrates the prevalence of oral diseases affecting nearly half of the global population, including untreated tooth decay (2.5 billion), complete tooth loss (350 million), severe gum disease or periodontitis (1 billion), and oral cancer (380,000). It underscores the importance of early intervention for the prevention and treatment of these conditions [26].



	2527	2532	2537	2543-2544	2550	2555	2560	2566
35-44 ปี	58.2	45.3	57.6	37.3	37.6	15.6	25.9	32.6
60-74 ปี	84.1	71.2	74.4	61.6	84.2	32.1	36.3	48.7

Figure 4: Prevalence of Oral Diseases Among Populations Aged 60-74 Years (Years 2527 to 2566). This bar graph illustrates the prevalence of oral diseases in the population aged 60-74 years from the year 2527 to 2566. Notably, the latest survey in Year 2566 (2023) indicated that 48.7% of older patients in Thailand are affected by periodontitis, representing an increase from 36.3% in the previous survey [23].



	2532	2537	2543-44	2550	2555	2560	2566
ประเทศ	71.2	74.4	61.6	84.2	32.1	36.3	48.7
กลาง	77.9	73.4	65.6	85.9	17.6	22.0	42.3
เหนือ	65.9	76.2	63.1	85.6	40.7	41.6	58.4
ตอ.-น.	71	70.5	61.8	79.5	37.7	46.0	47.1
ใต้	71.5	81.2	67.8	91.2	36.4	39.2	56.7

Figure 5: The highest prevalence of periodontitis was observed in the Northern Region at 58.4%, followed by the Southern Region at 56.7%, the North-Eastern Region at 47.1%, and the Central Region at 42.3% [23].

Focusing on periodontitis, its prevalence is quite high in Thailand. Periodontitis is a chronic inflammatory disease that damages the tissues supporting teeth, leading to attachment loss, tooth mobility, and potentially tooth loss [27]. It affects a large portion of the global population and is a significant public health concern. A new classification system introduced in 2018 uses staging and grading to assess the severity of attachment and bone loss and the progression rate, considering systemic health and smoking. Using existing databases is essential for validating this system [28, 29].

Panoramic radiography, commonly used in dental practice, captures the entire dentition in one image, providing comprehensive diagnostic information on impacted teeth, orthodontic issues, developmental anomalies, TMJ disorders, and maxillofacial trauma [30-32]. This imaging technique offers a holistic view of oral and maxillofacial health, identifying missing teeth, dental prostheses, restorations, implants, caries, and periodontal disease. It is crucial for diagnosing periodontal conditions, planning treatments, and monitoring disease progression. Although it has some diagnostic limitations, panoramic radiography offers a lower radiation dose compared to 3D imaging methods like Cone Beam Computed Tomography (CBCT) [33].

Artificial Intelligence (AI) mimics human cognitive functions, mainly through machine learning, where algorithms learn from data to make predictions [34-37]. This process begins with creating a well-prepared training dataset, which undergoes preprocessing for effective training. Training involves using 2D and 3D convolutional neural networks (CNNs) on large datasets to recognize structures' boundaries, translating this knowledge into output through multi-layered artificial neural networks [38]. In radiology, AI improves visual diagnosis, reduces errors, and enhances clinical and research capabilities, aiding in lesion detection, image segmentation, data analysis, feature extraction, and automatic report generation [39, 40].

In the medicine, AI enhances healthcare by improving diagnosis, prediction, and prevention. However, machine learning (ML) and deep learning (DL) face challenges, such as the need for massive data during training and the costly, time-consuming process of labeling data, especially for rare or new diseases [41]. In dentistry, AI focuses on caries, periodontal diseases, endodontic lesions, and jawbone pathologies [42, 43]. CNNs have been successful with both two-dimensional (2D) and three-dimensional (3D) images [44, 45]. While 3D evaluations are common in implantology, surgery, endodontics, and orthodontics, periodontology mainly uses them to assess furcations, craters, bone defects, root form, and alveolar relationships [46]. Standard periodontal assessments typically use periapical, bite-wing, and panoramic radiography for cost-effective, quick, and lower-radiation evaluations of alveolar bone levels [47]. These issues have led to the development of supportive diagnostic tools to improve accuracy.

Research Questions:

1. How can artificial intelligence (AI) improve the accuracy and efficiency of periodontal disease diagnosis using panoramic radiographs?

2. What are the limitations of current conventional methods in periodontal diagnosis and how can AI address these challenges?

3. How do the diagnostic capabilities of AI models compare to those of general practitioners and specialized periodontists in detecting periodontal diseases?

Objectives:

1. To critically review existing literature on periodontal diagnosis and prognostication, identifying the limitations of traditional diagnostic methods.

2. To develop a comprehensive protocol for periodontal diagnosis and prognostication that incorporates advanced image analysis techniques using AI.

3. To evaluate the performance of AI models in diagnosing periodontal diseases through a comparative analysis with general practitioners and specialized periodontists, focusing on diagnostic accuracy and efficiency.

Hypothesis:

1. The integration of artificial intelligence (AI) into periodontal diagnostics will significantly enhance diagnostic accuracy compared to current methods.

2. AI-driven image analysis techniques will outperform dental professionals in diagnosing periodontal diseases, demonstrating higher sensitivity and specificity.

3. The implementation of a novel AI protocol for periodontal diagnosis, dental professionals can provide faster, less labor-intensive, more precise, and comprehensive care.

Definitions:

Periodontitis: Periodontitis is a chronic inflammatory disease that affects the supporting structures of the teeth, leading to gingival tissue damage and potential tooth loss. It is caused by the long-term effects of plaque deposition, which triggers an immune response that damages the gingival tissues and supporting structures [27].

Cemento-enamel junction: The cemento-enamel junction (CEJ) refers to the anatomical area where the enamel of the crown meets the cementum of the root of the tooth. It marks the boundary between the crown and the root and is important in periodontal assessments [28, 29].

Clinical Attachment Level (CAL): Clinical attachment level is a measurement used in periodontal assessment to determine the extent of attachment loss of the periodontal tissues, indicating the degree of periodontal disease progression [28, 29].

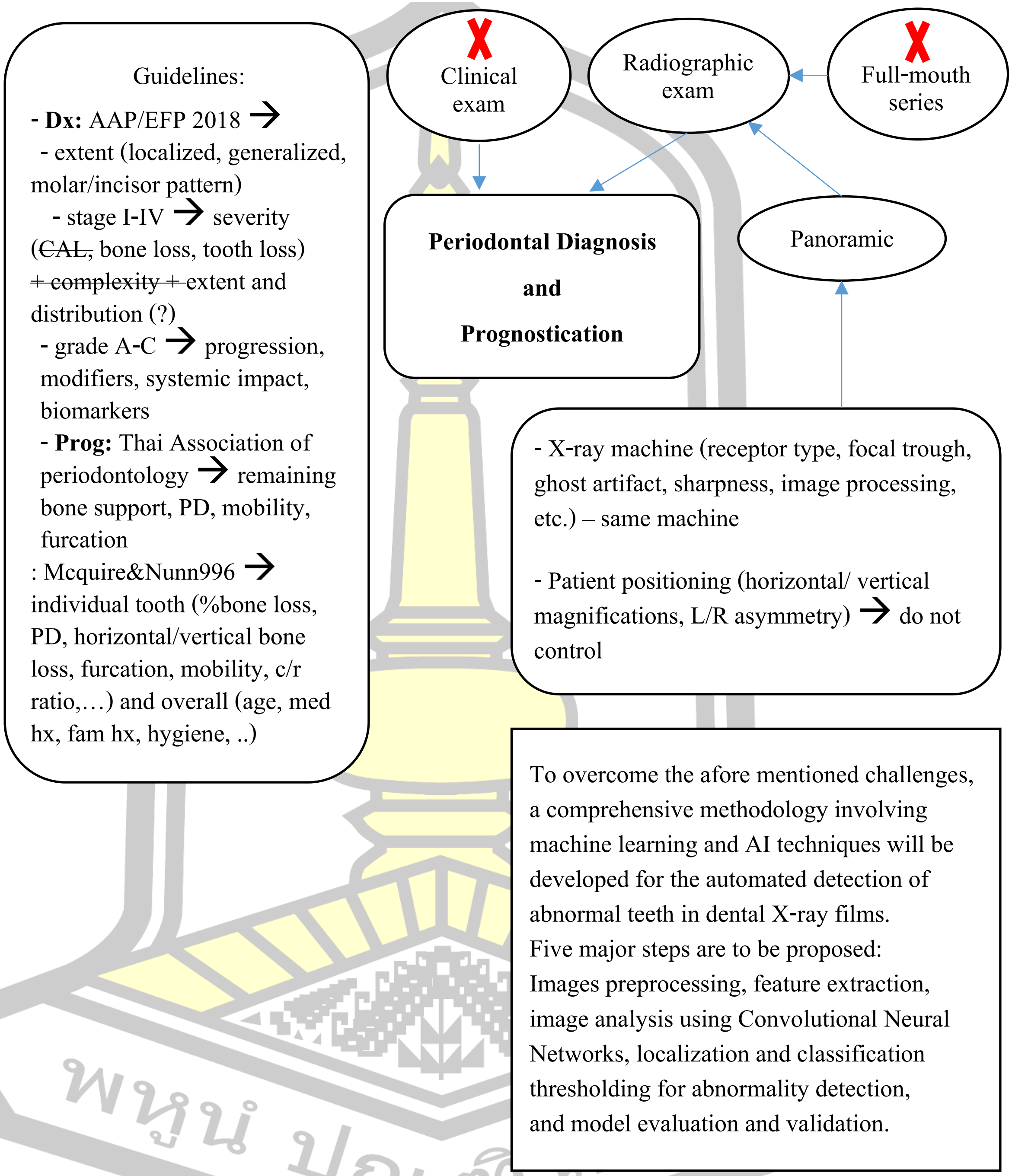
Probing Depth (PD): Probing depth is the measurement of the distance from the gingival margin to the bottom of the periodontal pocket, indicating the presence of inflammation and the severity of periodontal disease [28, 29].

Prognosis: Prognosis is defined as the expected outcome or the prospect of recovery from a disease, based on the usual course of the disease or the particularities of the case.

Panoramic Radiography: Panoramic radiography, also known as a panoramic X-ray, is a two-dimensional (2-D) dental X-ray examination that captures the entire mouth in a single image, including the teeth, upper and lower jaws, and surrounding structures and tissues [33].

Artificial Intelligence (AI): Artificial Intelligence simulates human cognitive functions, primarily through machine learning, which involves creating algorithms that learn from data and make predictions [34-37].

Conceptual framework:



CHAPTER 2

Literature review

The outline of this literature review is as follows:

2.1 Review of existing literature on periodontal diseases, diagnosis, and prognosis.

2.2 Examination of the role of panoramic radiographs in periodontal assessment.

2.3 Introduction to Artificial Intelligence (AI) and discussion of AI integration in medicine.

2.4 Discussion of AI and medical image processing techniques and their potential in dental diagnostics.

2.5 Identification of research gaps and the need for enhanced diagnostic and prognostic tools.

2.1 Review of existing literature on periodontal diseases, diagnosis, and prognosis.

Periodontitis is a chronic inflammatory disease that damages the gingival tissues and supporting structures of the teeth, often leading to tooth loss. It is caused by plaque accumulation, which triggers an immune response [27] (Fig. 6). Moreover, periodontitis is the major cause of tooth loss in the adult population [48]. In 2022, severe periodontal disease affects 19% of adults worldwide, over 1 billion people, making it the 11th most prevalent disease [24, 25]. This widespread condition poses a significant public health concern, affecting oral function, aesthetics, social equality, and quality of life [28]. Recently, in 2018, a new classification system was introduced, using a multidimensional staging and grading approach based on attachment loss, radiographic bone loss, progression rate, systemic health, and smoking status. This system helps in patient risk stratification, and utilizing existing databases is essential for its validation [28, 29].

Figure 6: Example of the clinical appearance of a case of periodontitis.

Clinical Definition of Periodontitis:

Periodontitis involves inflammation caused by microbial factors, leading to the loss of periodontal tissue attachment. This loss is measured as clinical attachment loss (CAL) using a periodontal probe relative to the cement-enamel junction (CEJ).

Important Considerations:

1. CAL can occur in conditions other than periodontitis.

2. Defining periodontitis solely by marginal radiographic bone loss is limited and may miss mild to moderate cases [49]. Radiographic definitions are primarily useful during mixed dentition and tooth eruption when CAL measurement is not feasible. In such cases, bitewing radiographs, typically used for caries detection, can be used to assess marginal bone loss.

The measurement of CAL with a periodontal probe has a margin of error, leading to potential misclassification in early periodontitis. As the disease worsens, CAL measurements become more accurate. Adjusting the CAL threshold affects sensitivity and specificity; lower thresholds increase sensitivity, while higher thresholds improve specificity. Until advanced methods like salivary biomarkers or soft-tissue imaging are validated, accurate early detection relies on the clinician's training and experience.

Bleeding on probing (BOP) is useful for assessing treatment outcomes and residual disease risk but does not change the initial case definition based on CAL or impact the classification of periodontitis severity. Various periodontitis definitions, including those from the American Association of Periodontology /Centers for Disease Control (AAP/CDC) and the European Federation of Periodontology (EFP), exist with some differences.

According to the 2017 World Workshop, a unified definition for periodontitis diagnosis in clinical care is recommended:

A patient is considered to have periodontitis if:

1. Interdental CAL is found at ≥2 non-adjacent teeth, or
2. Buccal or lingual CAL ≥3 mm with probing depth (PD) >3 mm is found at ≥2 teeth.

These criteria exclude CAL due to non-periodontal causes such as:

1. Trauma-induced gingival recession
2. Dental caries extending to the cervical area
3. CAL on the distal aspect of a second molar due to third molar issues
4. Endodontic problems draining through the marginal periodontium
5. Vertical root fractures (VRF)

The definition emphasizes "detectable" interdental CAL, meaning clinicians must identify attachment loss during probing or visually at the CEJ. Detection accuracy depends on clinician skill and local factors like gingival margin position and presence of calculus. This definition avoids specifying a CAL threshold to prevent misclassification and maintain consistency. For epidemiological surveys, thresholds may be adjusted for measurement errors.

According to the 1999 International Classification Workshop [50], it has become evident that a more comprehensive approach is required in diagnosing and classifying periodontitis cases. Such an approach should not only consider the specific form of periodontitis, severity, and extent of periodontal breakdown but should also encompass the potential systemic implications of the disease. This broader clinical diagnosis should account for both oral effects and systemic impacts of periodontitis.

Severity:

Conventionally, the degree of periodontal breakdown observed at diagnosis has been a key descriptor for classifying individual cases of periodontitis. The 1999 case definition also focused on severity, considering management complexity and disease extent. However, recent therapeutic advancements necessitate refining severe periodontitis definitions to distinguish the most severe cases better [51]. A key limitation is the paradoxical decrease in severity when the worst affected teeth are lost. Thus, tooth loss due to periodontitis should be included in the severity definition.

Complexity of Management:

Several factors increase periodontal treatment complexity, including probing depths [52], type of bone loss (vertical and/or horizontal) [53], furcation status [54], tooth mobility [55-57], missing teeth, bite collapse [58], and residual ridge defect size can increase the complexity of periodontal treatment These elements, crucial for diagnostic classification, affect the skill and experience needed for the best treatment outcomes.

Extent:

The 1999 classification defined chronic periodontitis by the percentage of affected teeth [50, 59], and aggressive periodontitis by the distribution of lesions (localized or generalized) [60, 61]. This information remains valuable in the classification system as specific patterns of periodontitis offer indirect insights into host-biofilm interactions.

Rate of Progression:

A key aspect of classifying periodontitis is accounting for variability in progression rates. The 1989 AAP classification recognized rapidly progressing periodontitis [62]. However, assessing progression rates at initial examination is challenging without older diagnostic radiographs for comparison of bone loss over time.

Risk Factors:

In the past, recognized risk factors for periodontitis, such as smoking or diabetes mellitus, were not formally integrated into the classification system. Instead, they were primarily used as descriptors to identify specific patient characteristics. However, with advancements in our understanding of how these risk factors influence periodontitis, it has become evident that they should play a more integral role in the classification process.

This updated perspective on risk factors is supported by several key findings. First, research has shown that individuals with these risk factors tend to experience more severe and extensive periodontitis at an earlier age. Second, their response to treatment is often less favorable, with smaller improvements in surrogate outcomes. Additionally, these patients are at a higher risk of experiencing tooth loss during supportive periodontal therapy [63, 64]. Given these insights, it is advisable to formally incorporate recognized risk factors into the classification of periodontitis. This inclusion can enhance the accuracy of the classification system by accounting for the impact of these factors on disease severity, progression, and treatment outcomes.

Interrelationship with General Health:

Since the 1999 workshop, evidence has linked periodontitis to systemic diseases. Oral bacteria and inflammatory mediators from periodontal pockets can enter the bloodstream, raising systemic inflammation levels and impacting conditions like coronary artery disease, stroke, and Type II diabetes [65-77]. Studies have shown that periodontitis increases overall inflammation, and there is initial evidence suggesting systemic inflammation may also increase the risk of periodontitis. Treatment of periodontitis in individuals with uncontrolled Type II diabetes has shown benefits in reducing hyperglycemia, though larger studies have been less conclusive [78, 79]. Health economics analyses indicate reduced healthcare costs for various conditions following periodontitis treatment [80]. While the evidence suggests potential systemic health benefits from treating periodontitis, further research is needed. In diagnostic classification, consider the patient's medical status and required expertise. Severe systemic diseases, as indicated by the American Society of Anesthesiologists (ASA) status, can hinder disease management due to the patient's limited ability to tolerate treatment or attend maintenance care.

In the staging of periodontitis, severity and complexity are key dimensions assessed for each case at diagnosis using patient history, clinical examination, and imaging. Severity is primarily determined by interdental CAL measurements due to their specificity, with marginal bone loss considered as an additional descriptor. The severity score reflects the attachment loss attributed solely to periodontitis, based on the most affected tooth.

Grading in periodontitis adds another dimension, considering the rate of disease progression. It is based on direct or indirect evidence of progression. Direct evidence comes from longitudinal observations or older radiographs, while indirect evidence assesses bone loss relative to age at the most affected tooth. Moreover, risk factors can modify the grade of disease. The goal of grading periodontitis is to assess the likelihood of rapid disease progression or unpredictable response to treatment. Clinicians should start by assuming a moderate progression rate (grade B) and refine this based on patient history and evidence of disease progression. Risk factors, like poorly controlled Type II diabetes, can adjust the grade to a higher value, indicating a faster progression rate (grade C).

1. Severity of periodontitis (Fig. 7):

1.1 Stage I: Interdental CAL of 1–2 mm and <15% radiographic bone loss.

1.2 Stage II: Interdental CAL of 3–4 mm and 15–33% radiographic bone loss.

1.3 Stage III: Interdental CAL of ≥5 mm, bone loss to the middle third of root and beyond, and ≤4 teeth lost due to periodontitis.

1.4 Stage IV: Interdental CAL of ≥5 mm, bone loss to the middle third of root and beyond, and ≥5 teeth lost due to periodontitis.

Periodontitis stage		**Stage I**	**Stage II**	**Stage III**	**Stage IV**
Severity	Interdental CAL at site of greatest loss	1 to 2 mm	3 to 4 mm	≥5 mm	≥5 mm
	Radiographic bone loss	Coronal third (<15%)	Coronal third (15% to 33%)	Extending to middle or apical third of the root	Extending to middle or apical third of the root
	Tooth loss	No tooth loss due to periodontitis		Tooth loss due to periodontitis of ≤4 teeth	Tooth loss due to periodontitis of ≥5 teeth
Complexity	Local	Maximum probing depth ≤4 mm Mostly horizontal bone loss	Maximum probing depth ≤5 mm Mostly horizontal bone loss	In addition to stage II complexity: Probing depth ≥6 mm Vertical bone loss ≥3 mm Furcation involvement Class II or III Moderate ridge defect	In addition to stage III complexity: Need for complex rehabilitation due to: Masticatory dysfunction Secondary occlusal trauma (tooth mobility degree ≥2) Severe ridge defect Bite collapse, drifting, flaring Less than 20 remaining teeth (10 opposing pairs)
Extent and distribution	**Add to stage as descriptor**	For each stage, describe extent as localized (<30% of teeth involved), generalized, or molar/incisor pattern			

Figure 7: Staging of Periodontal Disease According to the 2018 Classification Criteria [28]

2. Extent and distribution in periodontal disease

In the context of periodontal disease classification, the extent and distribution of the condition are categorized into three main patterns: localized, generalized, and molar-incisor distribution. These categories help in assessing the scope and spread of periodontal involvement in a patient's oral health.

2.1 Localized: This category refers to cases where periodontal disease is confined to specific areas or a limited number of teeth in the oral cavity. The extent of localized disease is typically evaluated by calculating the percentage of total teeth affected by attachment loss in relation to the overall number of teeth present. If the affected teeth constitute less than 30% of the total, it is classified as localized periodontal disease.

2.2 Generalized: Generalized periodontal disease, on the other hand, encompasses a broader distribution and involves a higher percentage of teeth. In this case, if more than 30% of the total teeth exhibit attachment loss due to periodontal inflammation, it is categorized as generalized periodontal disease.

2.3 Molar-Incisor Distribution:

This distinctive category, known as molar-incisor distribution, arises from the original diagnosis of aggressive periodontitis. It characterizes cases where periodontal inflammation predominantly affects molars and incisors, typically indicating a more aggressive form of the disease.

The assessment of extent and distribution in periodontal disease classification is essential for treatment planning and determining the appropriate management approach. It helps clinicians tailor interventions based on the pattern and severity of periodontal involvement in individual patients, ultimately contributing to effective periodontal treatment.

3. Rate of progression (Fig. 8):

3.1 Grade A—Slow progression: Characterized by no bone loss or attachment loss over five years, or a percentage of bone loss relative to age of less than 0.25. This grade includes nonsmokers and individuals without a diagnosis of diabetes.

3.2 Grade B—Moderate progression: Defined by less than 2 mm of bone loss or attachment loss over five years, or a percentage of bone loss relative to age between 0.25 and 1.0.

This grade applies to individuals who smoke fewer than 10 cigarettes per day and have an HbA1c level below 7.0% if they have diabetes.

3.3 Grade C—Rapid progression: Identified by 2 mm or more of bone loss or attachment loss over five years, or a percentage of bone loss relative to age greater than 1.0. This grade includes individuals who smoke 10 or more cigarettes per day and have an HbA1c level of 7.0% or higher if they have diabetes.

Periodontitis grade			**Grade A: Slow rate of progression**	**Grade B: Moderate rate of progression**	**Grade C: Rapid rate of progression**
Primary criteria	Direct evidence of progression	Longitudinal data (radiographic bone loss of CAL)	Evidence of no loss over 5 years	<2 mm over 5 years	≥2 mm over 5 years
	Indirect evidence of progression	% bone loss/age	<0.25	0.25 to 1.0	>1.0
		Case phenotype	Heavy biofilm deposits with low levels of destruction	Destruction commensurate with biofilm deposits	Destruction exceeds expectation given biofilm. deposits; specific clinical patterns suggestive of periods of rapid progression and/or early onset disease (e.g. molar/incisor pattern: lack of expected response to standard bacterial control therapies)
Grade modifiers	Risk factors	Smoking	Non-smoker	Smoker <10 cigarettes/day	Smoker ≥10 cigarettes/day
		Diabetes	Normoglycemic/no diagnosis of diabetes	HbAlc <7.0% in patients with diabetes	HbAlc ≥7.0% in patients with diabetes

Figure 8: Grading of periodontal disease according to the 2018 classification criteria [28]

According to Merriam-Webster, "prognosis" is the expected course and recovery from a disease. In dentistry, especially periodontology, various systems assess prognosis. A deep CNN algorithm has shown performance comparable to experienced periodontists in predicting periodontal disease using radiographic images [81]. Most prognostic systems focus on tooth mortality, predicting the likelihood of extractions [82-84]. Accurate tooth prognosis benefits both patients and clinicians by indicating the success likelihood of periodontal and restorative treatments. However, no universally accepted gold standard for periodontal prognosis exists due to disease complexity and influencing factors like systemic conditions, local factors, and practitioner skill [85].

The most widely used prognosis system, proposed by McGuire and Nunn in 1996 [56, 86], includes five categories: good, fair, poor, questionable, and hopeless (Fig. 9). Clinicians categorize each tooth based on factors such as disease etiology control, attachment loss, furcation involvement, crown/root ratio, and tooth mobility.

McGuire and Nunn's categories for periodontal prognosis are:

Good Prognosis: Effective control of periodontal disease factors and sufficient periodontal support. The tooth is easy to maintain with proper care.

Fair Prognosis: Approximately 25% attachment loss and/or Class I furcation involvement. Maintenance is feasible with patient compliance.

Poor Prognosis: 50% attachment loss and Class II furcation involvement. Maintenance is possible but difficult.

Questionable Prognosis: Over 50% attachment loss, unfavorable crown-to-root ratio, poor root form, difficult-to-maintain Class II or Class III furcations involvement, grade II mobility or more, and close root proximity. Maintenance and long-term retention are challenging.

Hopeless Prognosis: Inadequate attachment to sustain stability. Extraction is recommended or performed.

Prognosis	Each Category
Good	Adequate bone support, good patient compliance, and minimal risk factors for disease progression.
Fair	Up to 25% attachment loss, Class I furcation involvement, and adequate maintenance possible with good patient compliance.
Poor	50% attachment loss, Class II furcation involvement, and questionable patient compliance.
Questionable	Greater than 50% attachment loss, poor crown-to-root ratio, Class II or III furcation involvement, and poor patient compliance.
Hopeless	Inadequate attachment to maintain the tooth, extraction indicated.

Figure 9: Periodontal prognosis as defined by McGuire and Nunn [56, 86]

In addition to the periodontal prognosis system proposed by McGuire and Nunn in 1996, the Thai Association of Periodontology has established its own classification for periodontal prognosis, as described in the table below **(Table 1.)**:

Table 1: Periodontal Prognosis as Defined by the Thai Association of Periodontology [87]

Prognostic level	Bone support (from the most severe site)	Probing depth	Mobility	Furcation involvement
Good	> 75%	< 6 mm	0	0
Fair	50-75%	< 6 mm	0-1	0-1
Poor	50-75%	≥ 6 mm	0-2	0-2 (B, Li)
Questionable	25-50%	≥ 6 mm	0-3	2-3
Hopeless	< 25%	≥ 6 mm	2-3	3

These prognosis categories play a crucial role in treatment planning and guide clinicians in making informed decisions regarding the management of periodontal disease and the retention or removal of affected teeth.

2.2 Examination of the role of panoramic radiographs in periodontal assessment.

In standard periodontal examinations, periapical radiographs and periodontal probes are crucial diagnostic tools for assessing and predicting periodontitis affected teeth, but these methods are time-consuming and depend on clinician expertise [88]. Currently, panoramic radiography, a commonly used imaging modality in routine dental practice [30], offers distinct advantages compared to other conventional X-ray techniques, including bitewing and periapical radiography. It provides a holistic view of the dentition, quick, and valuable diagnostic information, including impacted teeth, orthodontic issues, anomalies, temporomandibular joint (TMJ) disorders, and trauma within a single image [31, 32]. Furthermore, its capability to visualize periodontal structures, bone levels, tooth positioning, and associated pathologies makes it a vital tool for diagnosing periodontal conditions, planning treatments, and monitoring disease progression. Additionally, it is important for diagnosing periodontal conditions, treatment planning, and monitoring progression, with lower radiation doses than 3D methods like CBCT [33].

The studies compared periapical radiographs with panoramic radiographs in detecting key features such as alveolar bone levels, bone resorption patterns, and furcation involvement. They concluded that both periapical and panoramic radiographs can reliably identify these characteristics. Therefore, panoramic radiographs can be credibly used for diagnosing periodontal disease [89, 90]. This finding aligns with Takeshita W. and colleauges, which evaluated various radiographic techniques for assessing alveolar bone loss. Their study found that CBCT produced average bone loss values most similar to the control group, while panoramic radiographs showed slightly lower values. However, statistical analysis revealed no significant difference. Thus, the study concluded that panoramic radiographs can be effectively used for preliminary assessment of alveolar bone loss [91]. Therefore, the panoramic radiograph may be used as an alternative to a periapical full-mouth radiographs, serving to reduce the overall radiation exposure [92]. Assessing the extent of supporting tooth tissues, particularly the quantity of bone surrounding the tooth, is crucial in preventing tooth loss due to periodontal diseases [93]. Novel radiological techniques, especially those involving average percentage values of bone loss, which significant promise for early diagnosis and also timely treatment plan for periodontal diseases [94].

Routine panoramic radiographs are indispensable for evaluating the degree of alveolar bone loss, which is vital for the diagnosis and prognostication detection of periodontal diseases [95]. Alveolar bone loss serves as a primary parameter for determining the severity of periodontitis, as outlined in the current periodontal classification [28, 29]. The development of automated systems for classifying periodontal diseases based on clinical and radiological features dates back to 1987. However, the assessment of alveolar bone loss, an important factor in detecting periodontal diseases, is a relatively recent focus, particularly in AI studies [96, 97]. Furthermore, it is essential to emphasize that the results of AI studies aimed at detecting periodontal bone loss and facilitating periodontal diagnosis can exhibit variability based on factors such as the choice of imaging processing techniques, the volume of available data, and the specific algorithms utilized.

2.3 Introduction to Artificial Intelligence (AI) and discussion of AI integration in medicine.

In recent years, scientific advancements in electronics and computing have progressed significantly. Various tools and devices have been developed for application across a wide range of disciplines. As a result, we have become accustomed to hearing the term AI. AI represents to the intelligence or knowledge created from non-living entities, which integrates multiple components to meet human needs. AI can think and assist in various areas, such as autonomous vehicle navigation systems, intelligent assistants in smartphones, as well as applications in medicine and dentistry.

Since its inception in 1955 by McCarthy, AI has evolved to enable machines to undertake tasks that typically need human intellect, such as learning and problem-solving [98]. A key breakthrough in AI is machine learning, which revolves around creating algorithms that can learn from data to make predictions. Starting with a well-prepared and labeled training dataset is crucial. This data undergoes formatting and pre-processing for effective training with both 2D and 3D CNN architectures. Simplified, the process involves training the system with extensive datasets by outlining specific structures for it to autonomously learn and produce results through complex ANNs [99]. Additionally, AI has begun to flourish in medicine and dentistry, offering a range of applications from diagnostics and decision-making to treatment planning and predicting outcomes [100].

Machine learning is the process that machines learn to use a set of instructions to distinguish and analyze data. From this data, they create models to make decisions or predictions about various subjects. Instead of writing code as a set of specific instructions, machine learning involves training with large datasets to learn how to perform tasks. There are various techniques to teach a computer to learn effectively [101].

Deep learning is a subset of machine learning that employs hierarchical mechanisms using groups of algorithms or mathematical equations to solve processing problems. It can function both with and without supervision, relying on ANNs that mimic the workings of human brain. These networks consist of neurons, each connected to form a network. In software, neurons are referred to as nodes, and these nodes are organized into layers [98, 102]. In image analysis or image classification, CNNs are commonly used. CNNs are a type of neural network commonly used for image recognition and computer vision tasks. They employ a process called convolution to extract features from images. This involves sliding a small window, known as a filter or kernel, over the image and performing mathematical operations on the pixels within the window. The result of this convolution operation is a feature map that highlights the important features of the image. CNN architecture is well-known for its performance in learning and validation contests using the ImageNet dataset. It provides developers with pre-trained weights that can be utilized in new projects. These pre-trained models are essential due to the high complexity and resource demands of deep learning, which result in lengthy initial training times. Additionally, after training on vast amounts of data, the model contains numerous weight factors that need to be randomized and adjusted. Once these weights stabilize, the model can be used for ongoing applications. At this point, Real-time object detection is crucial in autonomous vehicles, robotics, video surveillance, and augmented reality. The YOLO (You Only Look Once) framework stands out for its speed and accuracy, providing quick and reliable object identification in images. Since its inception, YOLO has seen several iterations, each enhancing performance and addressing previous limitations (Fig. 10) [103].

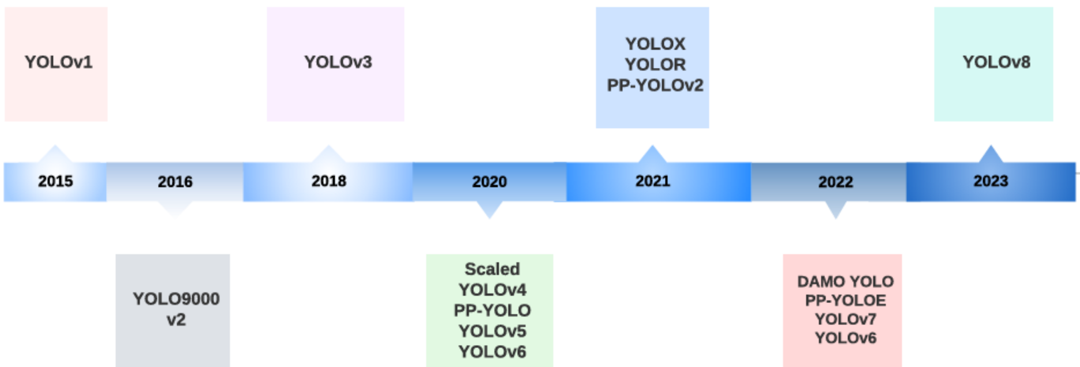


Figure 10: A timeline of YOLOv1 to the latest YOLOv8 [103].

In the medical field, YOLO has been used for cancer detection, skin segmentation, and pill identification, improving diagnostic accuracy and treatment processes. In remote sensing, YOLO assists in object detection and classification in satellite and aerial imagery, aiding land use mapping, urban planning, and environmental monitoring. Recently, the medical images are produced using various equipment, including ultrasound, X-rays, computed tomography (CT), magnetic resonance imaging (MRI), microscopy, and scintigraphy. These techniques generate diverse images, all of which can be analyzed by AI algorithms to investigate and predict different diseases. To understand how each AI-based model assists in diagnosing and predicting diseases, it is crucial to examine the application of multiple algorithms [104].

In this study, we used YOLOv8, released in January 2023 by Ultralytics [105]. No official paper has been published on YOLOv8 yet, so insights are based on available information. YOLOv8 is anchor-free, reducing box predictions and speeding up the Non-Maximum Suppression (NMS) process. It uses mosaic augmentation during training, which is disabled for the last ten epochs to avoid detrimental effects. YOLOv8 can be run from the command line interface (CLI) or installed as a PIP package and offers integrations for labeling, training, and deployment. It is available in five scaled versions: YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large) [106].

The integration of AI in medicine is seen in the study by Steimann et al. [107], who developed a neural network called ProstAsure Index to classify prostate diseases as aggressive or non-aggressive. Their study found that the program provided accurate diagnoses up to 90%, with a sensitivity of 81% and a specificity of 92%. Moreover, Pranav R and colleagues [108] conducted a study that utilized AI to develop a program called CheXNet. The aim was to evaluate its capability in analyzing and detecting pneumonia-related abnormalities in comparison to expert radiologists. The study concluded that CheXNet outperformed radiologists in detecting atelectasis, achieving an AUC of 0.862 compared to the radiologists' AUC of 0.808, which was statistically significant. Early detection and treatment initiation are vital in managing respiratory infections. AI algorithms offer valuable support to healthcare providers in the detection and analysis of pulmonary diseases (Fig. 11).

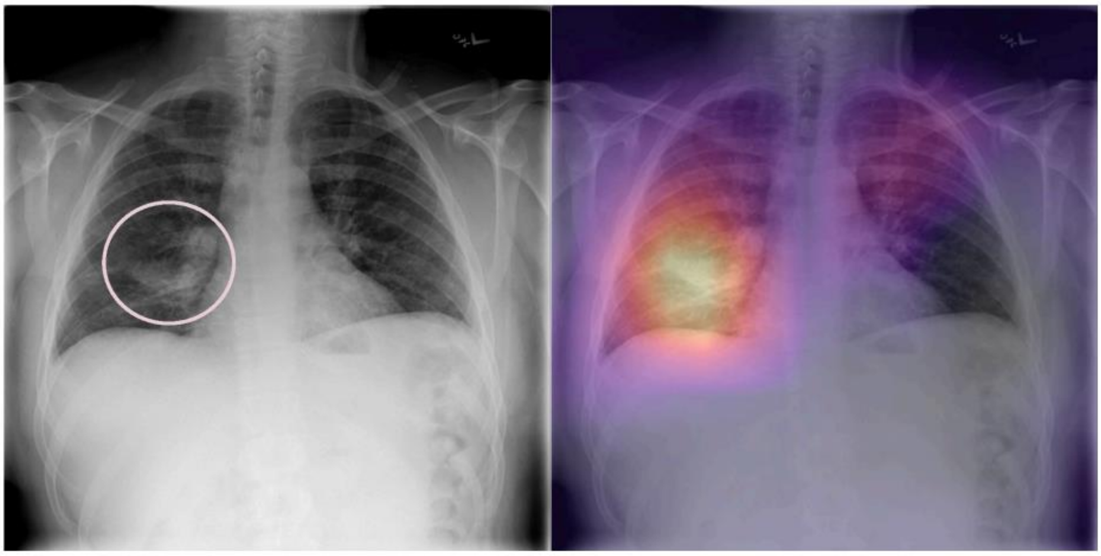


Figure 11: An example of frontal chest radiograph shows airspace opacity in the right lower lobe, indicating pneumonia. The algorithm accurately identified and located the abnormality [108].

Recently, a deep learning-based CNN model was created to analyze respiratory audio data for detecting Chronic Obstructive Pulmonary Disease (COPD), achieving 93% accuracy [109]. Additionally, a CNN-based framework was developed to diagnose COVID-19 using X-ray images, reaching an accuracy of 95.7% (Fig. 12) [110].

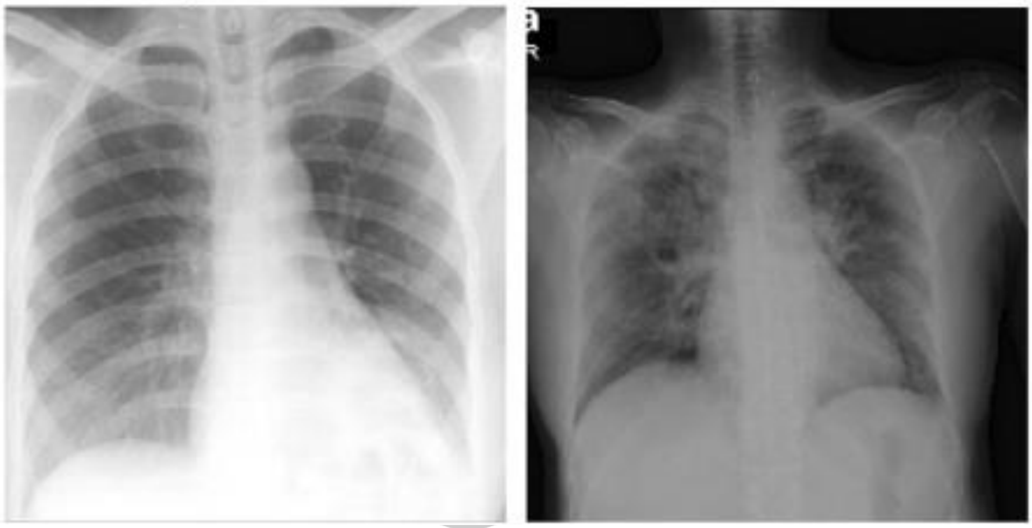


Figure 12: These chest X-ray images show both non-COVID (left) and COVID-19 (right) cases [110].

In the present, many studies reveal that AI plays a wide role in healthcare, aiding in diagnosis, prediction, and prevention. However, there are challenges in using machine learning and deep learning for disease diagnosis and prediction. A significant challenge is the need for massive amounts of data during training, which is often impractical for many diseases. Additionally, labeling data requires expertise, is time-consuming, and expensive, making it difficult to develop accurate models for rare or new diseases [111]. One potential solution is data augmentation, which can artificially increase the size of the dataset [112].

Furthermore, numerous AI techniques are currently utilized in medicine for various purposes. Table 2 below highlights some AI techniques and their descriptions, while Table 3 provides examples of their use in diagnosing different diseases, along with their accuracy rates [113].

Table 2: AI Techniques in Medicine

AI Technique	Description
Support Vector Machines (SVM)	SVM is used for classification and regression by identifying the optimal hyperplane that separates different classes [114, 115].
K-Nearest Neighbors (KNN)	KNN classifies data points based on the majority class among its k-nearest neighbors, making it effective for classification and regression tasks [116, 117].
Naïve Bayes	A probabilistic classifier based on Bayes' theorem, assuming independence among predictors, simplifying computation [118, 119].
Decision Trees	Decision Trees use a tree-like model of decisions to split data based on feature values, identifying significant variables and relationships [120, 121].
AdaBoost	AdaBoost combines multiple weak classifiers to create a strong classifier by adjusting weights of incorrectly classified instances to improve accuracy [122, 123].

Table 2: Cont.

AI Technique	Description
Random Forest	An ensemble method constructing multiple decision trees and aggregating their results for improved accuracy and control over-fitting [124, 125].
K-Means Clustering	An unsupervised algorithm that partitions data into k clusters based on feature similarity, aiding in pattern recognition and segmentation [126, 127].
Recurrent Neural Networks (RNN)	RNNs handle sequential data by maintaining a 'memory' of previous inputs, suitable for time-series predictions and sequential data analysis [128, 129].
Convolutional Neural Networks (CNN)	CNNs are used for image analysis, learning spatial hierarchies of features, extensively applied in medical imaging for detecting abnormalities [130, 131].
Deep-CNN	These networks have multiple layers to learn complex features from the data, providing high accuracy in image classification tasks [132-134].
Generative Adversarial Networks (GAN)	GANs consist of a generator and a discriminator network, generating realistic data samples useful for augmenting medical datasets [135, 136].
Long Short-Term Memory (LSTM)	LSTMs are a type of RNN designed to remember long-term dependencies, making them ideal for processing sequential data such as patient health records [137, 138].

Table 3: AI Techniques and their accuracy in diagnosing diseases [113]

Disease	AI Technique	Accuracy
Cancer Detection	SVM	85-95%
Diabetes	KNN	75-90%
Heart Disease	Naïve Bayes	70-85%
Various Conditions	Decision Trees	80-90%
Skin Cancer	AdaBoost	85-95%
Breast Cancer	Random Forest	90-98%
Pattern Recognition	K-Means Clustering	Not directly applicable
Disease Progression	RNN	85-92%
Radiology Analysis	CNN	90-98%
Medical Imaging	Deep-CNN	92-99%
Data Augmentation	GAN	85-95%
Chronic Disease	LSTM	88-93%

Moreover, in the medical field, research has extensively examined the use of both machine learning and deep learning models to diagnose a variety of diseases. These include cancer, diabetes, chronic conditions, heart disease, Alzheimer's, stroke and cerebrovascular diseases, hypertension, skin disorders, and liver diseases. Among machine learning techniques, Random Forest Classifiers, Logistic Regression, Fuzzy Logic, Gradient Boosting Machines, Decision Trees, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) are frequently employed. In the context of deep learning, Convolutional Neural Networks (CNN) are predominantly utilized for disease diagnosis. Furthermore, models such as Recurrent Convolutional Neural Networks, Multilayer Perceptrons, and Long Short-Term Memory (LSTM) networks have also seen widespread application in the literature [113].

2.4 Discussion of AI and medical image processing techniques and their potential in dental diagnostics.

In the field of medicine, there has been a recent increase in studies aimed at evaluating anatomical and pathological structures using artificial intelligence [139–141]. When examining the primary challenges that contribute to develop the AI applications in dentistry, several issues come to light. These include the potential for human-induced diagnostic errors due to factors like a shortage of experienced clinicians, time constraints for radiographic interpretation, and the necessity for radiograph reporting. These challenges can impact both the timeliness and cost of treatment. However, as the utilization of AI in the field of dentistry continues to expand, and more sophisticated programming methods are devised, these challenges are expected to gradually diminish. Furthermore, the implementation of AI programs can expedite the diagnostic process and improve reliability, making it more practical and efficient to diagnose dental restorations, maxillofacial abnormalities, dental deformities, and periodontal and endodontic lesions from panoramic radiographs [142, 143].

In Periodontology, AI has found applications in the diagnosis of periodontitis and the classification of various types of periodontal diseases [144, 145]. For instance, Krois and colleagues used CNNs to detect periodontal bone loss (PBL) in panoramic X-ray images [146]. Lee and colleagues conducted research to explore the ability of a CNN algorithm for the automatic identification of periodontitis affected teeth, assessing its accuracy [147]. Moreover, Yauney and colleagues made a notable contribution by developing a CNN algorithm capable of evaluating periodontal conditions using systemic health-related data [148]. These studies have leveraged AI in the context of periodontal disease diagnosis and management [149]. They provide valuable insights into the integration of advanced technology in Periodontology. Given the relatively early stages of AI's integration into healthcare, it is not unexpected to observe substantial heterogeneity in methodology and reporting outcomes among the reviewed studies. It is imperative that future research endeavors strive to align with increasingly recognized gold standards for research and reporting. The establishment of an international consensus on a gold standard for assessing these tools would greatly aid readers in evaluating the utility of this technology for diagnosis, prognostication, and the development of treatment protocols for patients with periodontal disease. Consequently, at this stage, it remains challenging to draw definitive conclusions regarding the efficacy and utility of AI in Periodontology. Most often, researchers chose to use individualized networks, possibly because many pretrained networks were not well-suited for the relatively small datasets commonly used in these investigations. On average, these studies had around 1,000 images in their datasets, whereas most pretrained CNNs were trained on much larger datasets, often unrelated to the medical field, where limited data is a common challenge [150].

According to the study conducted by Thanathornwong B. and colleague [151], a novel approach was introduced to identify periodontitis affected teeth using a deep learning-based object detection method on digital panoramic X-ray images (Fig. 13). This method utilized a state-of-the-art deep detection network called Faster Regional Convolutional Neural Network (Faster R-CNN). Adapted from the natural image domain and trained on a relatively small annotated clinical dataset, Faster R-CNN demonstrated satisfactory performance in detecting periodontitis affected teeth. Using Faster R-CNN could streamline the diagnostic process by reducing assessment time and enabling automated screening documentation. This model achieved a sensitivity of 0.84, a specificity of 0.88, and an F-measure of 0.81, respectively, indicating its effectiveness in this context.

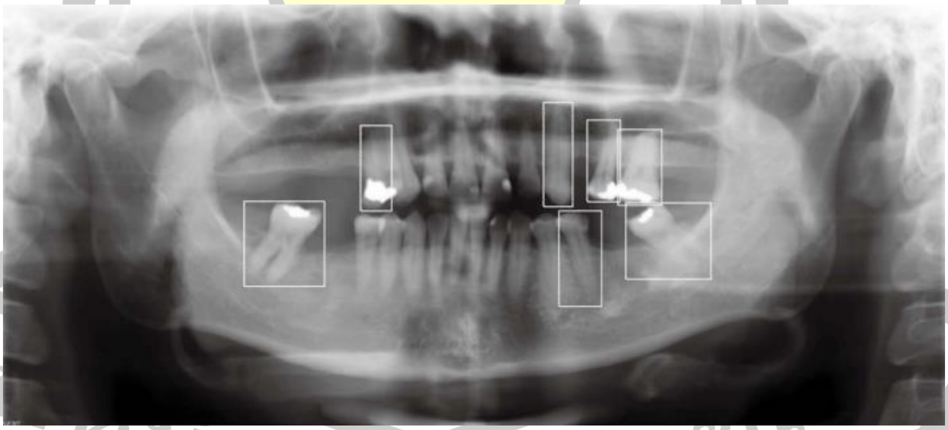


Figure 13: Example of a panoramic X-ray image of the provided dataset showing periodontitis affected teeth (No. 14, 23, 25, 26, 37, 35, and 47 in the boxes) [151].

In the study conducted by Huang Y.C. and colleagues [152], an innovative approach is introduced for automating the segmentation of panormaic X-ray images (Fig. 14), focusing on isolating individual teeth and accurately placing each segmented tooth within a predefined reference table. It also includes an automated process for identifying the precise location of each tooth within a panoramic X-ray image. The image processing phase uses various techniques of image enhancement to improve image quality, including sharpening, histogram equalization, and flat-field correction. Iterative image processing is applied to improve contrast between teeth and cavities. An additional step detects dental cavities by identifying segments and points that separate the upper and lower jaws based on pixel value differences. These sections are used to connect cavity feature points, creating a detailed representation of the jaw sections.

Adjustments are made by shifting the curve to identify gaps between teeth, which helps in identifying missing teeth and overlap issues. The study adopts the Fédération Dentaire Internationale (FDI) two-digit notation system, assigning unique codes to each tooth for clinical use. To address the challenge of accurately marking missing teeth on conventional X-ray films, the paper introduces artificial center positioning and ensures uniform counts of gap feature points, which are then connected to the jaw curve for visual dental segmentation. This proposed method achieves an accuracy rate of 89.95% in tooth positioning. For tooth cutting, where the position of each tooth is determined by the edge of the cutting box, the accuracy reaches 92.78%.

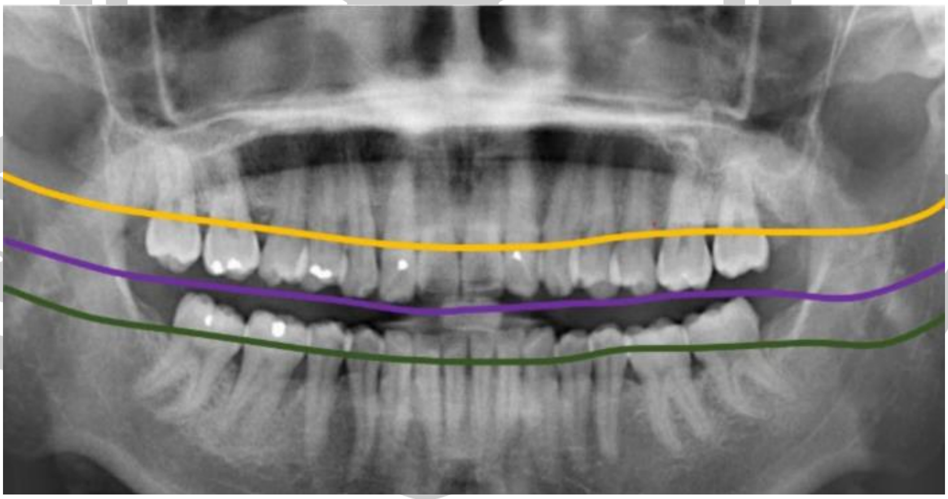


Figure 14: Automated tooth position determination in dental panoramic X-ray imaging through Image Enhancement Technique [152].

A recent study by Uzun Saylan B.C. and colleagues [153] assessed the effectiveness of AI models in detecting alveolar bone loss of periodontitis affected teeth in periodontal disease using panoramic X-ray images. The findings indicated that AI models hold significant potential for analyzing periodontal bone loss (Fig. 15).

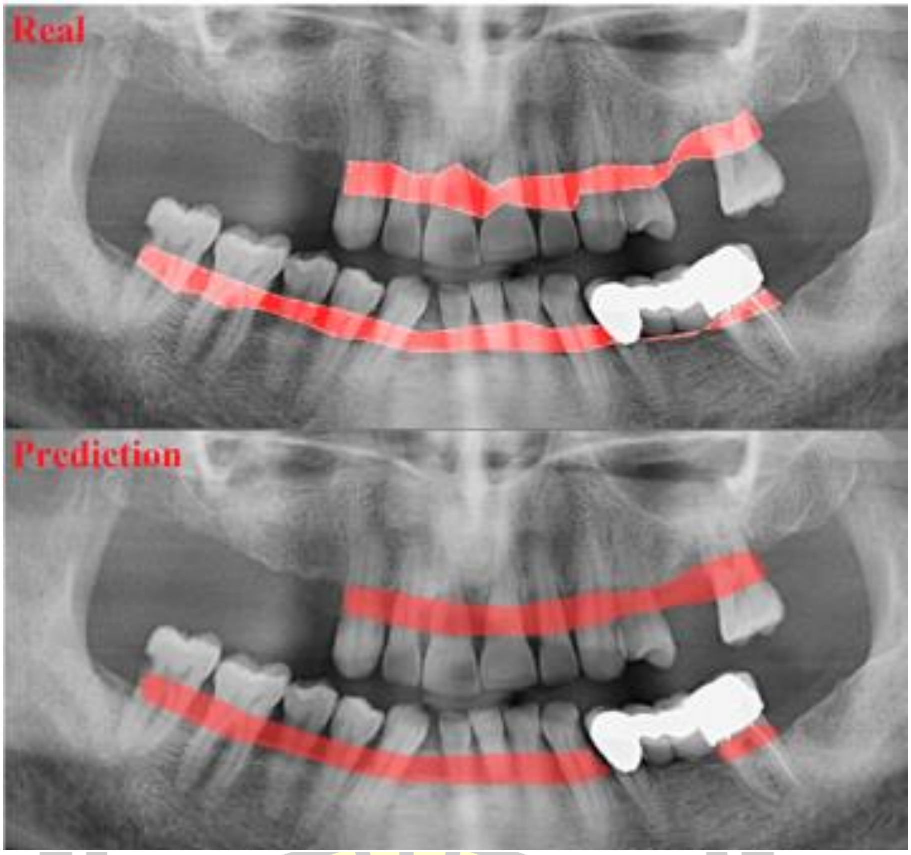


Figure 15: AI Predictions of alveolar bone loss in panoramic X-ray images and testing results [153].

2.5 Identification of research gaps and the need for enhanced diagnostic and prognostic tools.

In the present situation, The Global Burden of Disease Study reported that severe periodontal disease affects 19% of adults worldwide, over 1 billion people, making it the 11th most prevalent disease [24, 25]. At Fang Hospital in Chiangmai Province, Thailand, 35.65% of patients (2,391 out of 6,706) had periodontitis from June 2023 to May 2024. Furthermore, the current periodontal classification system introduced in 2018, grounded in current evidence and employing a multidimensional staging and grading approach, and there are a limited number of periodontists who are experts in Periodontology. Moreover, the current diagnostic challenges include errors from inexperienced dentists, limited time for radiograph analysis, and mandatory reporting, affecting the delay in treatment planning.

Limitations of current periodontal diagnosis involve analyzing various aspects of the diagnostic process, from clinical practices to technological applications include:

- **4.1 Reliance on Classical Methods:**

Subjectivity in clinical examination, such as variability in manual probing and visual examination, leads to inconsistencies in diagnosis. Inaccuracies in depth measurement due to factors like probe angulation and pressure are also concerns [50].

- **4.2 Diagnostic Sensitivity and Specificity:**

Challenges exist in early disease detection and differentiating between stable conditions and active disease progression [154, 155].

- **4.3 Technological Limitations:**

Radiographs, while essential, have limitations in early bone loss detection and 3D bone defect assessment [156]. The method discussed has limitations in providing exact measurements of periodontal bone loss due to inconsistencies in image magnification and distortion common in dental panoramic radiography. Future research should focus on enhancing this method's accuracy, potentially through collaborations across different organizations to validate and improve its performance [157].

- **4.4 Integration of New Technologies:**

Currently, research on integrating digital technologies into dentistry is somewhat limited. The exploration of these technologies could potentially revolutionize diagnostic methods, treatment planning, and patient care in the dental field. Further studies and investments are needed to fully understand and leverage digital innovations for improving dental practices and patient outcomes. Incorporating advanced diagnostic tools and methodologies is an ongoing process, aiming to overcome the limitations of classical methods [158].

Despite these advancements, research on AI's integration into dentistry, particularly periodontology, remains limited **(Table 4)**. Further studies are needed, such as AI assistance in periodontal diagnosis and prognosis, to develop innovative diagnostic software (Fig. 16). This could lead to tailored treatment protocols based on individual periodontal diagnoses.

Table 4: Examples of AI technologies enhancing the detection of periodontal bone loss through dental panoramic X-ray images

Study	Year	Description	Total data	Summary of model performances
Krois et al. [146]	2019	Used CNN to identify periodontal bone loss on dental panoramic X-ray images.	2,001	The model has an accuracy, sensitivity, and specificity all at 0.81.
Kim et al. [159]	2019	Created a system for automatically identifying periodontal bone loss using panoramic dental X-ray images.	12,179	The developed model outperformed dental clinicians on the test set with an F1 score of 0.75, compared to the clinicians' average score of 0.69.
Chang et al. [94]	2020	Created a system to automatically classify stages of periodontitis using deep learning techniques on dental panoramic X-ray images.	340	The accuracy levels were recorded at 0.93 for periodontal bone and 0.91 for both CEJ level and teeth identification.
Bayrakdar et al. [160]	2020	Used CNN to identify periodontal bone loss on dental panoramic X-ray images.	2,276	The model's accuracy is measured at 0.9.

Table 4: Cont.

Study	Year	Description	Total data	Summary of model performances
Thanathornwong et al. [151]	2020	Used CNN to identify periodontally compromised teeth on dental panoramic X-ray images.	100	The model reached a sensitivity of 0.84, specificity of 0.88, and an F-measure of 0.81.
Jiang et al. [161]	2022	Created a model for radiological staging of periodontal alveolar bone loss on dental panoramic X-ray images.	640	The model's overall accuracy rate was recorded at 0.77.
Zadrozny et al. [162]	2022	Evaluated the accuracy of AI in automatically analyzing panoramic dental X-rays.	30	The tested CNN displayed poor reliability in evaluating caries (Intra-Class Correlation (ICC) = 0.681) and periapical lesions (ICC = 0.619). However, it showed good reliability for identifying fillings (ICC = 0.920), endodontically treated teeth (ICC = 0.948), and periodontal bone loss (ICC = 0.764).
Uzun Saylan et al. [153]	2023	Assessed how well AI models can detect the presence or absence of alveolar bone loss in various areas.	685	The models in detecting alveolar bone loss (ABL) across various teeth regions showed sensitivity, precision, and F1 score ranges as follows:

Table 4: Cont.

Study	Year	Description	Total data	Summary of model performances
				For general alveolar bone loss, the scores were 0.75, 0.76, and 0.76. Specifically, maxillary incisor ABL had perfect precision at 1, with an F1 score of 0.95. Maxillary canine, premolar, and molar ABL showed balanced scores, with the highest F1 score of 0.91 for molar ABL. In the mandible, incisor, canine, premolar, and molar ABL scores varied, with mandibular incisor ABL scoring an F1 of 0.86 and molar ABL at 0.79, indicating the models' varied effectiveness in different dental regions.
Kong et al. [163]	2023	Used two-stage CNN-based periodontitis detection network in periodontitis bone loss diagnosis in panoramic radiographs	1747	The model for radiographic bone loss (RBL) classification has an accuracy of 0.762.

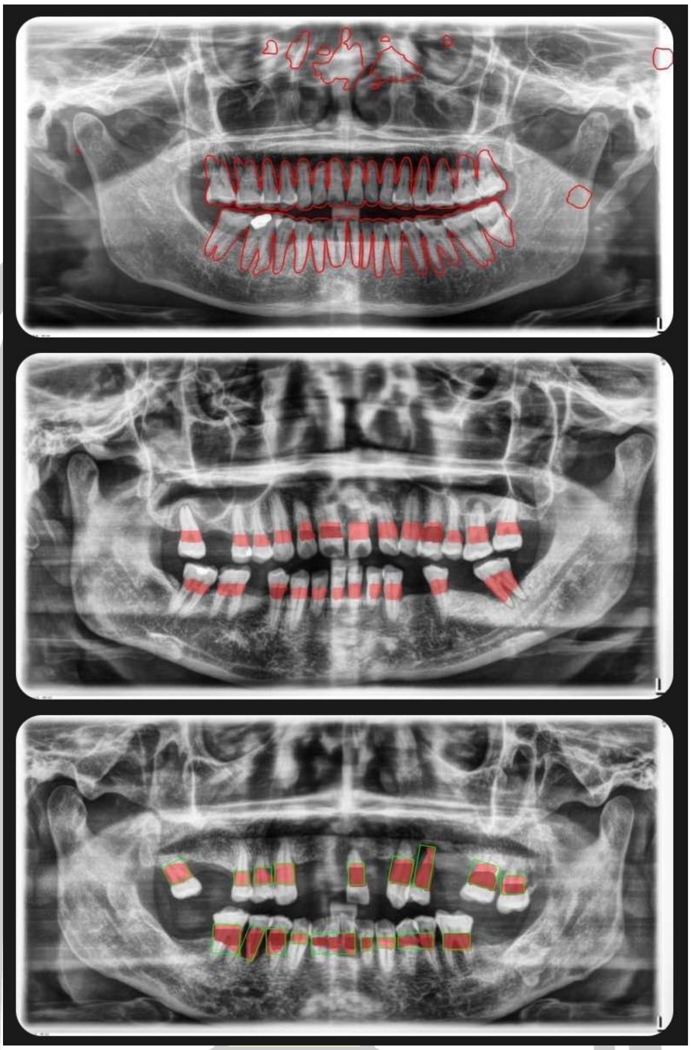


Figure 16: The example of AI in illustrating the detection of periodontal bone loss on dental panoramic X-ray image.

Additionally, AI has also been increasingly applied in dentistry for diagnosing and predicting various dental diseases. These techniques encompass both machine learning and deep learning models, each providing different levels of accuracy for specific conditions. The following table (Table 5) highlights some of these techniques and their corresponding applications in dental diagnostics.

Table 5: AI Techniques in Dentistry

Disease	AI Technique	Accuracy
Dental Caries [164, 165]	Convolutional Neural Networks (CNN)	89-94%
Periodontal Disease [146, 166]	Random Forest, SVM	85-90%
Tooth Fracture [167, 168]	CNN, Deep-CNN	92-97%
Oral Cancer [169, 170]	CNN, LSTM	90-95%
Orthodontics [171, 172]	SVM, KNN	88-93%
Root Canal Treatment [173, 174]	Decision Trees, Random Forest	87-92%
Implantology [175, 176]	CNN, RNN	90-94%

This research aims to fill that gap by focusing on enhancing the accuracy and efficiency of periodontal diagnosis and prognostication detection using medical image processing techniques and AI. By employing advanced image analysis algorithms on dental panoramic X-ray images, this study strives to make a valuable contribution to improving periodontal disease management and, consequently, enhancing overall patient care outcomes.

This represents a novel innovation designed to assist periodontists and general practitioners in screening diagnoses and making prognostication decisions using panoramic X-ray images, which are valuable tools in treatment planning.

CHAPTER 3

Materials and methods

3.1 Study Design

This research is divided into three phases:

Phase I - Review Study: This phase critically evaluates the existing literature on periodontal diagnosis and prognostication, emphasizing the limitations of traditional diagnostic methods. A comprehensive review was conducted following PRISMA guidelines. We searched several databases, including PubMed, Scopus, Wiley Online Library, and ScienceDirect, for studies published between January 2018 and December 2023. The search utilized keywords such as "artificial intelligence," "panoramic radiograph," "periodontitis," "periodontal disease," and "diagnosis." Inclusion criteria were established for studies that involved the application of AI in diagnosing periodontitis, included human subjects, were published in English, and were accessible as open access. Conversely, the exclusion criteria eliminated non-AI studies, studies unrelated to periodontitis, those not utilizing panoramic radiographs, as well as abstracts, editorials, and letters.

Phase II - Retrospective Study: The panoramic radiographs used in this study were obtained from the Dental Department of Fang Hospital, Chiang Mai, Thailand. It is important to note that all radiographs were captured using the same imaging device, the SIDEXIS Next Generation Program (Sirona, Bensheim, Germany). Only one radiograph per patient was included in the analysis. The dataset comprised 2,000 panoramic radiographs, divided into 1,000 periodontally healthy radiographs and 1,000 periodontitis radiographs. Following the collection of these radiographs, a comprehensive model for periodontal diagnosis and prognostication was developed, integrating advanced image analysis techniques utilizing artificial intelligence (AI). The assessment was based solely on radiographic evaluation, with the primary focus being the assessment of the alveolar bone crest relative to the cemento-enamel junction (CEJ) of each tooth. The distance between the CEJ and the alveolar bone crest was measured. Periodontal diagnosis followed the 2018 periodontal classification, and prognostication was performed using medical image processing techniques, as follows:

Teeth Segmentation Model: A machine learning framework designed to accurately identify and classify individual teeth within panoramic radiographs.

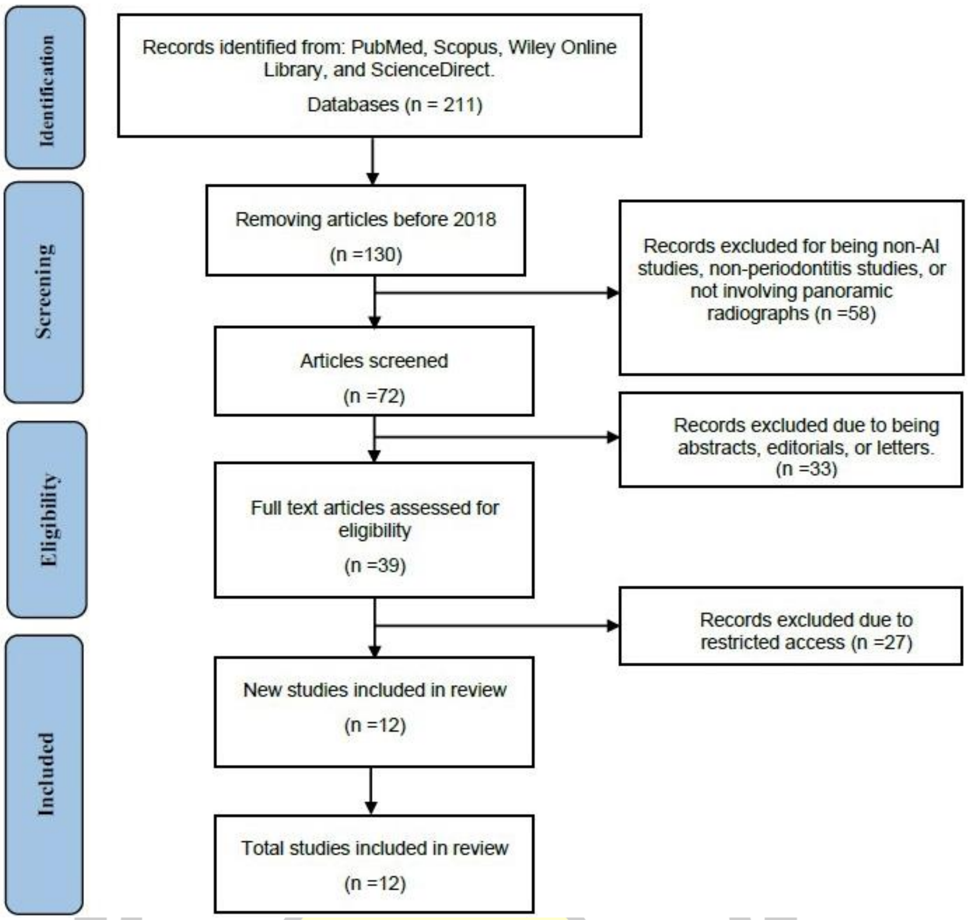
Distance Between the Cemento-Enamel Junction (CEJ) and the Crestal Bone Model: A method to measure the vertical distance between the CEJ of each tooth and the corresponding alveolar bone crest on panoramic radiographs.

Phase III - Analytical Study: This phase aims to evaluate the performance of AI models in diagnosing periodontal diseases through a comparative analysis with general practitioners (GPs) and specialized periodontists. The evaluation will be based on the assessments made by expert periodontists with over 10 years of experience in periodontology, focusing on diagnostic accuracy and efficiency.

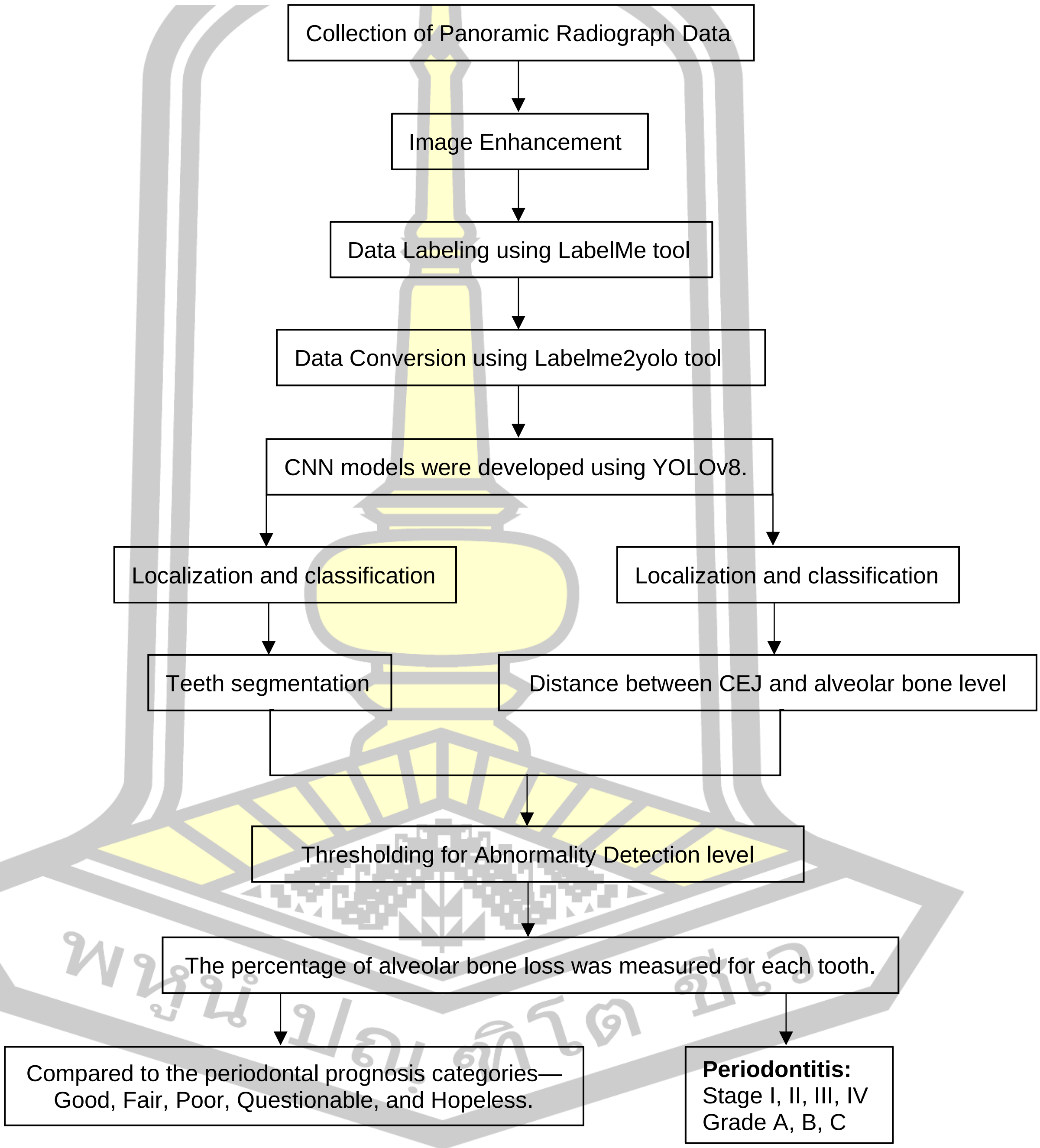
3.2 Research Workflow

3.2.1 Phase I: To critically review existing literature on periodontal diagnosis and prognostication, identifying the limitations of traditional diagnostic methods.

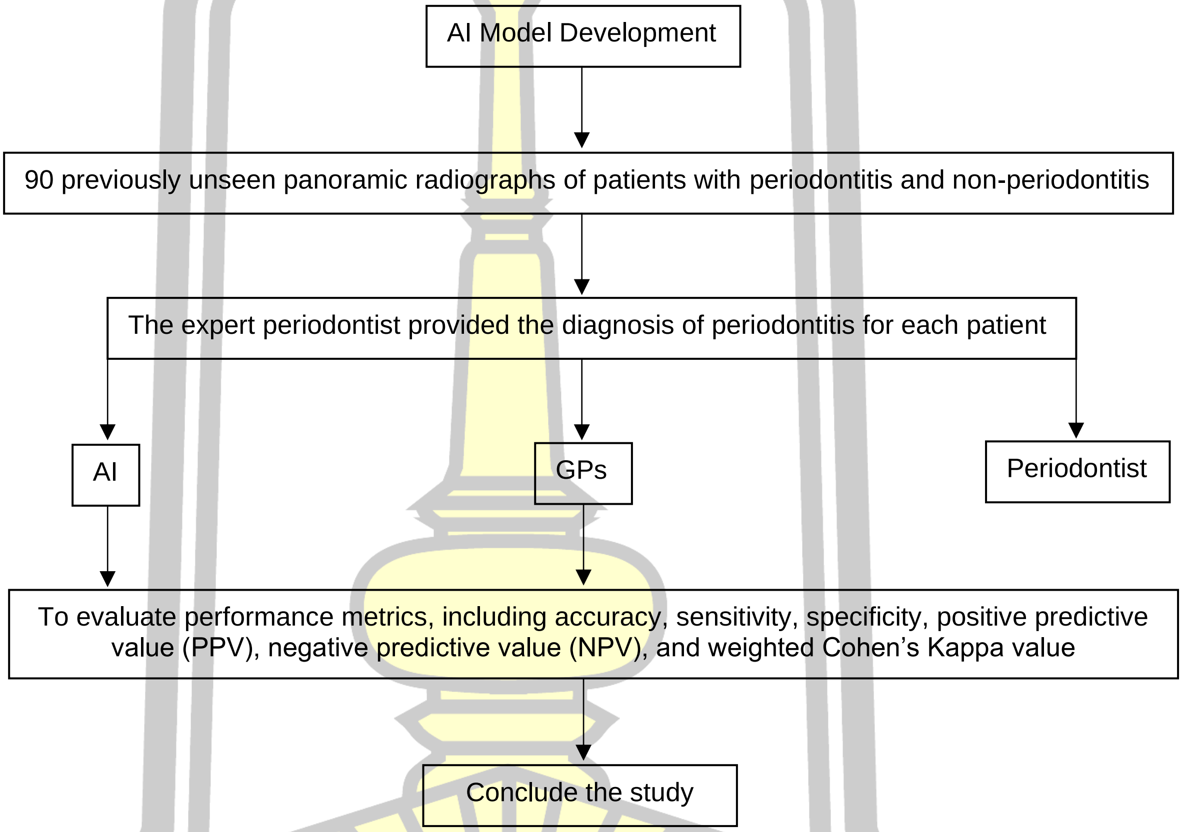
A comprehensive literature review was conducted following PRISMA guidelines. We searched multiple databases, including PubMed, Scopus, Wiley Online Library, and ScienceDirect, for studies published between January 2018 and December 2023. The keywords employed in the search included “artificial intelligence,” “panoramic radiograph,” “periodontitis,” “periodontal disease,” and “diagnosis.” Inclusion criteria were established for studies that involved the application of AI in diagnosing periodontitis, included human subjects, were published in English, and were accessible as open access. Conversely, the exclusion criteria eliminated non-AI studies, studies unrelated to periodontitis, those not utilizing panoramic radiographs, as well as abstracts, editorials, and letters, as illustrated in the flowchart below.


Identification
Screening
Eligibility
Included
Records identified from: PubMed, Scopus, Wiley Online Library, and ScienceDirect.
Databases (n = 211)
Removing articles before 2018
(n =130)
Records excluded for being non-AI studies, non-periodontitis studies, or not involving panoramic radiographs (n =58)
Articles screened
(n =72)
Records excluded due to being abstracts, editorials, or letters.
(n =33)
Full text articles assessed for eligibility
(n =39)
Records excluded due to restricted access (n =27)
New studies included in review
(n =12)
Total studies included in review
(n =12)

3.2.2 Phase II: To develop a comprehensive model for periodontal diagnosis and prognostication that integrates advanced image analysis techniques utilizing artificial intelligence (AI). The overall procedure for the development of the AI model includes phases for image enhancement, model training, and evaluation, as shown in the flowchart below.



3.2.3 Phase III: To evaluate the performance of AI models in diagnosing periodontal diseases through a comparative analysis with general practitioners (GPs) and specialized periodontists. This evaluation will reference the assessments made by expert periodontists with over 10 years of experience in the field of periodontology, focusing on diagnostic accuracy and efficiency, as illustrated in the flowchart below.



3.3 Study Population and Sample size

The research will utilize the rule of ten, supplemented by weighting factors, to determine the necessary volume of data required for training. This study will evaluate ten critical aspects (Fig. 17), namely:

1. Tooth position,
2. Contrast between teeth and gum,
3. Contrast between teeth and bone,
4. Tooth edge,
5. Tooth reference point,

6. Tooth angle,

7. Distance between the reference point and the end of the tooth root,

8. Tooth shape,

9. Degree of alignment between upper and lower jaws, and

10. Degree of bone loss.

The Rule of 10 is a practical guideline suggesting that, for the development of an efficient AI model, the number of training datasets should ideally be ten times greater than the total number of model parameters, also referred to as degrees of freedom. The primary objective behind this '10 times' rule is to reduce data variability and enhance data diversity. Consequently, this rule of thumb serves as a valuable initial reference point for determining the necessary quantity of datasets to commence your project. Recognizing the intricate nature of CNNs, we will expand the training dataset tenfold, resulting in a total of 1,000 datasets for AI training.

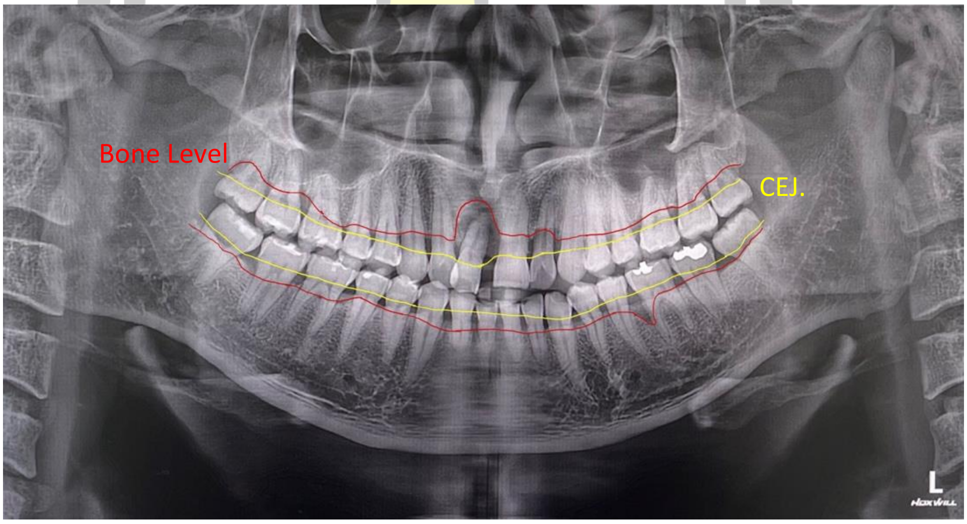


Figure 17: An illustrative of bone level and cementoenamel junction (CEJ) from panoramic radiograph

3.4 Inclusion and Exclusion Criteria

The dataset of panoramic radiographs of patients obtained from the Dental Department of Fang Hospital, Chiangmai, Thailand following the inclusion and exclusion criteria below:

Inclusion criteria:

1. Age: Participants aged 18 years and older to ensure that only fully erupted molars are included, while excluding erupting or unerupted molar teeth.

2. Diagnosis: Individuals diagnosed with periodontitis, as identified through diagnosis codes from the HOSxP Program (Bangkok Medical Software, Bangkok, Thailand).

3. Radiograph Quality: High-quality panoramic radiographs obtained from the SIDEXIS Next Generation Program (Sirona, Bensheim, Germany) and captured using a consistent device.

Exclusion criteria:

1. Missing Radiographs: Absence of panoramic radiographs in the SIDEXIS Next Generation Program.

2. Image Quality: Radiographs were excluded if they exhibited improper patient positioning, poor quality due to movement, uncommon bone morphologies (Fig. 18), or if the alveolar bone loss in the affected area could not be accurately assessed (Fig. 19).

3. Panoramic radiographs of patients with craniofacial anomalies, as these conditions may affect bone morphology.

Figure 18: An illustration of panoramic X-ray image where the area could not be accurately selected for determining periodontal bone destruction.

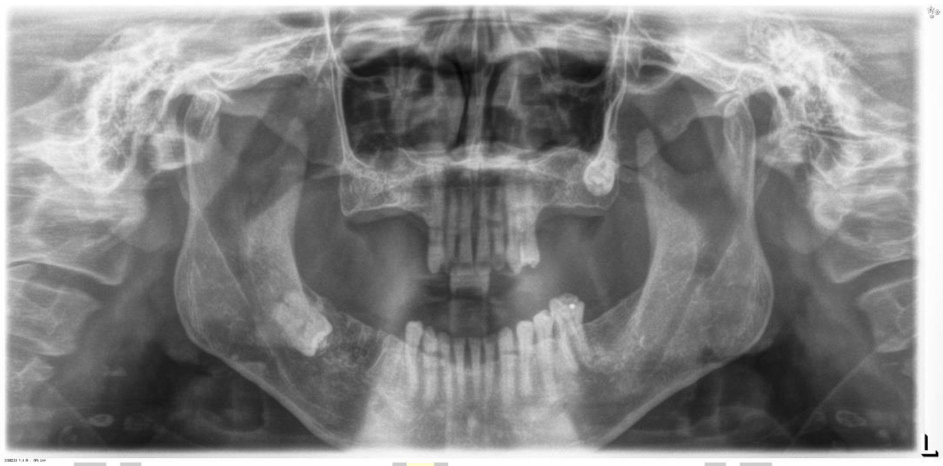


Figure 19: An illustration of panoramic X-ray image with incorrect patient positioning and low quality radiograph.

3.5 Data collections

The good quality panoramic radiographs of patients both periodontitis (Fig. 20) and non-periodontitis patients (Fig. 21) were recruited from the SIDEXIS next Generation Program (Sirona, Bensheim, Germany) (Fig. 22) from January 2015 - December 2023. Panoramic X-ray images with incorrect patient positioning, low quality due to patient movement, rare bone morphologies, and those where the affected area could not be accurately selected for periodontal bone destruction determination were excluded. The dataset included 2,000 panoramic radiographs of patients diagnosed with periodontitis, identified using diagnosis codes from the HOSxP Program (Bangkok Medical Software, Bangkok, Thailand) (Fig. 23). It is noteworthy that all radiographs employed in this study were captured using the same imaging device (ORTHOPHOS XG, Sirona, Bensheim, Germany) (Fig. 24).

Figure 20: An illustrative panoramic radiograph of periodontitis patient captured from the SIDEXIS Next Generation Program

Figure 21: An illustrative panoramic radiograph of non-periodontitis patient captured from the SIDEXIS Next Generation Program

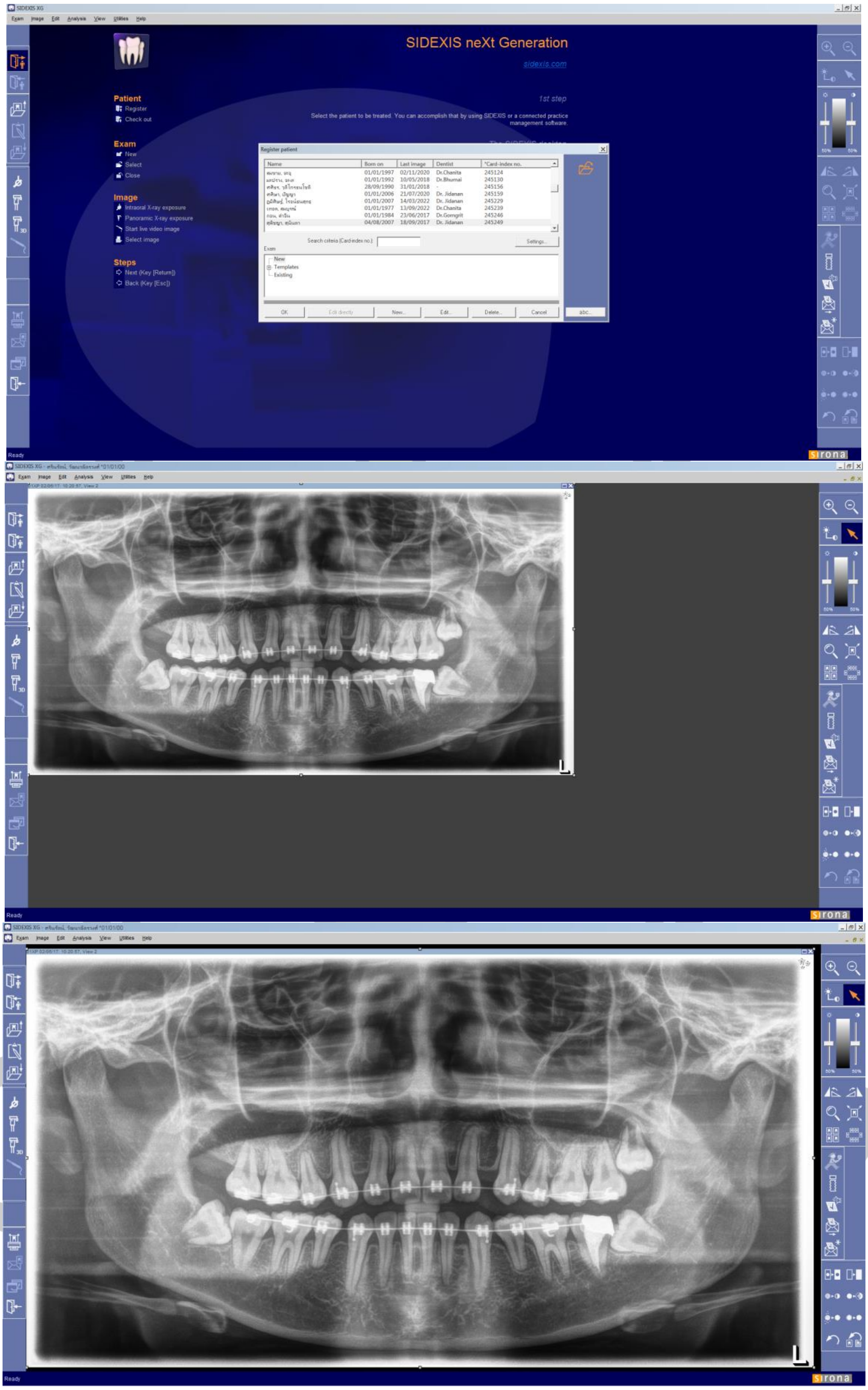


Figure 22: An illustrative of panoramic radiographs from the SIDEXIS Next Generation Program

Figure 23: Examples of panoramic radiographs from the SIDEXIS Next Generation Program

Figure 24: Imaging device (ORTHOPHOS XG, Sirona, Bensheim, Germany).

3.6 Medical Image Processing and AI Techniques

To overcome the afore mentioned challenges, a comprehensive methodology involving machine learning and AI techniques will be developed for the automated detection of abnormal teeth in dental X-ray films. Five major steps are to be proposed: Images preprocessing, image analysis using CNNs, localization and classification thresholding for abnormality detection, and model evaluation and validation (Fig. 25).

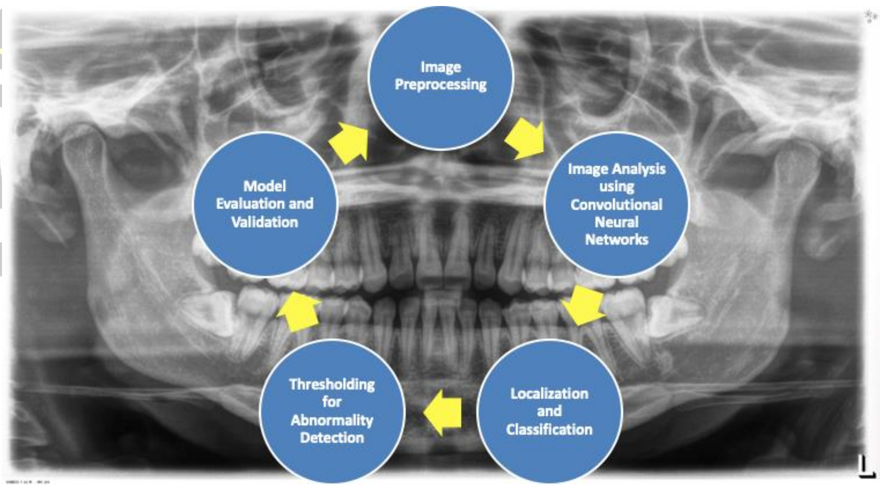


Figure 25: Workflow of AI model development

1. Image Preprocessing [152]

Image preprocessing and enhancement is an important part of the proposed algorithm to produce more suitable images for the applications than the original image.

1.1 Image sharpening **(Fig. 26)**

One of the most commonly used modification techniques is sharpening, which enhances edges and makes pixel boundaries more distinct. This clarity improves subsequent processing steps. Psychophysical experiments indicate that edge-enhanced images, including those in radiology, are often more visually pleasing and easier for the human visual system to interpret.

Figure 26: An illustration of image sharpening: original image (left), sharpened image (right).

1.2 Image Contrast Adjustment **(Fig. 27)**

In this stage, the histogram equalization is used to equalize the brightness level of the X-ray picture. The contrast is adjusted to distinguish the target teeth from the background using a histogram equalization method. This technique transforms the original image's grayscale values from a concentrated range to an evenly distributed range. Histogram equalization expands the image nonlinearly, redistributing the grayscale values so that the proportions of the image in each range are approximately equal.

Histogram transformation, a type of grayscale transformation, defines the relationship between input and output grayscale values. This transformation relates the input and output random variables, allowing for more effective processing. In digital image processing, continuous variables are used for deriving generalizations that can be applied to discrete data.

Figure 27: An illustrative of image contrast adjustment using Histogram equilibrium.

1.3 Gaussain filtering **(Fig. 28, 29)**

Before this step, Gaussian filtering is applied to the processed X-ray film to reduce noise and smooth the image using a 3x3 kernel matrix.

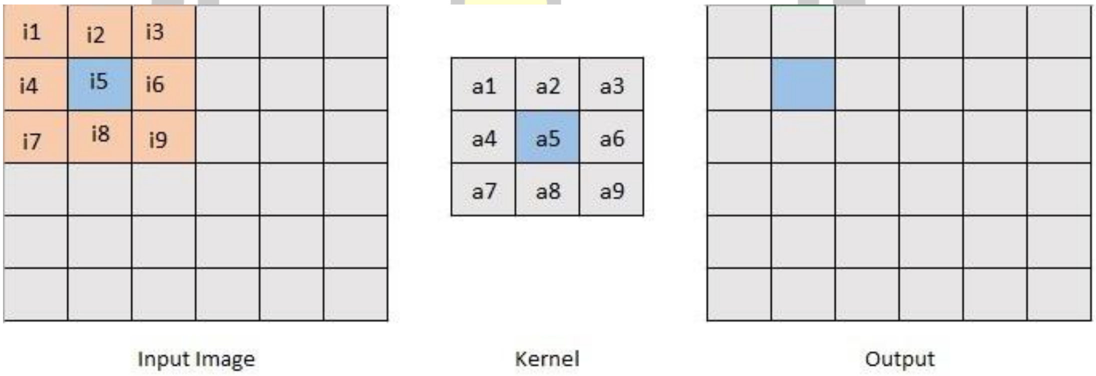


Figure 28: Image show kernel of size 3x3 for Gaussian blur filter.

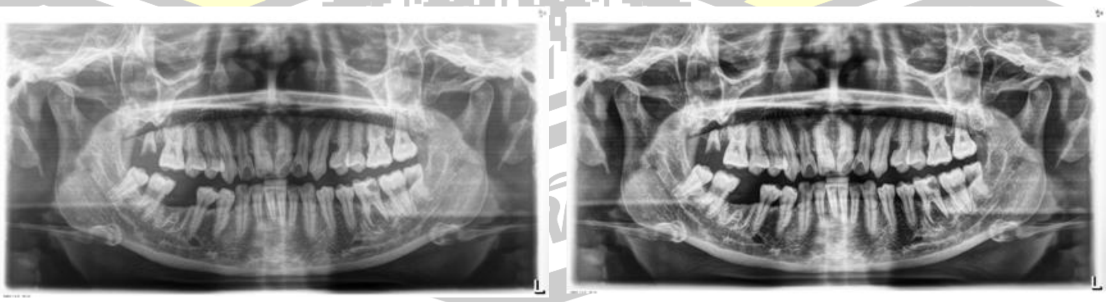


Figure 29: An illustration of Gaussian filtering: original image (left), the image after preprocessing (right).

2. Data labeling (Fig. 30):

Recognizing the importance of labeled data in supervised machine learning, labeling tools have been introduced. This research utilizes LabelMe [177] as a labeling tool for object segmentation, while Labelme2yolo is used for converting data into a ready-to-train format.

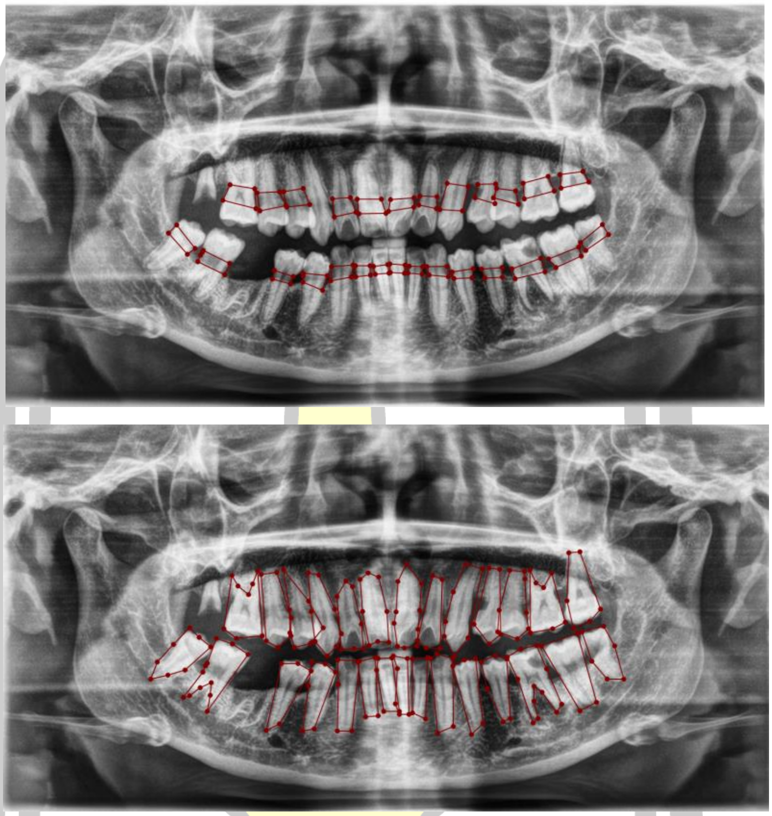


Figure 30: Image showing the distance between the CEJ and the bone (upper) and teeth (lower), labeled using LabelMe.

3. Distance between crestal bone level and CEJ, and the teeth analysis using CNNs:

CNNs will be employed to extract meaningful features from dental X-ray images. Transfer learning from pre-trained models will be explored to leverage existing knowledge in image recognition tasks. These images were randomly assigned to the training, validation, and test sets in a 70:10:20 ratio.

To address existing issues, we selected a dataset that includes 2000 X-ray images of both healthy and infected teeth. We propose using the YOLOv8 [178, 179] model to extract regions of interest and minimize the background's impact on target segmentation.

3.1 Training Environment

The experimental setup included an Intel Core i7-8700K CPU, 16 GB of RAM, an Nvidia GeForce RTX2080 GPU with 8 GB of video memory, the CUDA Toolkit 9.0, CUDNN V11.7, and Python 3.11.5.

4. Localization and Classification (Fig. 31):

The developed model is trained to not only classify teeth but also localize the area between CEJ and the attachment level within the X-ray images. Localization will involve generating bounding boxes or heat maps indicating the presence and location of abnormal teeth

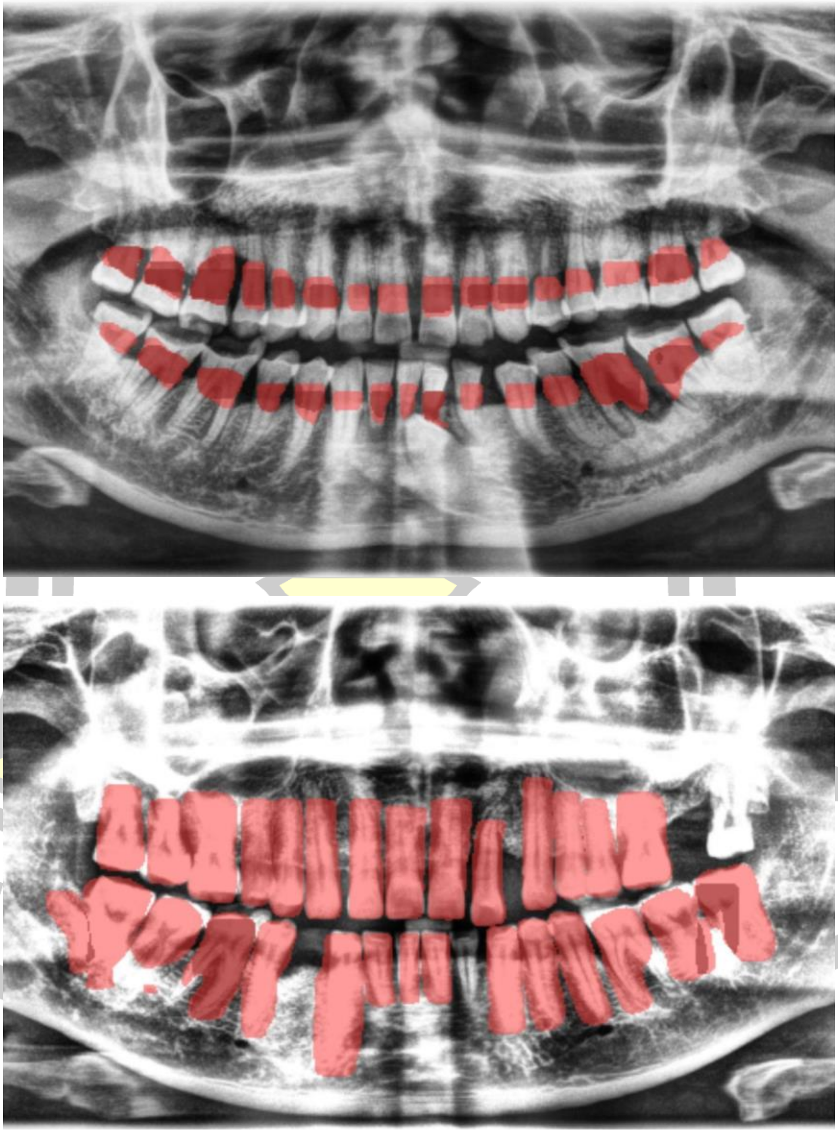


Figure 31: Image showing the predicted area between the CEJ and the bone level (upper), and teeth segmentation (lower).

5. Thresholding for Abnormality Detection (Fig. 32):

A thresholding mechanism will be devised to determine the extent of abnormality based on the width of the gap between the tooth and the bone structure. Teeth with gaps exceeding the predefined threshold (e.g., >2mm) will be flagged as abnormally positioned.

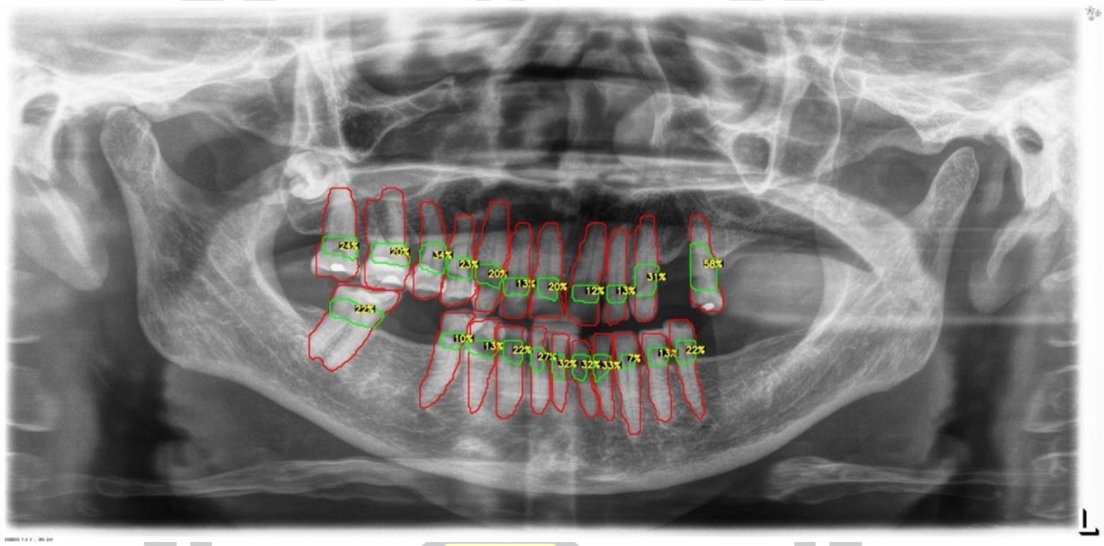


Figure 32: Panoramic X-ray image showing the percentage of thresholding for abnormality detection.

A thresholding mechanism will be developed to assess the extent of abnormality by measuring the distance between the CEJ and the bone structure (Fig. 33). The percentage of bone loss is calculated using the following formula [22, 180]:

$$\boldsymbol{Percentage\ of\ \ bone\ loss} = \frac{\boldsymbol{(CEJ - Alveolar\ bone\ crest) - 2mm}}{\boldsymbol{(CEJ - Root\ apex) - 2mm}} \boldsymbol{x100}$$

Where each variable is as follow:

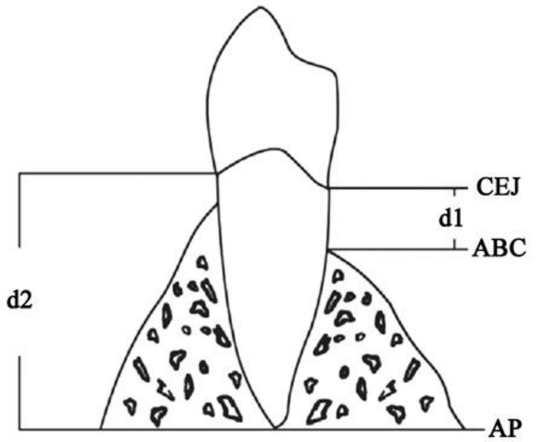


Figure 33: CEJ stands for the cemento-enamel junction. ABC refers to the alveolar bone crest or crestal bone. AP indicates the root apex of the tooth. Here, d1represents the distance from the CEJ to the crestal bone, and d2 represents the distance from the CEJ to the root apex [180].

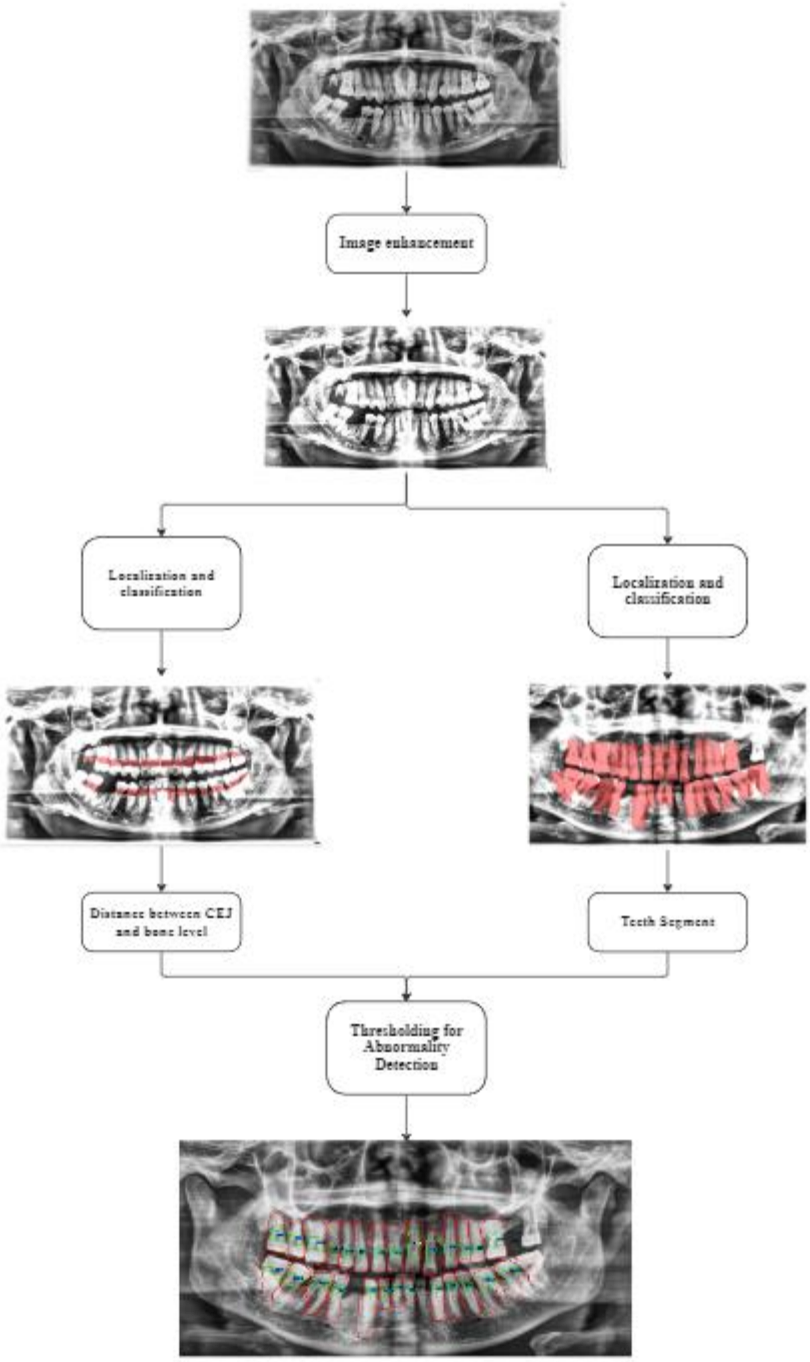


Figure 34: he overall procedure for developing the AI model encompasses phases for image enhancement, model training, and evaluation, aimed at detecting and classifying periodontal bone loss

6. Model Evaluation and Validation:

The trained models, including the teeth segmentation model and the CEJ and bone level segmentation model, will be evaluated using sensitivity, specificity, F1 score, precision, and accuracy metrics. Cross-validation and testing on new, unseen X-ray images will be conducted to validate the models' performance.

3.7 Statistical Analysis

A confusion matrix visually represents a model's prediction accuracy on a dataset. For binary class datasets, such as those with "positive" and "negative" classes, the confusion matrix consists of four key elements [181, 182]. To gauge the model's effectiveness, a set of performance metrics were computed, including (Fig. 35):

True Positive (TP): The count of correctly labeled areas indicating bone loss.

True Negative (TN): The count of accurately identified areas without bone loss.

False Positive (FP): The count of areas erroneously labeled as having bone loss when there was none.

False Negative (FN): The count of areas with bone loss that were not labeled.

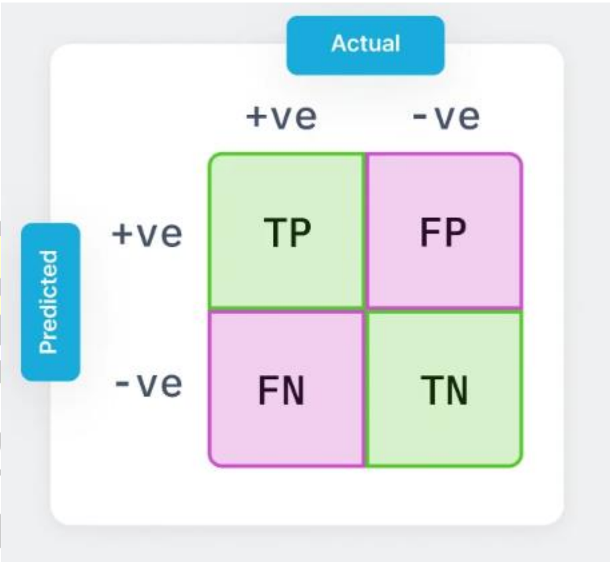


Figure 35: The structure of the confusion matrix [181].

These metrics were used to evaluate the model's performance using the following calculations:

Sensitivity or Recall (TP / (TP + FN)): The proportion of actual positive cases correctly identified by the model.

Specificity (TN / (TN + FP)): The proportion of actual negative cases correctly identified by the model.

F1-Score: The harmonic means of precision and recall, balancing the trade-off between them. A high F1-Score indicates a good balance between detecting true positives and avoiding false positives. These metrics collectively provide a comprehensive evaluation of the model's performance in identifying and classifying bone loss areas in dental radiographic images.

$$\text{F1 Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy and Precision can be computed as follow:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

3.8 Sample Size Calculation for Evaluating the Effectiveness of a New Tool Compared to the Standard Tool

1. Sample Size Calculation for Evaluating Sensitivity

When researchers aim to estimate the sensitivity of a tool or diagnostic method to differentiate between diseased and non-diseased individuals, the sample size calculation for estimating the sensitivity of a new tool or method compared to the standard tool or method can be performed using the following formula [183]:

$$n_{se} = \frac{z_{1-\frac{\alpha}{2}}^{2} Se(1-se)}{d^2(prev)}$$

When n_{Se} is the sample size for estimating sensitivity.

$z_{1-\frac{\alpha}{2}}^{2}$ is the Z-value from the standard normal distribution at the1-α/2 quantile.

α is the error rate for the confidence interval, typically set at 0.05.

se is the sensitivity.

d is the allowable error margin from the reviewed work.

$Prev$ is the prevalence of the disease being studied.

From the research conducted by Bayrakdar SK et al. [160], the sensitivity was found to be 0.9429, tested on a sample of 210, with 105 samples indicating bone loss (50%). When calculating the sample size, the researcher set d (the allowable error margin of sensitivity from the referenced research) at 5%, which equals 0.9429×0.05=0.04710.9429 \times 0.05 = 0.04710.9429×0.05=0.0471. The sample size calculation is as follows:

$$n_{se} = \frac{z_{1-\frac{\alpha}{2}}^{2} 0.9429(1-0.9429)}{0.0471^2(0.50)}$$

$$n_{se} = \frac{(1.96^2)0.9429(0.0571)}{0.0471^2(0.50)}$$

$$n_{se} = 186.47 \approx 187$$

Table 6 represents a sample size of 187, determined based on the sensitivity value from previous research (0.9429) and a prevalence of 0.50, with an allowable error margin of 5% (0.0471). The allowable error margin can be adjusted. When the allowable error margin is set at 5%, 10%, 15%, and 20%, the resulting sample sizes are as follows:

Table 6: Sample Size Calculation for Estimating Sensitivity with Adjusted Error Margins of 5%-20%

Formula	Sensitivity	Prevalence	Error Margin (%)	Allowable Error	Sample Size
1	0.9429	0.50	5	0.0471	187
2	**0.9429**	**0.50**	**6**	**0.0565**	**130**
3	**0.9429**	**0.50**	**7**	**0.0660**	**95**
4	0.9429	0.50	8	0.0754	73
5	0.9429	0.50	9	0.0848	58
6	0.9429	0.50	10	0.0942	47
7	0.9429	0.50	15	0.1414	21
8	0.9429	0.50	20	0.1885	12

2. Sample Size Calculation for Measuring Agreement Using Kappa Statistics

When researchers aim to study agreement measurement, which involves evaluating the opinions or diagnostic results of two or more raters or tools (inter-rater agreement) to determine if they are in concordance, the sample size can be calculated to estimate agreement using Cohen’s kappa coefficient. The calculation method is as follows [184, 185]:

$$n = \left[\frac{z_{1-\frac{\alpha}{2}}\sqrt{Q_0} + z_{1-\beta}\sqrt{Q_1}}{k_1 - k_0}\right]^2$$

$$Q = (1-\pi_e)^{-4}\Big\{\Sigma_i \pi_{ii}[(1-\pi_e) - (\pi_{.i} + \pi_{i.})(1-\pi_0)]^2 + (1-\pi_0)]^2 \Sigma\Sigma_{i\neq j}\pi_{ij}(\pi_{.i} + \pi_{j.})^2 - (\pi_0\pi_e - 2\pi_e + \pi_0)^2\Big\}$$

When n is the sample size for estimating agreement:

k_1 is the alternative hypothesis value of the Kappa statistic.

k_0 is the null hypothesis value of the Kappa statistic.

π_e is the probability that Rater 1 gives a positive result.

π_o is the probability that Rater 2 gives a positive result.

Based on the research conducted by Lee JH et al. [147], the agreement values between the convolutional neural network (CNN) and periodontists were reported. For premolars, the agreement values were 0.828 and 0.797, respectively, and for molars, the values were 0.734 and 0.766, respectively. When calculating the sample size, the researcher set d, the deviation of the agreement values from previous studies, at 5%, 10%, 15%, and 20%. The results are shown in Table 7:

Table 7: Sample Size Calculation for Molar Cases with Adjusted Error Rates (5%-30%)

Formula	**P(CNN)**	**P(periodontists)**	**k_o**	**Deviation (%)**	**k_1**	**Sample Size (n)**
1	0.734	0.766	0.766	5	0.8043	2,842
2	0.734	0.766	0.766	10	0.8426	673
3	0.734	0.766	0.766	15	0.8809	281
4	**0.734**	**0.766**	**0.766**	**20**	**0.9192**	**146**
5	**0.734**	**0.766**	**0.766**	**25**	**0.9575**	**83**
6	0.734	0.766	0.766	30	0.9958	46

In the clinical implementation of this study, we calculated a sample size of 83 panoramic X-ray images, accounting for an adjusted error rate of 25%. However, we ultimately used 90 images to assess the accuracy of the AI model in comparison to general practitioners (GPs) and periodontists, relative to expert periodontists. The expert periodontists in this context are certified specialists in the field of Periodontology with over 10 years of experience.

In this study, intraoral examinations were not conducted, and retrospective evaluation of radiological data was performed. This study was approved by the Ethical Review Board of Fang Hospital (COA No. 03/2566) and the Ethics Committee of Research Involving Human Subjects of Mahasarakham University (No. 533-589/2023). Moreover, the consent letter for data collection for this research project was granted by the director of Fang Hospital in Chiang Mai, Thailand (No. 0033.306/3674).

CHAPTER 4

Results

This research is divided into three phases: **Phase I - Review Study:** This phase critically evaluates the existing literature on periodontal diagnosis and prognostication, emphasizing the limitations of traditional diagnostic methods. A comprehensive review was conducted following PRISMA guidelines. We searched several databases, including PubMed, Scopus, Wiley Online Library, and ScienceDirect, for studies published between January 2018 and December 2023. The search utilized keywords such as "artificial intelligence," "panoramic radiograph," "periodontitis," "periodontal disease," and "diagnosis." Inclusion criteria were established for studies involving the application of AI in diagnosing periodontitis, including human subjects, published in English, and accessible as open access. Exclusion criteria eliminated non-AI studies, studies unrelated to periodontitis, those not utilizing panoramic radiographs, as well as abstracts, editorials, and letters.

Phase II - Retrospective Study: The panoramic radiographs used in this study were obtained from the Dental Department of Fang Hospital, Chiang Mai, Thailand. It is important to note that all radiographs were captured using the same imaging device, the SIDEXIS Next Generation Program (Sirona, Bensheim, Germany). Only one radiograph per patient was included in the analysis. The dataset comprised 2,000 panoramic radiographs, divided into 1,000 periodontally healthy radiographs and 1,000 periodontitis radiographs. Following the collection of these radiographs, a comprehensive model for periodontal diagnosis and prognostication was developed, integrating advanced image analysis techniques utilizing artificial intelligence (AI). The assessment was based solely on radiographic evaluation, with the primary focus being the assessment of the alveolar bone crest relative to the cemento-enamel junction (CEJ) of each tooth. The distance between the CEJ and the alveolar bone crest was measured. Periodontal diagnosis followed the 2018 periodontal classification, and prognostication was performed using medical image processing techniques.

Phase III - Analytical Study: This phase aims to evaluate the performance of AI models in diagnosing periodontal diseases through a comparative analysis with general practitioners (GPs) and specialized periodontists. The evaluation will be based on the assessments made by expert periodontists with over 10 years of experience in periodontology, focusing on diagnostic accuracy and efficiency.

In Phase I, a critical review of the existing literature on periodontal diagnosis and prognostication was conducted to identify the limitations of traditional diagnostic methods. Following PRISMA guidelines, an initial search identified 211 records. After applying the inclusion and exclusion criteria, 12 studies were included in the final review, as shown in Figure 36 below, with the details provided in Table 8.

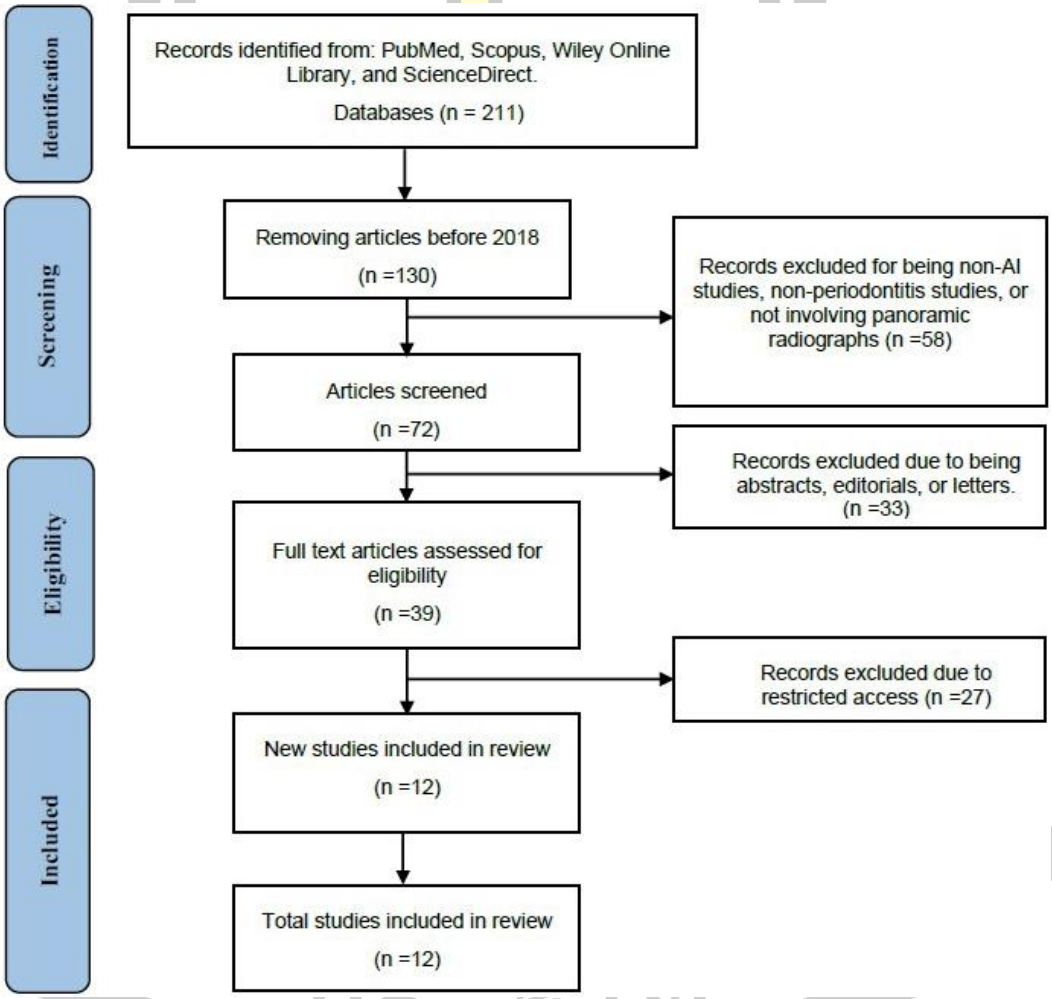


Figure 36: PRISMA flow diagram.

This process involved excluding articles that were not related to artificial intelligence (AI), did not focus on periodontitis, lacked panoramic radiographs, or were categorized as abstracts, editorials, or letters. Additionally, a significant number of papers were excluded due to restricted access to full texts. The remaining 12 studies employed advanced models, particularly convolutional neural networks (CNNs), with accuracy rates for periodontal bone loss detection ranging from 0.76 to 0.98 [94, 146, 160, 161, 163, 186, 187, 188]. The methodologies utilized in these studies included deep learning hybrid approaches, automated identification systems, and machine learning classifiers, all contributing to improved diagnostic precision and efficiency.

Table 8: Examples of AI technologies enhancing the detection of periodontal bone loss through dental panoramic X-ray images

Study	**Year**	**Description**	**Total data**	**Summary of model performances**
Krois et al. [146]	2019	Used CNN to identify periodontal bone loss on dental panoramic X-ray images.	2,001	The model has an accuracy, sensitivity, and specificity all at 0.81.
Kim et al. [159]	2019	Created a system for automatically identifying periodontal bone loss using panoramic dental X-ray images.	12,179	The developed model outperformed dental clinicians on the test set with an F1 score of 0.75, compared to the clinicians' average score of 0.69.
Chang et al. [94]	2020	Created a system to automatically classify stages of periodontitis using deep learning techniques on dental panoramic X-ray images.	340	The accuracy levels were recorded at 0.93 for periodontal bone and 0.91 for both CEJ level and teeth identification.

Table 8: Cont.

Study	Year	Description	Total data	Summary of model performances
Bayrakdar et al. [160]	2020	Used CNN to identify periodontal bone loss on dental panoramic X-ray images.	2,276	The model's accuracy is measured at 0.9.
Thanathornwong et al. [151]	2020	Used CNN to identify periodontally compromised teeth on dental panoramic X-ray images.	100	The model reached a sensitivity of 0.84, specificity of 0.88, and an F-measure of 0.81.
Jiang et al. [161]	2022	Created a model for radiological staging of periodontal alveolar bone loss on dental panoramic X-ray images.	640	The model's overall accuracy rate was recorded at 0.77.
Zadrozny et al. [162]	2022	Evaluated the accuracy of AI in automatically analyzing panoramic dental X-rays.	30	The tested CNN displayed poor reliability in evaluating caries (Intra-Class Correlation (ICC) = 0.681) and periapical lesions (ICC = 0.619). However, it showed good reliability for identifying fillings (ICC = 0.920), endodontically treated teeth (ICC = 0.948), and periodontal bone loss (ICC = 0.764).

Table 8: Cont.

Study	Year	Description	Total data	Summary of model performances
Ertas et al. [186]	2022	Used deep learning (DL) for classifying periodontitis and evaluate the accuracy of this method	144	The ResNet50 combined with the SVM machine learning architecture achieved an accuracy of 0.882, an F1 score of 0.072, a precision of 0.864, and a recall of 0.882.
Widyaningrum et al. [187]	2022	Assessed image segmentation for periodontitis staging using DL techniques	1100	The Multi-Label U-Net and Mask model achieved an accuracy of 95%, a recall of 0.88, and an F1-score of 0.87.
Uzun Saylan et al. [153]	2023	Assessed how well AI models can detect the presence or absence of alveolar bone loss in various areas.	685	The models in detecting alveolar bone loss (ABL) across various teeth regions showed sensitivity, precision, and F1 score ranges as follows: For general alveolar bone loss, the scores were 0.75, 0.76, and 0.76. Specifically, maxillary incisor ABL had perfect precision at 1, with an F1 score of 0.95. Maxillary canine, premolar, and molar ABL showed balanced scores,

Table 8: Cont.

Study	Year	Description	Total data	Summary of model performances
				with the highest F1 score of 0.91 for molar ABL. In the mandible, incisor, canine, premolar, and molar ABL scores varied, with mandibular incisor ABL scoring an F1 of 0.86 and molar ABL at 0.79, indicating the models' varied effectiveness in different dental regions.
Kong et al. [163]	2023	Used two-stage CNN-based periodontitis detection network in periodontitis bone loss diagnosis in panoramic radiographs.	1747	The model for radiographic bone loss (RBL) classification has an accuracy of 0.762.
Amasya et al. [188]	2023	Developed a web-based AI software, DiagnoCat, for detecting periodontal bone loss on panoramic radiographs.	6000	The study reported an overall F-score of 0.948, an accuracy of 0.977, and a Cohen's kappa coefficient of 0.933.

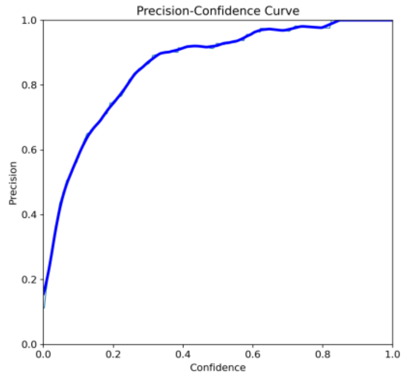
In Phase II, a comprehensive model for periodontal diagnosis and prognostication was developed, integrating advanced image analysis techniques utilizing artificial intelligence (AI). The panoramic radiographs used in this study were obtained from the Dental Department of Fang Hospital, Chiang Mai, Thailand. It is important to note that all radiographs were captured using the same imaging device, the SIDEXIS Next Generation Program (Sirona, Bensheim, Germany). Only one radiograph per patient was included in the analysis. The dataset comprised 2,000 panoramic radiographs of patients diagnosed with periodontitis, identified using diagnosis codes from the HOSxP Program (Bangkok Medical Software, Bangkok, Thailand). Image processing techniques were then applied to all images, which were randomly divided into training, validation, and test sets in a 70:10:20 ratio. The demographic data of the patients are presented in Table 9. To address the identified challenges, a robust methodology incorporating machine learning and AI techniques was developed for the automated detection of abnormal teeth in dental panoramic X-ray images. Following image enhancement, the LabelMe tool was utilized for object segmentation, while Labelme2yolo was employed to convert the data into a format suitable for training. Subsequently, two models were trained, validated, and tested: the teeth segmentation model and the CEJ and bone level segmentation model.

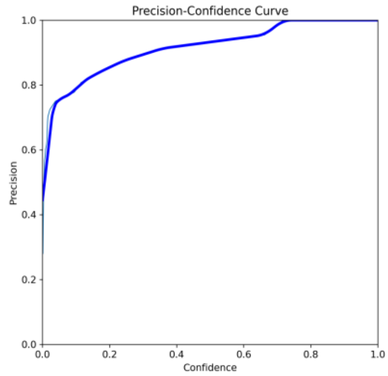
The teeth segmentation model achieved sensitivity, specificity, F1 score, precision, and accuracy of 0.90, 0.96, 0.80, 0.80, and 0.97, respectively. In contrast, the CEJ and bone level segmentation model recorded scores of 1.00, 0.98, 0.90, 0.90, and 0.98, as detailed in Table 10. Moreover, Figure 37 and 38 provide an example of the developed AI model applied to the diagnosis and prognostication detection of periodontitis from panoramic X-ray images.

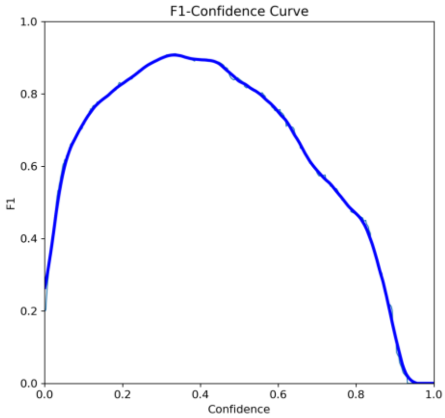
Table 9: The demographic data of the patients

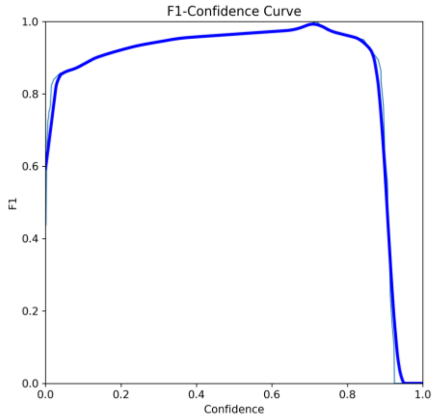
Sex	**Numbers of Patients**	**Mean Age(Years)**
Male	823	47.04
Female	1177	45.27

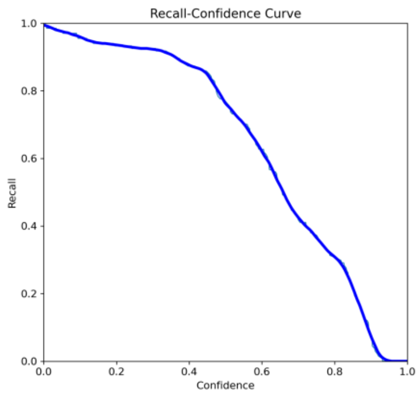
Table 10: The AI models developed achieved the following scores [189]:

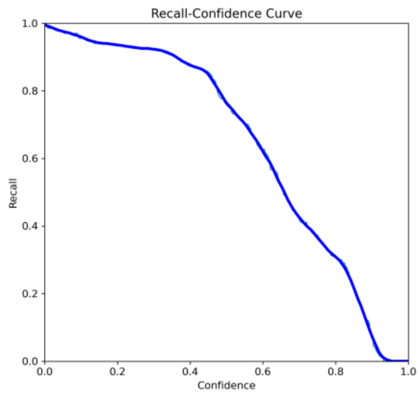
<table>
<tr><th></th><th>Teeth segmentation model</th><th>CEJ and bone level segmentation model</th></tr>
<tr><td>Precision</td><td>

0.80</td><td>

0.90</td></tr>
<tr><td>F1</td><td>

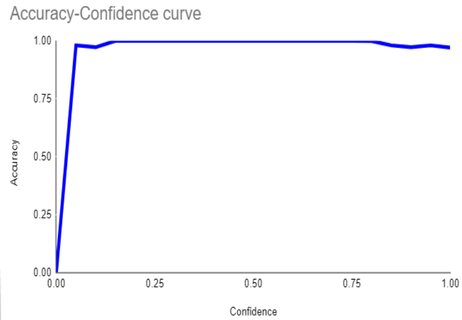
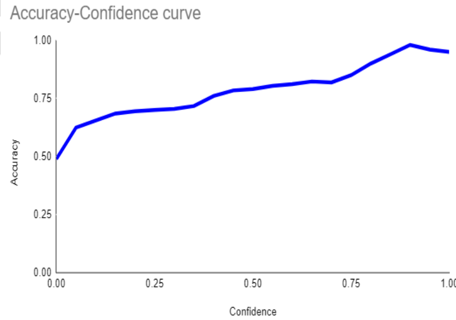
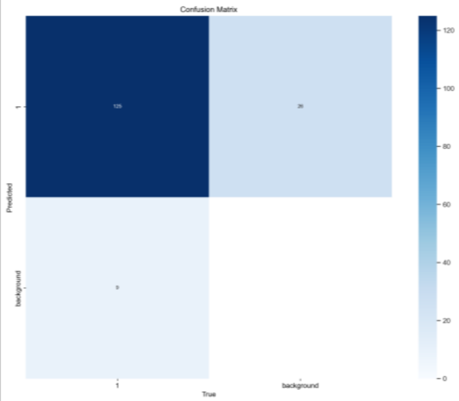
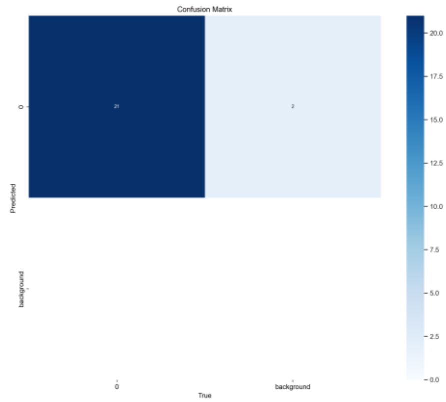
0.80</td><td>

0.90</td></tr>
<tr><td>Sensitivity</td><td>

0.90</td><td>

1.0</td></tr>
</table>

Table 9: Cont.

	Teeth segmentation model	**CEJ and bone level segmentation model**
Accuracy	 0.97	 0.98
mAP50	0.92	0.995
Confusion matrix		

Both the CEJ and bone level segmentation model (Table 11) and the teeth segmentation model (Table 12) demonstrated strong performance in accurately classifying relevant areas in panoramic radiographs. In Table 11, the CEJ and bone level model correctly predicted 18,385 instances, with only 234 false positives, indicating high precision. The model also exhibited strong recall, with minimal false negatives (11). Similarly, the teeth segmentation model (Table 12) performed well, accurately identifying 983 teeth instances and 18,687 true negatives. However, it had a slightly higher false positive rate (589), where non-teeth areas were incorrectly classified as teeth. Despite the higher false positive rate in the teeth model, both models exhibited high accuracy and efficiency in their respective tasks, with low false negative rates and a strong ability to differentiate between positive and negative classes in their predictions.

Table 11: Confusion matrix for the CEJ and bone level segmentation model

		Actual value	
Predicted value		Positive	Negative
	Positive	TP:508	FP:234
	Negative	FN:11	TN:17877

Legend:

True Positive (TP): Correctly identified areas indicating bone loss.

True Negative (TN): Correctly identified areas without bone loss.

False Positive (FP): Areas incorrectly labeled as having bone loss when none is present.

False Negative (FN): Areas with bone loss that were incorrectly identified as normal.

Table 12: Confusion matrix for the teeth segmentation model

		Actual value	
Predicted value		Positive	Negative
	Positive	TP:983	FP:589
	Negative	FN:11	TN:18687

Legend:

True Positive (TP): Correctly identified areas indicating bone loss.

True Negative (TN): Correctly identified areas without bone loss.

False Positive (FP): Areas incorrectly labeled as having bone loss when none is present.

False Negative (FN): Areas with bone loss that were incorrectly identified as normal.

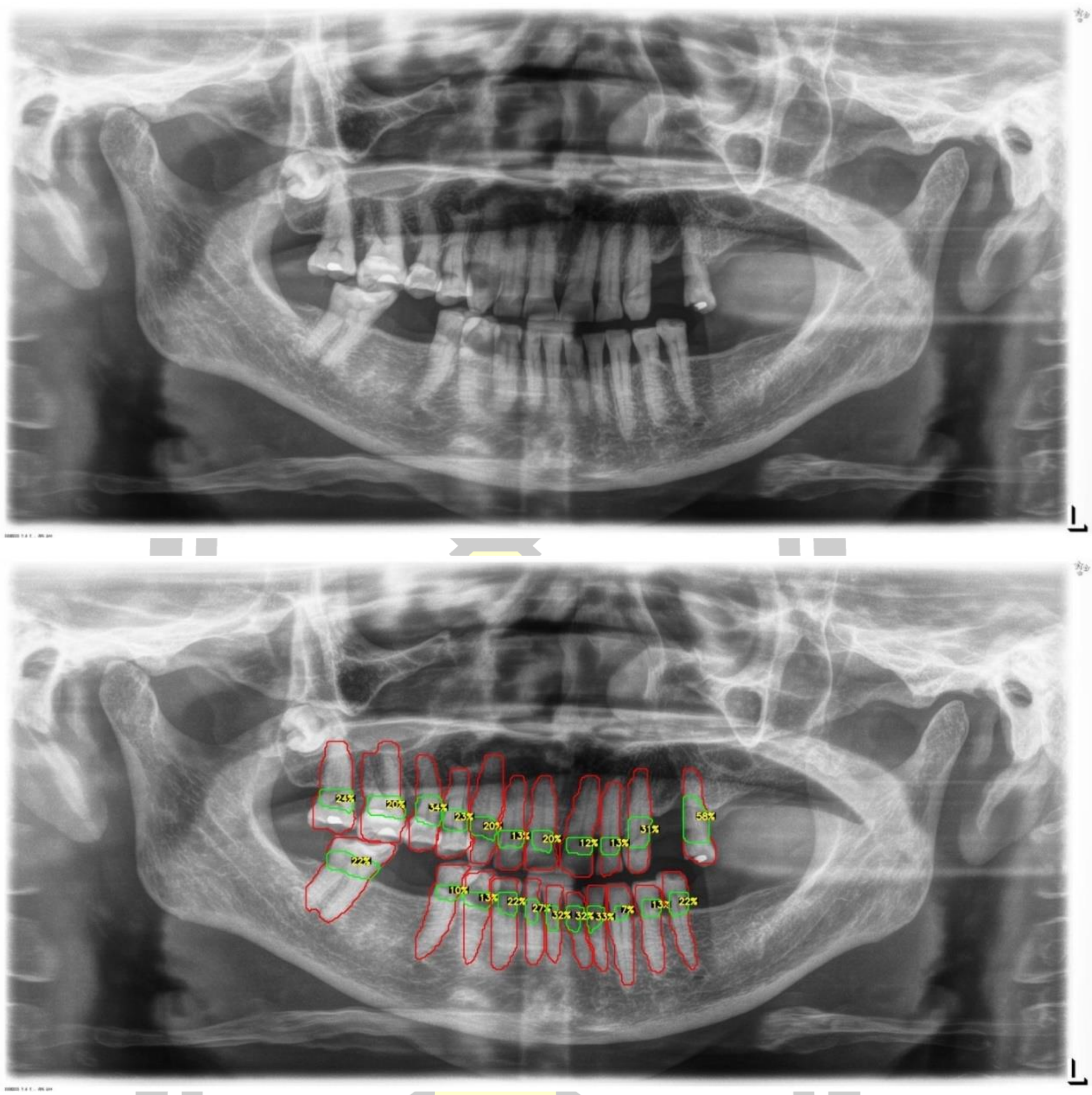
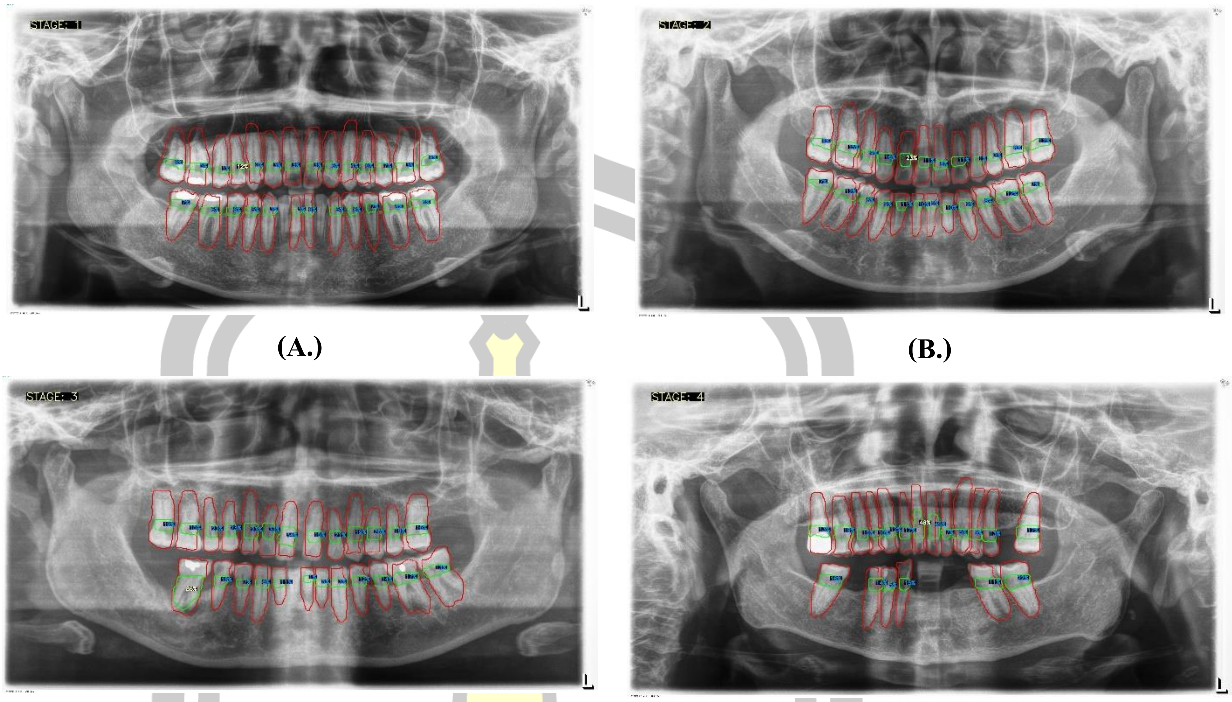


Figure 37: An example of our developed AI model in use is shown above: the original image is displayed on the top, and the final result after applying the model is shown on the bottom.



(A.) (B.)

(C.) (D.)

Figure 38: Panoramic X-ray images illustrating the threshold percentages for periodontitis severity: A represents Stage I, B represents Stage II, C represents Stage III, and D represents Stage IV.

Additionally, in Phase III: To evaluate the performance of AI models in diagnosing periodontal diseases through a comparative analysis with general practitioners (GPs) and specialized periodontists. In the clinical implementation, we calculated a sample size of 83 panoramic X-ray images with an adjusted error rate of 25%; however, we ultimately used 90 images to compare the accuracy of the AI model, general practitioners (GPs), and periodontists against expert periodontists. The demographic data of the patients are presented in Table 13.

Table 14 reveals that the AI model achieved the highest accuracy (94.4%) and perfect sensitivity (100%), indicating its ability to detect all positive cases. However, it struggled with specificity (0%), meaning it had difficulty ruling out false positives. Periodontists demonstrated strong overall performance with 91.1% accuracy, 90.6% sensitivity, and perfect specificity (100%), while GPs exhibited slightly lower accuracy (86.7%) and sensitivity (85.9%), yet also achieved perfect specificity (100%). The AI model's high sensitivity makes it effective at identifying true positives, although it requires human oversight for confirming negatives, as both periodontists and GPs performed more consistently in terms of sensitivity and specificity. The distribution of results among expert periodontists, periodontists, GPs, and the AI model is illustrated in Table 15.

Table 13: Demographic data of patients used to compare the accuracy percentage of the AI model, general practitioners (GP), and periodontists with expert periodontists

Sex	Numbers of Patients	Mean Age(Years)
Male	42	44.29
Female	48	43.56

Table 14: The diagnostic performances of the AI model, general practitioners (GP), and periodontists with expert periodontists

Test	Accuracy % (95%CI)	Sensitivity % (95%CI)	Specificity % (95%CI)	PPV % (95%CI)	NPV % (95%CI)
Periodontist	91.1	90.6	100	100	38.5
	(83.2 - 96.1)	(82.3 - 95.8)	(47.8 - 100)	(95.3 - 100)	(13.9 - 68.4)
GP	86.7	85.9	100	100	29.4
	(77.9 - 92.9)	(76.6 - 92.5)	(47.8 - 100)	(95.1 - 100)	(10.3 - 56)
AI	94.4	100	0	94.4	0
	(87.5 - 98.2)	N/A	N/A	N/A	N/A

Legend: Abbreviations: PPV, positive predictive value; NPV, negative predictive value; CI, confident interval.

Table 15: The distribution of result by expert periodontists, periodontists, general practitioners (GP) and AI model

	Expert									
	0		**1**		**2**		**3**		**4**	
	n	**(%)**	**n**	**(%)**	**n**	**(%)**	**n**	**(%)**	**n**	**(%)**
Periodontist										
0	5	(5.6)	1	(1.1)	6	(6.7)	1	(1.1)	0	(0.0)
1	0	(0.0)	4	(4.4)	8	(8.9)	0	(0.0)	0	(0.0)
2	0	(0.0)	0	(0.0)	20	(22.2)	8	(8.9)	0	(0.0)
3	0	(0.0)	0	(0.0)	2	(2.2)	34	(37.8)	0	(0.0)
4	0	(0.0)	0	(0.0)	0	(0.0)	0	(0.0)	1	(1.1)
GP										
0	5	(5.6)	4	(4.4)	8	(8.9)	0	(0.0)	0	(0.0)
1	0	(0.0)	1	(1.1)	14	(15.6)	3	(3.3)	0	(0.0)
2	0	(0.0)	0	(0.0)	11	(12.2)	15	(16.7)	0	(0.0)
3	0	(0.0)	0	(0.0)	3	(3.3)	22	(24.4)	0	(0.0)
4	0	(0.0)	0	(0.0)	0	(0.0)	3	(3.3)	1	(1.1)
AI										
1	0	(0.0)	1	(1.1)	0	(0.0)	0	(0.0)	0	(0.0)
2	4	(4.4)	0	(0.0)	29	(32.2)	6	(6.7)	0	(0.0)
3	1	(1.1)	4	(4.4)	6	(6.7)	35	(38.9)	1	(1.1)
4	0	(0.0)	0	(0.0)	1	(1.1)	2	(2.2)	0	(0.0)

Legend: 0 represents Non-periodontitis, 1 represents Periodontitis Stage I, 2 represents Periodontitis Stage II, 3 represents Periodontitis Stage III, and 4 represents Periodontitis Stage IV.

Table 15 illustrates the diagnostic distribution of results among expert periodontists, periodontists, general practitioners (GPs), and the AI model across different stages of periodontitis. The results show varying performance levels in detecting stages of periodontal disease, labeled from non-periodontitis (0) to periodontitis stage IV (4). The AI model showed a relatively balanced detection rate, especially for periodontitis stage III, where it correctly identified 38.9% of cases. However, it struggled with stage I, detecting only 1.1% of cases. Periodontists performed best in detecting stage III cases (37.8%), while GPs showed strong performance in stage II detection (16.7%). Overall, the AI model demonstrated high potential but requires further refinement for early-stage detection, as human experts outperformed the model in this area. These results suggest that AI can be a valuable tool in aiding periodontal diagnostics but may require human oversight, particularly in less severe stages.

Furthermore, we evaluated the diagnostic agreement between three different raters—AI, periodontists, and general practitioners (GPs)—and an expert, considered the gold standard. We used the weighted Cohen's kappa statistic to measure the level of agreement beyond chance. The statistical significance of these weighted kappa coefficients was tested at an alpha level of 0.05. The weighted Cohen's kappa coefficients are presented in Table 16.

Table 16: The weighted Cohen's kappa coefficient for the comparisons of the AI model, general practitioners (GP), and periodontists with expert periodontists

	Agreement (%)	**Kappa (95%CI)**		**p-value**
Periodontist vs. Expert	90.1	0.634	(0.621 - 0.694)	<0.001
GP vs. Expert	83.1	0.429	(0.298 - 0.542)	<0.001
AI vs. Expert	90.0	0.445	(0.398 - 0.471)	<0.001

According to guidelines suggested by Landis and Koch (1977), Cohen's Kappa values can be interpreted as follows [190]:

- 0.00 - 0.20: Slight agreement
- 0.21 - 0.40: Fair agreement
- 0.41 - 0.60: Moderate agreement
- 0.61 - 0.80: Substantial agreement
- 0.81 - 1.00: Almost perfect agreement

From Table 16, the study reveals that the evaluations made by periodontists showed a high level of agreement with those of the experts, evidenced by a Cohen's kappa coefficient of 0.634 (95% CI: 0.621 - 0.694, p-value <0.001). The assessments by general practitioners (GPs) demonstrated a moderate level of agreement with the experts, with a Cohen's kappa coefficient of 0.429 (95% CI: 0.298 - 0.542, p-value <0.001). Similarly, the AI model's evaluations also exhibited a moderate level of agreement with the experts, reflected by a Cohen's kappa coefficient of 0.445 (95% CI: 0.398 - 0.471, p-value <0.001). These results underscore the AI model's potential in achieving diagnostic consistency comparable to that of human practitioners, albeit at a moderate agreement level.

Additionally, we conducted the clinical implementation by calculating a larger sample size for comparison among groups, resulting in an adjusted error rate of 15%, which equated to 281 previously unseen panoramic images (Table 7). In this study, however, we utilized a total of 300 previously unseen panoramic images to compare the diagnostic accuracy of the AI model and periodontists against expert periodontists.

The general characteristics of the sample population revealed that the majority were female, accounting for 64.7%. The average age of participants was 40.26 ± 16.42 years, with females having an average age of 40.52 ± 15.74 years and males having an average age of 40.12 ± 16.82 years, as shown in Table 17.

Table 17: Demographic data of patients used to compare the accuracy percentage of the AI model and periodontists with expert periodontists

Variables	Total		Male		Female	
	n	**(%)**	**n**	**(%)**	**n**	**(%)**
All patients	300	(100.0)	106	(35.3)	194	(64.7)
Age (years), Mean ± SD	40.26 ± 16.42		40.52 ± 15.74		40.12 ± 16.82	

In Table 18, the study results indicate that the assessments made by expert periodontists revealed that 3.3% were non-periodontists, 10.3% were classified as periodontitis stage I, 47.0% as periodontitis stage II, 38.7% as periodontitis stage III, and 0.7% as periodontitis stage IV. When comparing the evaluations of periodontists with those of expert periodontists, a consistency rate of 62.7% was observed, which included 2% non-periodontists, 5% periodontitis stage I, 28% periodontitis stage II, 27% periodontitis stage III, and 0.7% periodontitis stage IV. Furthermore, the evaluation of the AI model in comparison to expert periodontists showed a consistency rate of 71.7%, including 0.3% non-periodontists, 2% periodontitis stage I, 40% periodontitis stage II, 29% periodontitis stage III, and 0.3% periodontitis stage IV.

Table 18: Distribution of result by expert periodontists, periodontists, and AI model

	Total		Expert									
			Non-periodontitis		Periodontitis							
					Stage I		Stage II		Stage III		Stage IV	
	n	(%)	n	(%)	n	(%)	n	(%)	n	(%)	n	(%)
All patients	300	(100.0)	10	(3.3)	31	(10.3)	141	(47.0)	116	(38.7)	2	(0.7)
Periodontists												
Non-periodontitis	40	(13.3)	6	(2.0)	11	(3.7)	20	(6.7)	3	(1.0)	0	(0.0)
Periodontitis stage I	48	(16.0)	4	(1.3)	15	(5.0)	29	(9.7)	0	(0.0)	0	(0.0)
Periodontitis stage II	121	(40.3)	0	(0.0)	5	(1.7)	84	(28.0)	32	(10.7)	0	(0.0)
Periodontitis stage III	89	(29.7)	0	(0.0)	0	(0.0)	8	(2.7)	81	(27.0)	0	(0.0)
Periodontitis stage IV	2	(0.7)	0	(0.0)	0	(0.0)	0	(0.0)	0	(0.0)	2	(0.7)
AI												
Non-periodontitis	1	(0.3)	1	(0.3)	0	(0.0)	0	(0.0)	0	(0.0)	0	(0.0)
Periodontitis stage I	6	(2.0)	0	(0.0)	6	(2.0)	0	(0.0)	0	(0.0)	0	(0.0)
Periodontitis stage II	172	(57.4)	7	(2.3)	18	(6.0)	120	(40.0)	27	(9.0)	0	(0.0)
Periodontitis stage III	117	(39.0)	2	(0.7)	7	(2.3)	20	(6.7)	87	(29.0)	1	(0.3)
Periodontitis stage IV	4	(1.3)	0	(0.0)	0	(0.0)	1	(0.3)	2	(0.7)	1	(0.3)

Moreover, In Table 19, the study results indicated a moderate agreement between the assessments of periodontists and experts, with a Cohen's kappa coefficient of 0.530 (95% CI: 0.457 - 0.584, p-value < 0.001). Similarly, the evaluation of the AI model compared to the expert assessments also showed moderate agreement, reflected in a Cohen's kappa coefficient of 0.497 (95% CI: 0.470 - 0.533, p-value < 0.001).

Table 19: The weighted Cohen's kappa coefficient for the comparisons of periodontists and the AI model with expert periodontists

	Agreement (%)	Kappa (95%CI)		p-value
Periodontist vs. Expert	88.5	0.530	(0.457 - 0.584)	<0.001
AI vs. Expert	91.3	0.497	(0.470 - 0.533)	<0.001

Finally, in Table 20, the findings revealed that the accuracy of the periodontist evaluations in comparison to the experts was 87.3% (95% CI: 83.0 - 90.9), with a sensitivity of 88.3% (95% CI: 84.0 - 91.7) and specificity of 60% (95% CI: 26.2 - 87.8). The positive predictive value was 98.5% (95% CI: 96.1 - 99.6), while the negative predictive value was 15% (95% CI: 5.7 - 29.8). In contrast, the AI model's evaluation compared to the experts demonstrated an accuracy of 97% (95% CI: 94.4 - 98.6), a sensitivity of 100% (95% CI: 98.7 - 100), a specificity of 10% (95% CI: 0.3 - 44.5), a positive predictive value of 97% (95% CI: 94.4 - 98.6), and a negative predictive value of 100% (95% CI: 2.5 - 100).

Table 20: Diagnostic performances for the comparisons of periodontists and the AI model with expert periodontists

Test	Accuracy % (95%CI)	Sensitivity % (95%CI)	Specificity % (95%CI)	PPV % (95%CI)	NPV % (95%CI)
Periodontist	87.3 (83.0 - 90.9)	88.3 (84 - 91.7)	60 (26.2 - 87.8)	98.5 (96.1 - 99.6)	15 (5.7 - 29.8)
AI	97 (94.4 - 98.6)	100 (98.7 - 100)	10 (0.3 - 44.5)	97 (94.4 - 98.6)	100 (2.5 - 100)

Abbreviations: PPV, positive predictive value; NPV, negative predictive value; CI, confident interval.

CHAPTER 5

Discussion and conclusion

In 2018, the field of periodontology updated its classification system, now focusing on the percentage of alveolar bone loss to assess disease severity [25]. Current standard periodontal evaluations, periapical, bite-wing, and panoramic radiographs are preferred methods for assessing interproximal alveolar bone levels because they are cost-effective, quick, and emit less radiation than 3D imaging techniques [47]. In the past, there have been extensive studies using panoramic radiographic images for various purposes, including disease diagnosis, prognosis, and treatment planning. However, panoramic radiographs have significant limitations, such as the overlap of structures in adjacent areas and image distortion in certain positions, which affect image clarity at a level perceivable by the human eye and in areas that cannot be distinguished. Despite these limitations, Persson RE and colleagues found that panoramic radiography is superior for scanning the entire jaw for lesions, with high consistency in measurements of the CEJ to crestal bone distances and their root length ratios when comparing intra-oral periapical with panoramic images [191]. However, manually measuring periodontal bone loss (PBL) for every tooth on a panoramic X-ray requires significant time and effort. Recent efforts have focused on overcoming the limitations of conventional periodontitis diagnostics through AI-assisted detection of periodontal bone loss from dental panoramic X-rays. These challenges have led to discussions about creating supportive diagnostic tools. In recent years, AI has begun to flourish in dentistry, offering a range of applications from diagnostics and decision-making to treatment planning and predicting outcomes. AI tools for dental applications are becoming increasingly sophisticated, precise, and dependable, with research extending across all dental disciplines [100].

One significant limitation of this study is the substantial decrease in the number of papers included in the study while adhering to the PRISMA methodology. Initially, 211 records were identified, but after applying the inclusion and exclusion criteria, only 12 studies were included in the final review. A considerable number of papers were excluded due to the lack of full-text accessibility, highlighting a critical barrier in conducting comprehensive reviews. This limitation underscores the importance of "open access" and the availability of current research to ensure that valuable studies are not overlooked due to access restrictions. Open access to research publications can significantly enhance the ability of researchers to conduct thorough and inclusive reviews, thereby advancing the field more effectively.

In the phase of AI development, the present study found that the teeth segmentation model achieved sensitivity, specificity, F1, precision, and accuracy scores of 0.9, 0.96, 0.8, 0.8, and 0.97, respectively. In contrast, the CEJ and bone level segmentation model attained scores of 1, 0.98, 0.9, 0.9, and 0.98, respectively. Despite the recent surge in publications on dental AI, comparing these studies is challenging due to discrepancies in study design, data distribution (training, testing, and validation sets), and performance metrics (accuracy, sensitivity, specificity, F1 score, AUC [Area Under the ROC Curve], recall). Many articles do not fully report these critical details. However, accuracy emerged as the most commonly referenced indicator of model performance in the studies, with detection rates for periodontal bone loss ranging between 0.76 to 0.98 [94, 146, 160, 161, 163, 186, 187, 188]. This is consistent with the findings of this study, which reported accuracy scores of 0.97 for the teeth segmentation model and 0.98 for the CEJ and bone level segmentation model. These accuracy scores are higher than those reported in all previous studies. The dataset of dental panoramic X-ray images used in various studies ranged from 100 to 6,000 images [94, 146, 151, 153, 160, 161, 163, 186-188], with only one study employing a significantly larger dataset of 12,179 images [159]. In this study, a dataset of 2,000 dental panoramic X-ray images was used, yet the accuracy rate remained high. Furthermore, many studies have aimed to detect periodontal bone loss on dental panoramic X-ray images. Specifically, Chang et al.'s advanced study, which sought to classify stages of periodontitis following the latest periodontal classification, found that the automatic method had a Pearson correlation coefficient of 0.73 with radiologist diagnoses for the entire jaw and an intraclass correlation of 0.91 for the entire jaw [94]. Similarly, Jiang et al. revealed creating a deep learning model to evaluate and categorize the stages of periodontitis, achieving an overall model accuracy of 0.77 [161]. Our study uniquely detects periodontal bone loss, classifies the stage of periodontitis, and identifies the percentage of bone loss for each tooth, aiding in prognosis evaluation. This novel innovation has not been previously achieved.

The strengths of these studies lie in their innovative approaches and high accuracy rates. For example, the integration of ResNet50 with SVM by Ertas et al. [186] achieved an accuracy of 0.882, showcasing the potential of hybrid models. Additionally, Widyaningrum et al. [187] used

Multi-Label U-Net and Mask R-CNN models, achieving 95% accuracy, which highlights the effectiveness of advanced segmentation techniques. However, a common weakness across several studies is the reliance on relatively small datasets, as seen in the work by ZadroŻny et al. [162], which included only 30 images. This limitation can affect the generalizability and robustness of the models. Moreover, discrepancies in performance metrics and lack of standardized reporting pose challenges for direct comparison and evaluation of the studies.

Explainability and trustworthiness are critical aspects of AI application in healthcare. Many reviewed papers highlighted limitations in these areas [144, 146]. For instance, the black-box nature of deep learning models often leads to a lack of transparency, making it difficult for clinicians to understand and trust AI decisions fully [147]. Additionally, some models, despite their high accuracy, require significant computational resources, which may not be feasible in all clinical settings [145]. To enhance trustworthiness, future research should focus on developing explainable AI models that provide clear insights into their decision-making processes and integrating these models into clinical workflows in a manner that complements rather than replaces human expertise [94].

In the clinical context, we evaluated the diagnostic agreement between three different raters—AI, periodontists, and general practitioners (GPs)—and an expert periodontist, considered the gold standard. We used the weighted Cohen's kappa statistic to measure the level of agreement beyond chance. The statistical significance of these weighted kappa coefficients was tested at an alpha level of 0.05. Studies in various medical fields have shown similar trends in the performance of AI systems. For instance, Esteva et al. (2017) demonstrated that AI could classify skin cancer with dermatologist-level accuracy, achieving a high level of agreement with expert diagnoses [192]. Similarly, Mazurowski et al. (2019) found that AI could significantly enhance the accuracy of radiological image analysis, aligning with our findings that AI can effectively support diagnostic processes in dentistry [193].

In dental research, Lee et al. (2018) reported that a CNN-based AI system achieved high agreement values with periodontists for diagnosing periodontally compromised teeth, with kappa values of 0.828 and 0.797 for premolars and molars, respectively [147]. While our AI model's kappa value of 0.445 is moderate, it demonstrates significant potential for further refinement and improvement. This analysis underscores the diagnostic capabilities of periodontists, GPs, and AI in comparison to an expert. While periodontists show the highest agreement, the AI system demonstrates promising results, potentially serving as a valuable diagnostic tool. GPs, although showing lower agreement, still provide a significant level of diagnostic accuracy. These findings emphasize the importance of specialized training and the potential of AI to augment diagnostic processes in periodontal care.

The discrepancy between matrix performance and clinical accuracy can be attributed to several factors. First, differences between controlled environments and real-world variability play a significant role. In experimental settings, data is often curated and preprocessed to optimize model performance. In contrast, clinical environments present numerous uncontrolled variables, such as varying patient positioning, and inconsistent imaging quality. These factors can adversely impact the performance of AI models trained under controlled conditions [194]. Second, the preprocessing steps used in studies, such as noise reduction, contrast enhancement, and normalization, ensure high-quality inputs for AI models. However, in clinical practice, such preprocessing may not be consistently applied, leading to suboptimal inputs and consequently lower accuracy [195]. Third, AI models often perform well on the datasets they were trained on but may struggle to generalize across diverse patient populations with different demographic characteristics, oral health conditions, and comorbidities. The training data might not fully represent the variability encountered in real clinical settings [196]. Moreover, clinical diagnoses involve more than just interpreting radiographs; they require a comprehensive assessment of the patient's medical history, symptoms, and other diagnostic tests. While AI models are proficient at image analysis, they lack the ability to integrate this holistic approach, which can limit their effectiveness in real-world diagnostics [197].

Additionally, we conducted the clinical implementation by calculating a larger sample size for comparison among groups, resulting in an adjusted error rate of 15%, which equated to 281 previously unseen panoramic images (Table 7). In this study, however, we utilized a total of 300 previously unseen panoramic images to compare the diagnostic accuracy of the AI model and periodontists against expert periodontists. The results from this study underscore the diagnostic capabilities of the AI model when compared to periodontists and expert periodontists in diagnosing periodontitis. The findings revealed a moderate agreement between assessments made by expert periodontists and those of regular periodontists, with a Cohen's kappa coefficient of

0.530, indicating a notable level of consistency in diagnosing various stages of periodontitis (Table 18). Similarly, the AI model demonstrated a kappa coefficient of 0.497, suggesting that the model's diagnostic performance is comparable to that of trained periodontists, aligning with findings from previous studies that highlight the potential of AI in enhancing diagnostic accuracy in dentistry [198, 199].

The accuracy rates reported in this study are particularly compelling, with the AI model achieving an impressive accuracy of 97% and a sensitivity of 100% (Table 19). This performance surpasses that of the periodontists, who had an accuracy of 87.3% and a sensitivity of 88.3%. The positive predictive value of the AI model was also high at 97%, indicating that when the AI model predicts the presence of periodontitis, it is likely to be correct. These results are consistent with other research that shows AI can achieve diagnostic performance levels similar to or exceeding those of human practitioners in the detection of dental diseases [200, 201].

Moreover, the study highlights the pressing need for the integration of advanced AI technologies in clinical settings to address limitations of current diagnostic methods, such as variability in human judgment and the time constraints faced by practitioners. This alignment with contemporary research emphasizes the potential of AI not only to augment diagnostic processes but also to promote more efficient treatment planning and patient management [202].

Based on the findings presented in the present and previous studies, it's quite clear that AI-assisted technologies significantly improve the detection of periodontal bone loss from panoramic radiographs, thereby enhancing periodontitis diagnosis, as detailed in Table 21 [203]. Given these challenges, the future direction of periodontitis diagnosis appears to lean towards using AI to develop supportive diagnostic tools.

Table 21: Advantages of AI-assisted technologies in detecting periodontal bone loss from panoramic radiographs significantly enhance the diagnosis of periodontitis [203]

Advantages	Roles of AI
1. Automated Detection	AI algorithms can automatically identify signs of bone loss, highlighting areas of concern for further examination by dental professionals.
2. Increased Accuracy	By analyzing subtle differences in radiographic images that may not be easily visible to the human eye, AI improves the accuracy of periodontitis diagnosis.
3. Time Efficiency	AI reduces the time needed for manual analysis of radiographs, enabling quicker diagnosis and allowing dentists to focus on treatment planning.
4. Consistency	AI offers consistent evaluation across different cases and patients, reducing variability that can arise from individual clinician assessments.
5. Progress Monitoring	AI can track changes in bone levels over time, aiding in the monitoring of disease progression or the effectiveness of treatment.
6. Enhanced Visualization	Some AI tools provide enhanced imaging capabilities, making it easier to visualize and understand the extent of periodontal bone loss.

The integration of AI and machine learning in dental diagnostics, particularly in periodontology, has shown promising results. The prevalence of periodontal disease, especially in the elderly, underscores the necessity for innovative diagnostic tools to enhance detection accuracy and efficiency. The study demonstrated that AI models could significantly improve the detection of periodontal bone loss from panoramic radiographs, offering several advantages over traditional diagnostic methods. AI algorithms can automatically identify signs of bone loss, providing consistent and accurate evaluations that reduce variability in clinical assessments. These tools can process large datasets quickly, enabling faster diagnosis and allowing dental professionals to focus on treatment planning. The enhanced visualization capabilities of AI tools also aid in better understanding the extent of periodontal bone loss, thereby improving patient outcomes.

One of the most significant issues highlighted by this study is the high prevalence of periodontal disease, particularly in developing countries like Thailand. According to the Bureau of Dental Health, Department of Health, the National Oral Health Survey conducted every five years indicates that the prevalence of periodontitis in Thailand is higher than the global average reported by the World Health Organization (WHO) [23]. The Global Burden of Disease Study reported that severe periodontal disease affects 19% of adults worldwide, over 1 billion people, making it the 11th most prevalent disease globally [24, 25]. However, the latest survey in 2023 revealed that 48.7% of older patients in Thailand suffer from periodontitis, an increase from 36.3% in the previous survey. The highest prevalence was found in the Northern Region at 58.4%, followed by the Southern Region at 56.7%, the North-Eastern Region at 47.1%, and the Central Region at 42.3% [23].

These alarming statistics underscore the urgent need for improved disease prevention and highlight the importance of periodontal health. The AI models developed in this study offer a promising solution by providing quicker, less labor-intensive, and more precise alternatives to current approaches. This is crucial for treatment planning, helping dentists decide on the management of periodontal disease, including whether to retain or extract affected teeth immediately after uploading the panoramic radiograph into the developed AI software for each patient. If the Ministry of Public Health, as the central policy-maker, prioritizes this critical issue and supports the deployment of our AI model nationwide and globally, we could significantly reduce the prevalence of periodontal disease, thereby improving the overall quality of life for the population.

Despite these advancements, the implementation of AI in dental diagnostics faces several challenges. One primary challenge is the variability in image quality and the need for standardized imaging protocols to ensure the consistency of AI model outputs. Additionally, there is a need for comprehensive training datasets that encompass a wide range of demographic and clinical scenarios to enhance the generalizability of AI models.

Limitations

The current study faced several limitations that need to be addressed in future research. Firstly, future studies should include comparisons with a broader range of dental professionals, including general practitioners and specialist dentists, to validate the AI models comprehensively.

Secondly, the study relied on panoramic radiographs from a single imaging device, which might limit the generalizability of the findings. Different imaging devices may produce variations in image quality and resolution, impacting the performance of AI models. Future research should test the AI models on panoramic radiographs obtained from various imaging devices to ensure robustness and applicability across different clinical settings.

Another limitation is the exclusion of certain patient demographics, such as those with rare bone morphologies or incorrect patient positioning during imaging. Including a more diverse patient population in future studies will help in developing more comprehensive AI models that can handle a wider range of clinical scenarios.

Future Research Directions

Future research should focus on several key areas to enhance the effectiveness and applicability of AI in periodontal diagnostics:

1. Comparative Studies: Conduct studies comparing the performance of AI models with various levels of dental expertise, including general practitioners, periodontists, and other dental specialists. This will provide a more comprehensive validation of the AI models' effectiveness.

2. Standardization of Imaging Protocols: Develop standardized protocols for capturing panoramic radiographs to ensure consistency in image quality and resolution. This will help in minimizing variability and improving the accuracy of AI models across different clinical settings.

3. Incorporation of Advanced Techniques: Explore the use of advanced CNN architectures and algorithms to enhance the sensitivity and accuracy of AI models. Techniques such as transfer learning and ensemble learning could be investigated to improve model performance.

4. Extended Datasets: Include a more extensive and diverse dataset comprising various demographic and clinical scenarios. This will help in developing AI models that are more generalizable and capable of handling a wide range of periodontal conditions.

5. Integration with Other Diagnostic Tools: Investigate the integration of AI models with other diagnostic tools such as Cone Beam Computed Tomography (CBCT) and intraoral scanners. Combining multiple diagnostic modalities could provide a more comprehensive assessment of periodontal health.

6. Patient-Centric Applications: Develop AI applications that are user-friendly and accessible to patients. This could include mobile applications that allow patients to upload their radiographs for preliminary assessments, thereby promoting early detection and intervention.

Conclusion

The integration of artificial intelligence (AI) into periodontal diagnostics represents a significant advancement in enhancing diagnostic accuracy over current methods. The AI-driven models demonstrated impressive performances, affirming their role as valuable tools for dental professionals. This study introduces an innovative protocol for periodontal diagnosis and prognostication, optimizing the assessment process and providing a reliable resource for clinical practice.

Moreover, the comparative analysis indicates that AI models match or even exceed the diagnostic capabilities of general practitioners (GPs) and specialized periodontists, underscoring the transformative potential of AI in dental diagnostics. By incorporating AI technologies, dental practitioners can improve patient outcomes, minimize diagnostic errors, and streamline care delivery. Given the profound economic, social, and health implications of periodontal disease, especially among the elderly, the integration of AI not only enhances the precision and efficiency of diagnostics but also contributes to better patient quality of life. The findings of this study pave the way for future research into the long-term impacts of AI in dental health, highlighting the urgent need for innovative solutions that address the complexities of periodontal disease management within healthcare systems.

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APPENDIX

Ethics Approved

Fang Hospital

COA No. 03/2566

ETHICAL REVIEW BOARD

Fang hospital

30 M.4 chottana Rd, T.weing, Fang, Chiangmai 50110, Thailand, Tel. 053-451144

Certificate of Approval

The following study is certified by The Ethical Review Board of Fang hospital. The study follows the International guidelines for human research protection mentioned in The Declaration of Helsinki and The Belmont Report.

Study Title

: Periodontal Diagnosis and Prognostication Detection Using Medical Image Processing

Principal Investigator: MR.JARUPAT JUNDAENG

Office: Dental Department, Fang Hospital, Chiang Mai

Certified Documents

- Research project
- Researchers
- Information sheets
- Consent form
- Interview guidelines

Date of Approval: November 02, 2023

Approval Expire Date: November 03, 2024

Progression Report: The researcher must report the status of the study at least once a year or submit the final report if the project is completed in a year.

Signature ....

(Dr.Orawan Chaosawat)

Chairperson of Ethical Review Board

MAHASARAKHAM UNIVERSITY ETHICS COMMITTEE FOR RESEARCH INVOLVING HUMAN SUBJECTS

Certificate of Approval

Approval number: 533-589/2023

Title : Periodontal Diagnosis and Prognostication Detection Using Medical Image Processing.

Principal Investigator : Mr. Jarupat Jundaeng
Responsible Department : Faculty of Medicine
Research site : Dental Group, Fang Hospital, Chiang Mai Provincial Public Health Office

Review Method : Expedited Review

Date of Manufacture : 20 December 2023 **expire :** 19 December 2024

This research application has been reviewed and approved by the Ethics Committee for Research Involving Human Subjects, Mahasarakham University, Thailand. Approval is dependent on local ethical approval having been received. Any subsequent changes to the consent form must be re-submitted to the Committee.

Ratree S.

(Asst. Prof. Ratree Sawangjit)
Chairman

Approval is granted subject to the following conditions: (see back of this Certificate)

คณะกรรมการจริยธรรมการวิจัยในคน มหาวิทยาลัยธรรมศาสตร์ สาขาแพทยศาสตร์

ประกาศนียบัตรฉบับนี้ให้ไว้เพื่อแสดงว่า

จารุพัฒน์ จุลแดง

ได้ผ่านการอบรมหลักสูตร GCP online training (Computer-based)

"แนวทางการปฏิบัติการวิจัยทางคลินิกที่ดี (ICH-GCP:E6(R2))"

ประกาศนียบัตรฉบับนี้มีผลตั้งแต่วันที่ 18 มีนาคม 2566 ถึงวันที่ 18 มีนาคม 2568

(รองศาสตราจารย์ นายแพทย์ไวพจน์ จันทร์วิเมลือง)
ประธานคณะกรรมการจริยธรรมการวิจัยในคน
มหาวิทยาลัยธรรมศาสตร์ สาขาแพทยศาสตร์

(รองศาสตราจารย์ นายแพทย์สมบัติ มุ่งทวีพงษา)
รองคณบดีฝ่ายวิจัยและนวัตกรรม

This is a consent letter for data collection for the research project titled "Periodontal Diagnosis and Prognostication Detection Using Medical Image Processing," granted by the director of Fang Hospital, Chiang Mai, Thailand (No. 0033.306/3674).

ที่ ชม ๐๐๓๓.๓๐๖/ ๓๖๗๔

โรงพยาบาลฝาง ถ.โชตนา
อ.ฝาง จ.เชียงใหม่ ๕๐๑๑๐

๒๑ พฤศจิกายน ๒๕๖๖

เรื่อง อนุญาตให้เก็บข้อมูลวิทยานิพนธ์ดุษฎีบัณฑิต

เรียน คณบดีคณะแพทยศาสตร์ มหาวิทยาลัยมหาสารคาม

อ้างถึง หนังสือคณะแพทยศาสตร์ มหาวิทยาลัยมหาสารคาม ที่ อว ๐๖๐๕.๒๐/๔๗๔๒
ลงวันที่ ๒๐ พฤศจิกายน ๒๕๖๖

ตามหนังสือที่อ้างถึง คณะแพทยศาสตร์ มหาวิทยาลัยมหาสารคาม ได้ขอความอนุเคราะห์ให้ทันตแพทย์จารุพัฒน์ จุลแดง นิสิตระดับปริญญาเอก เก็บข้อมูลวิทยานิพนธ์ดุษฎีบัณฑิต เรื่อง การวินิฉัยโรคปริทันต์และการพยากรณ์โรคโดยใช้การประมวลผลภาพทางการแพทย์ ซึ่งได้ผ่านการนำเสนอโครงร่างวิทยานิพนธ์และได้รับอนุมัติจริยธรรมวิจัย แล้วนั้น

ในการนี้ โรงพยาบาลฝาง ยินดีให้ทันตแพทย์จารุพัฒน์ จุลแดง เก็บข้อมูลวิทยานิพนธ์ดุษฎีบัณฑิต ตามวัน เวลาและสถานที่ดังกล่าว

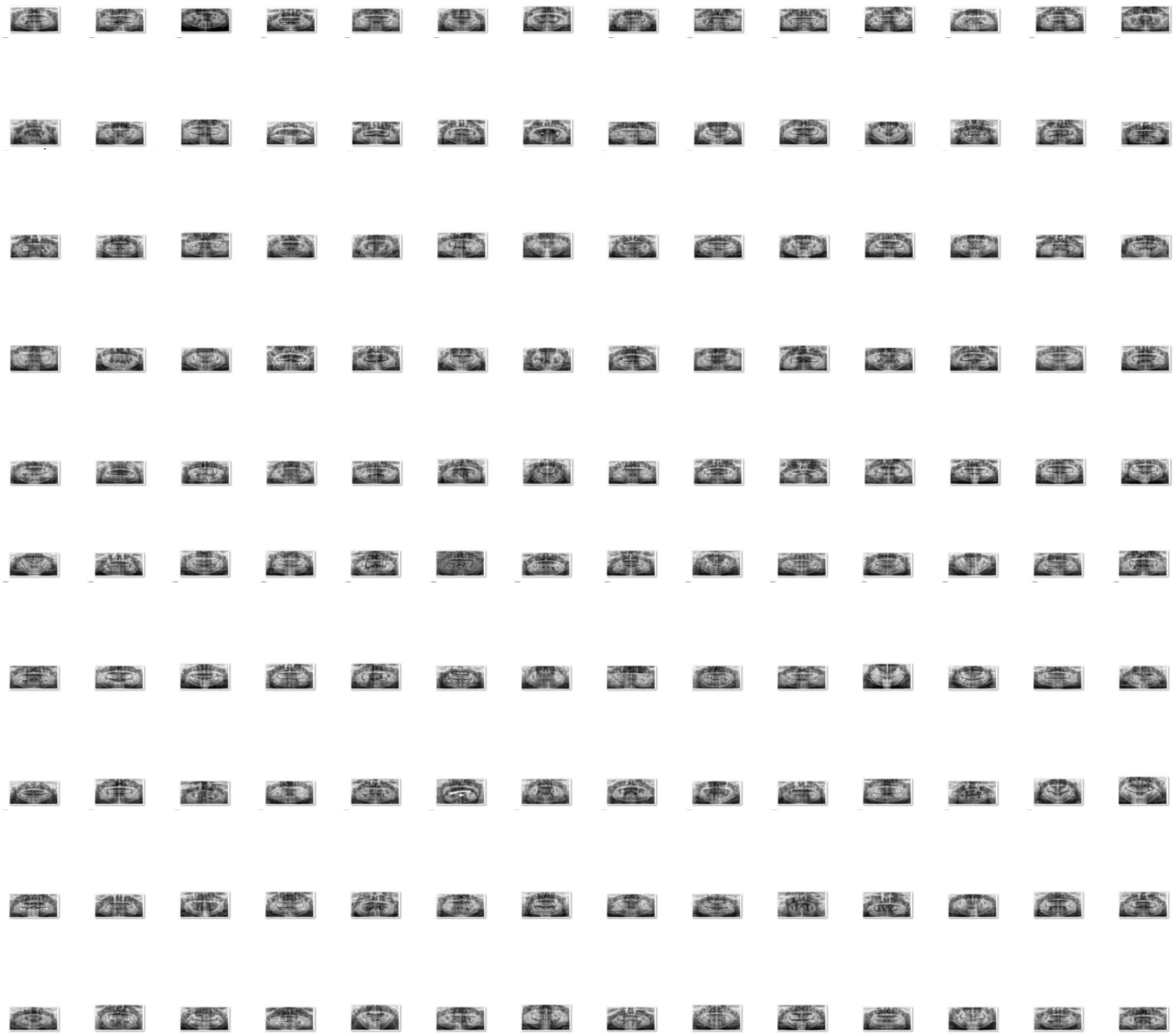
จึงเรียนมาเพื่อโปรดทราบ

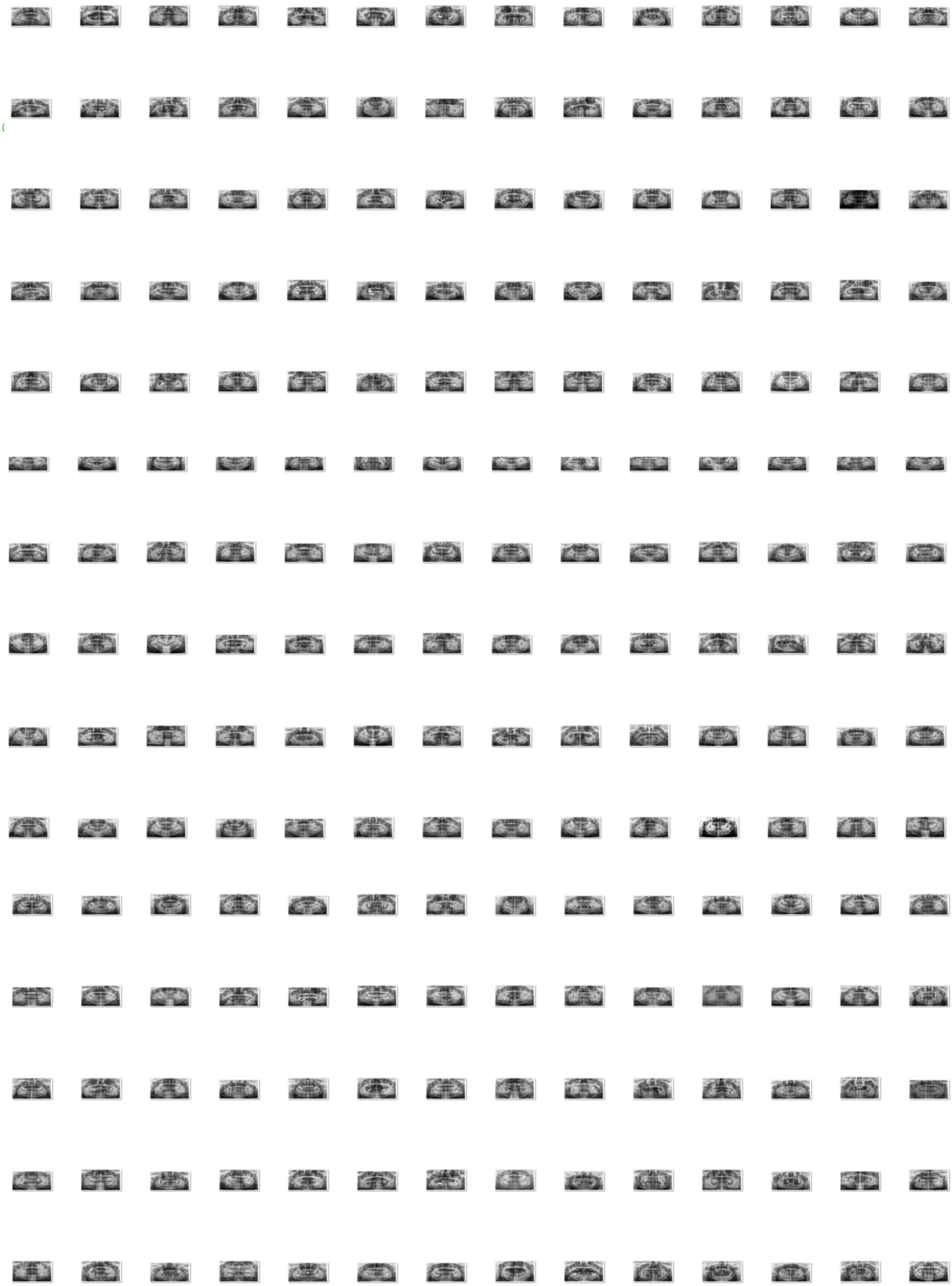
ขอแสดงความนับถือ

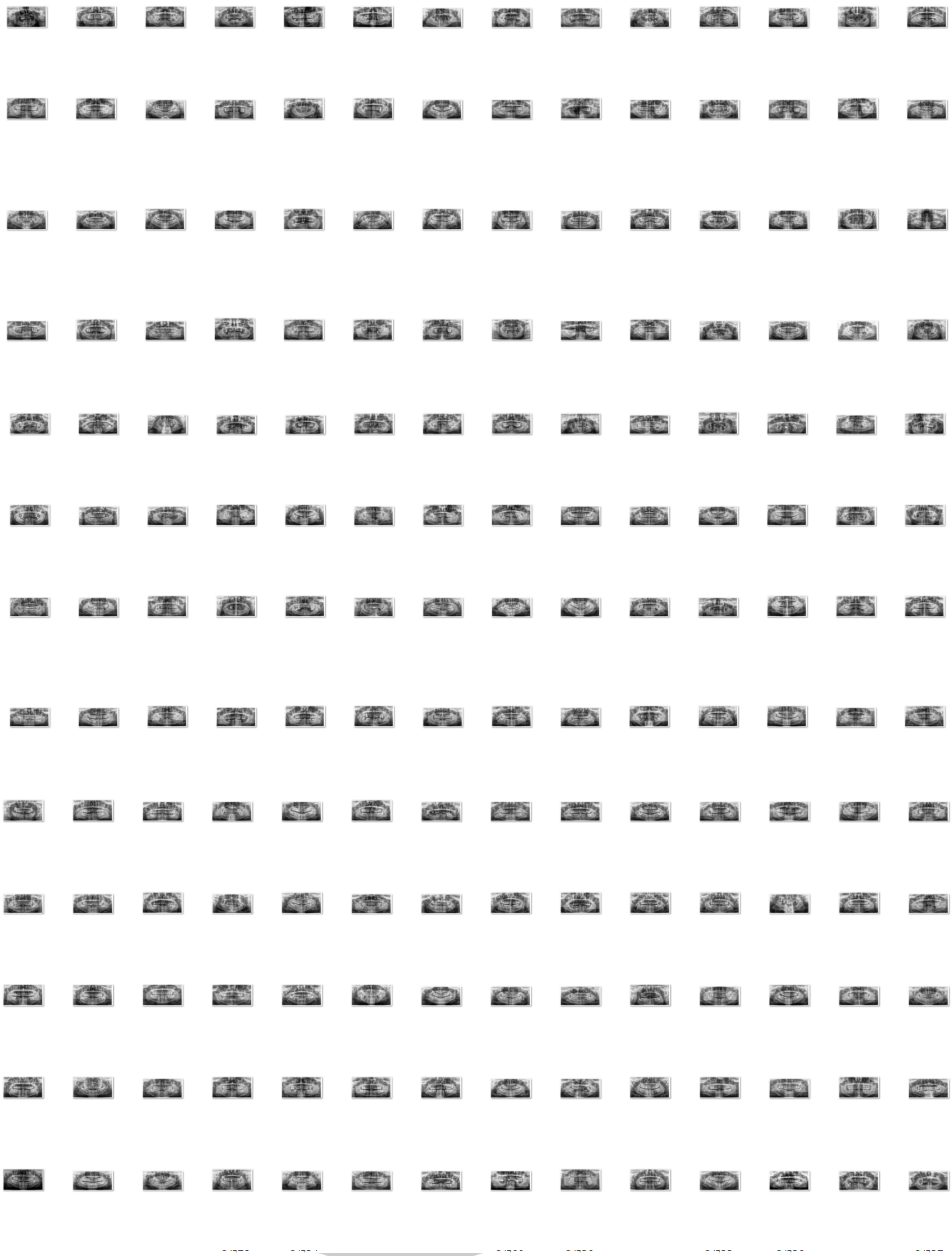
(นายวิชญ์ สิริโรจน์พร)
ผู้อำนวยการโรงพยาบาลฝาง

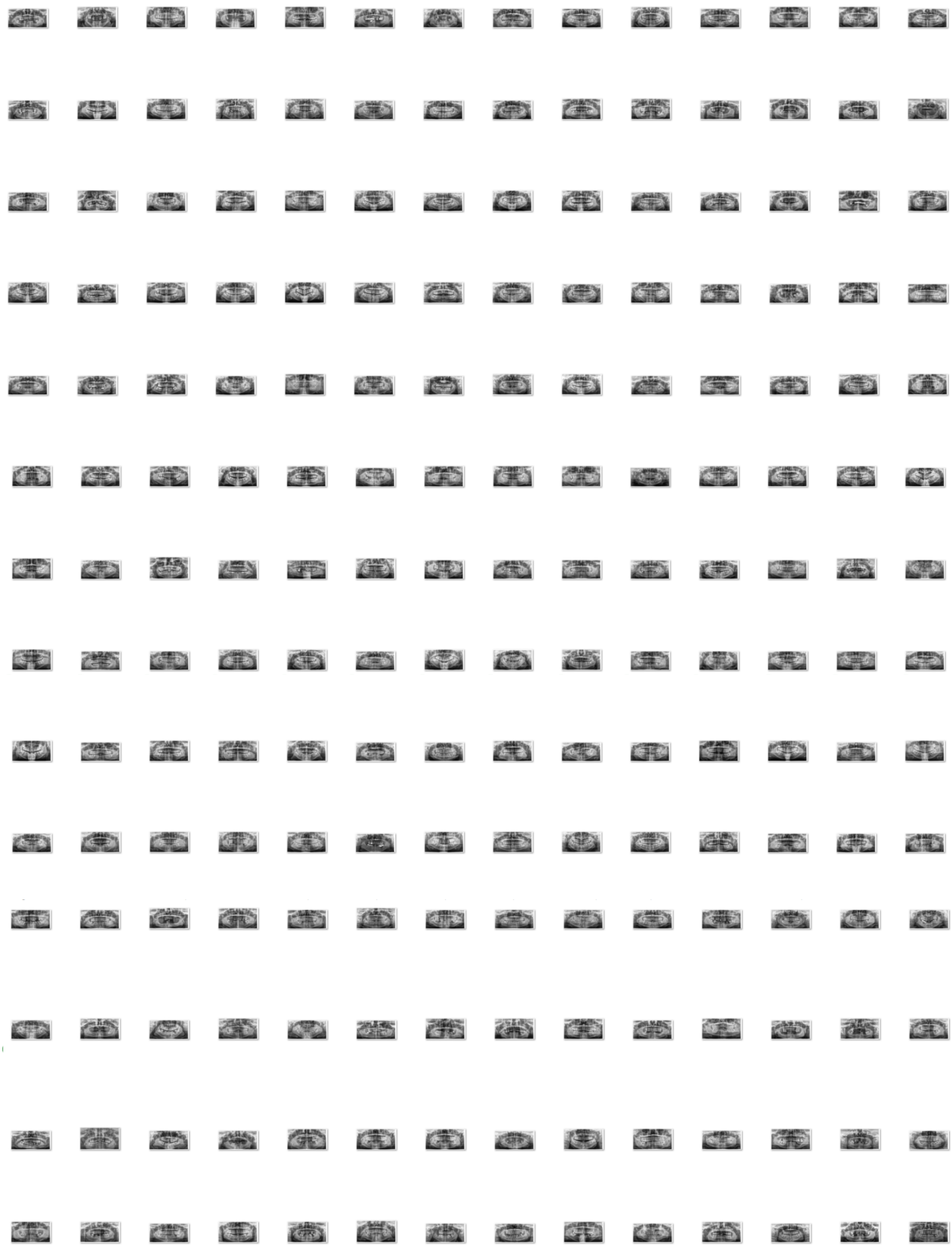
กลุ่มงานทันตกรรม
โทร ๐ ๕๓๔๕ ๑๑๔๔ , ๐ ๕๓๔๕ ๑๔๔๔ ต่อ ๒๖๒
โทรสาร ๐ ๕๓๔๕ ๑๑๕๒
ไปรษณีย์อิเล็กทรอนิกส์ : dentalfang@gmail.com

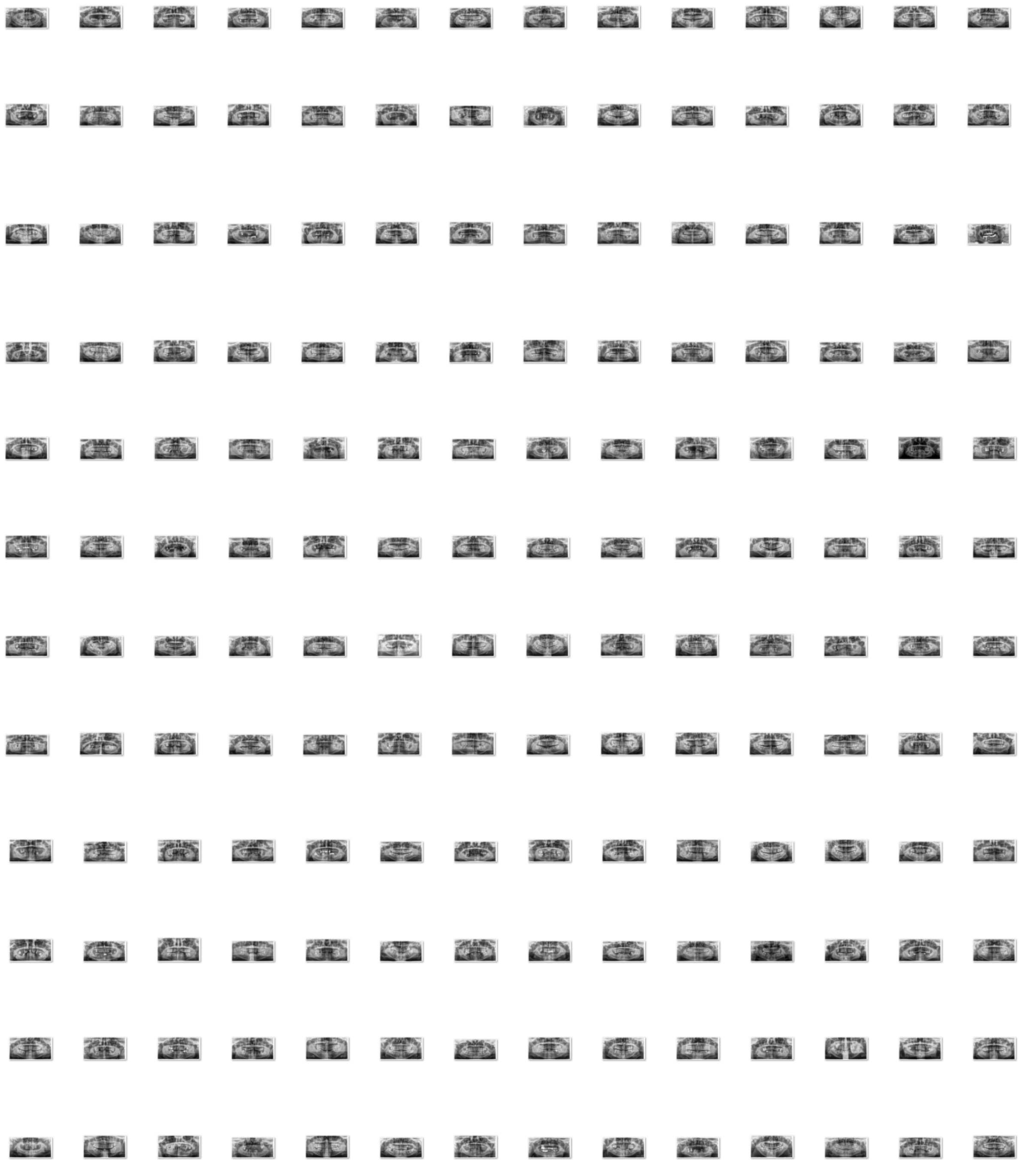
The dataset of 2000 panoramic radiographs from the SIDEXIS Next Generation Program

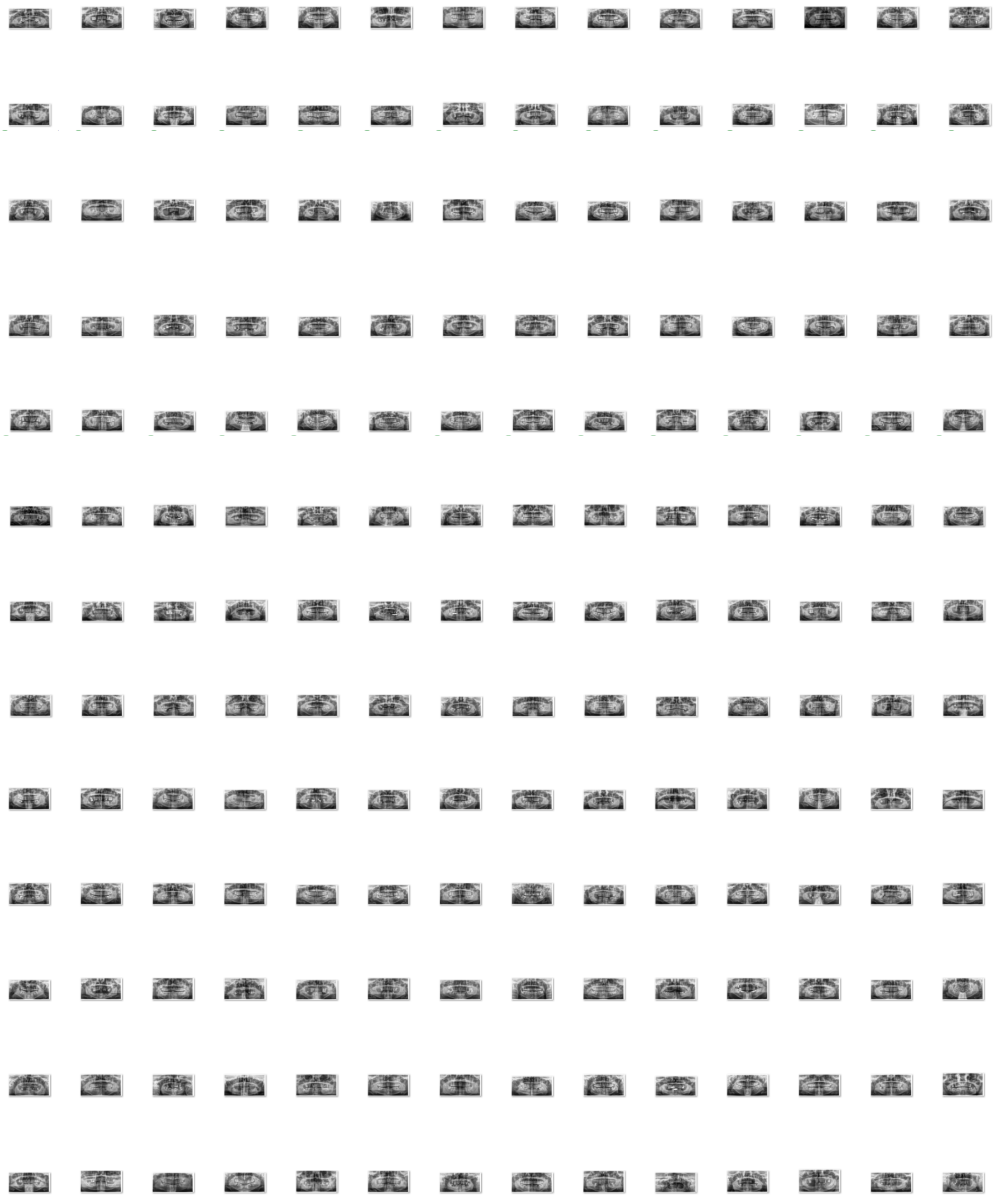


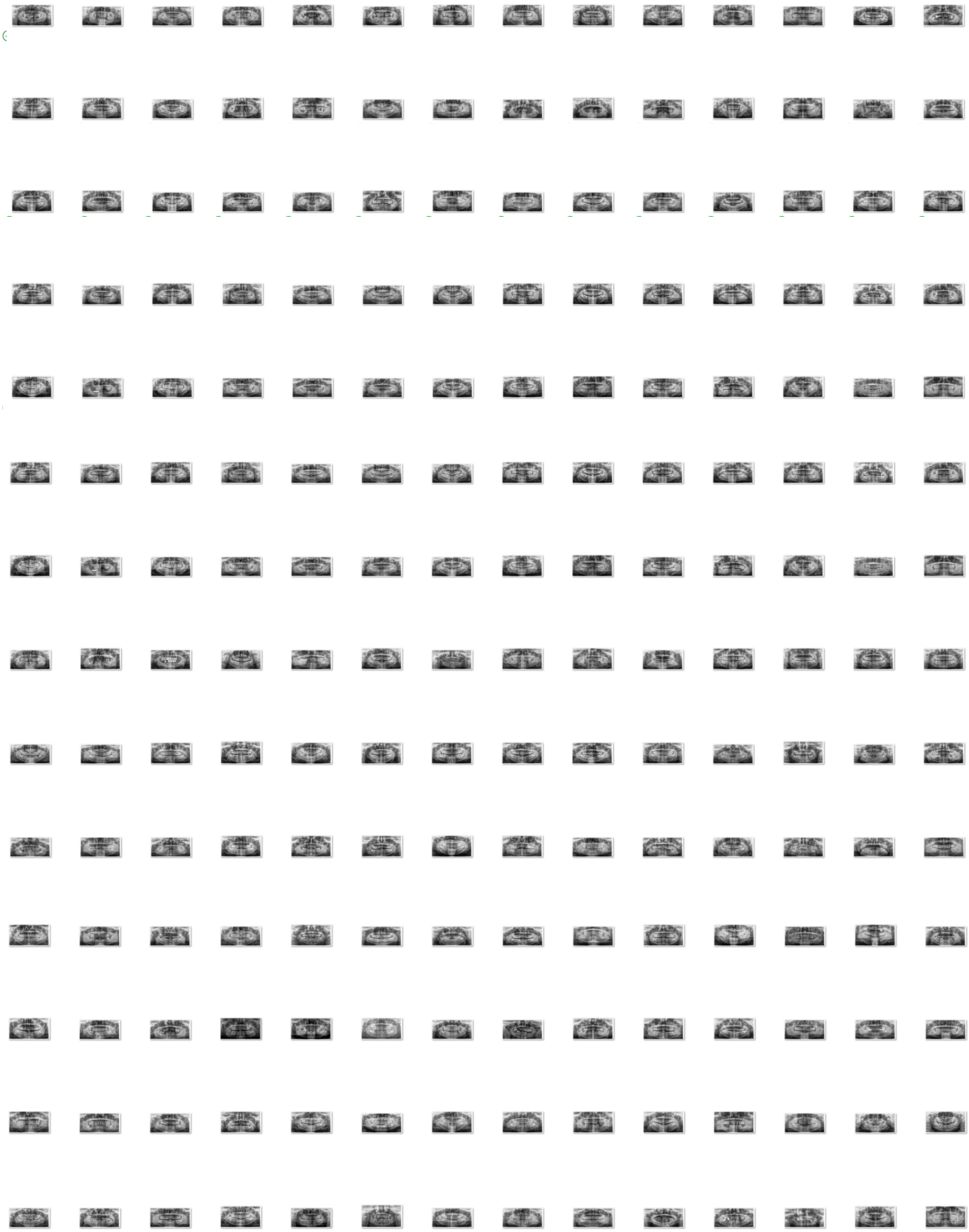


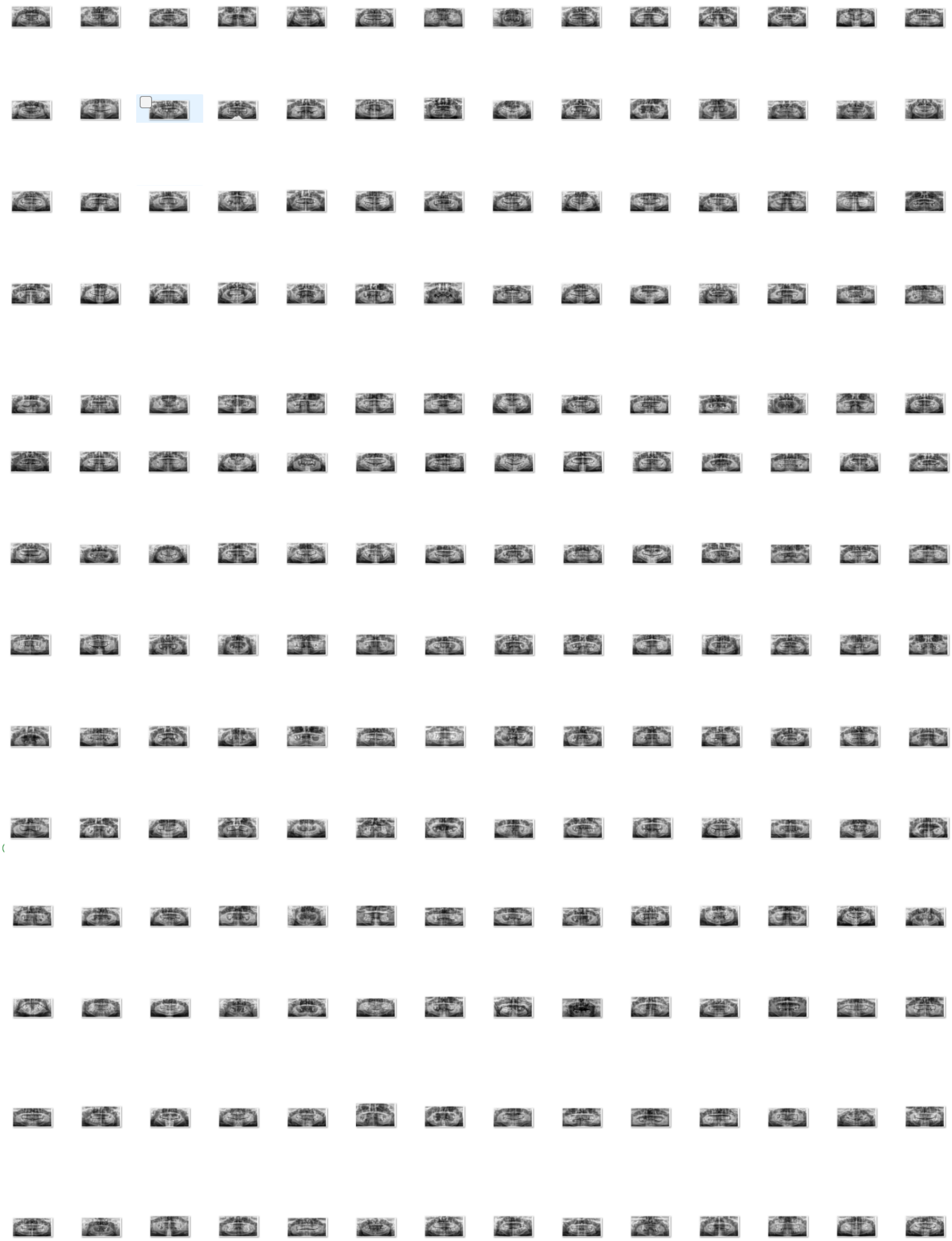


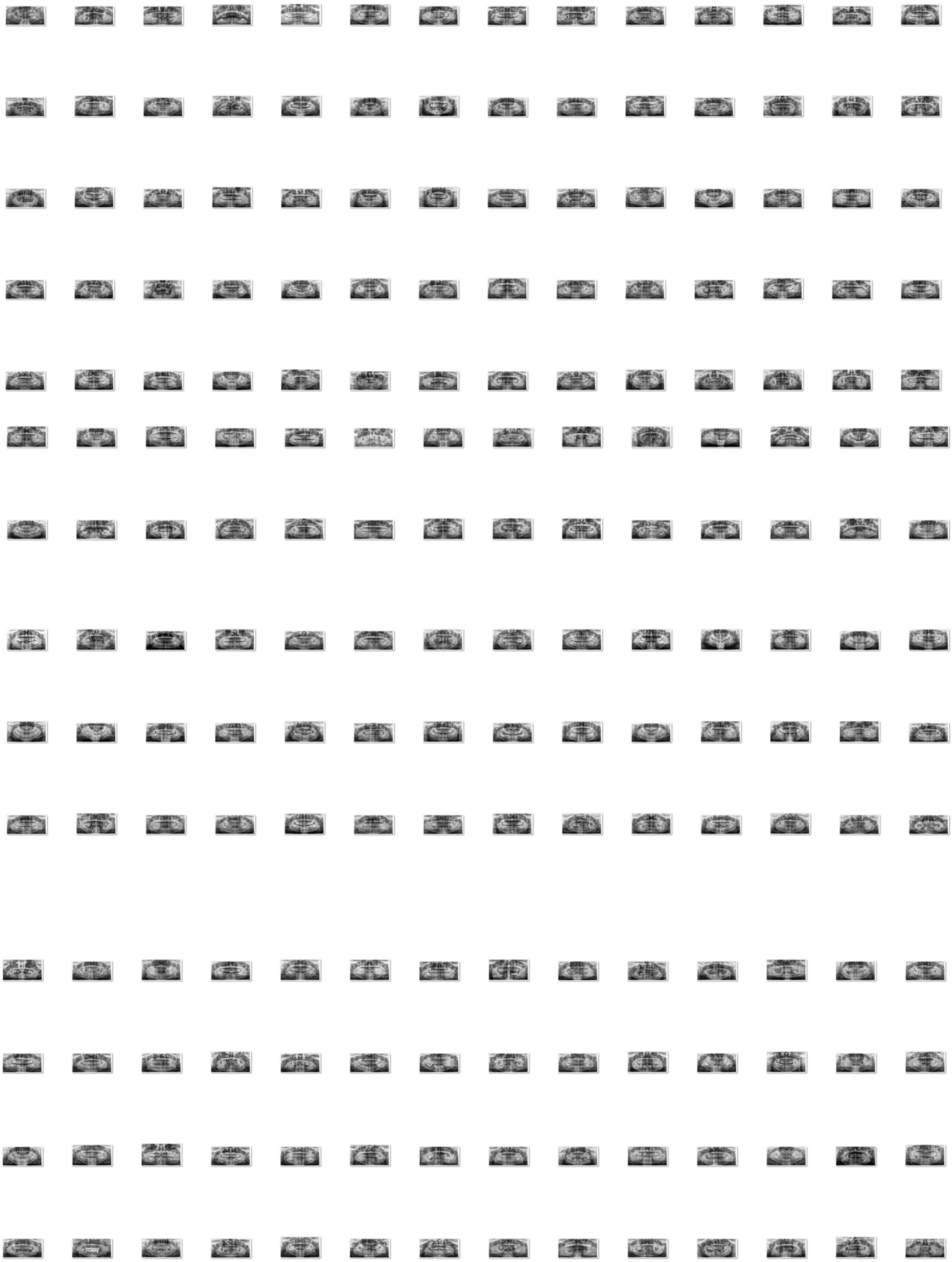


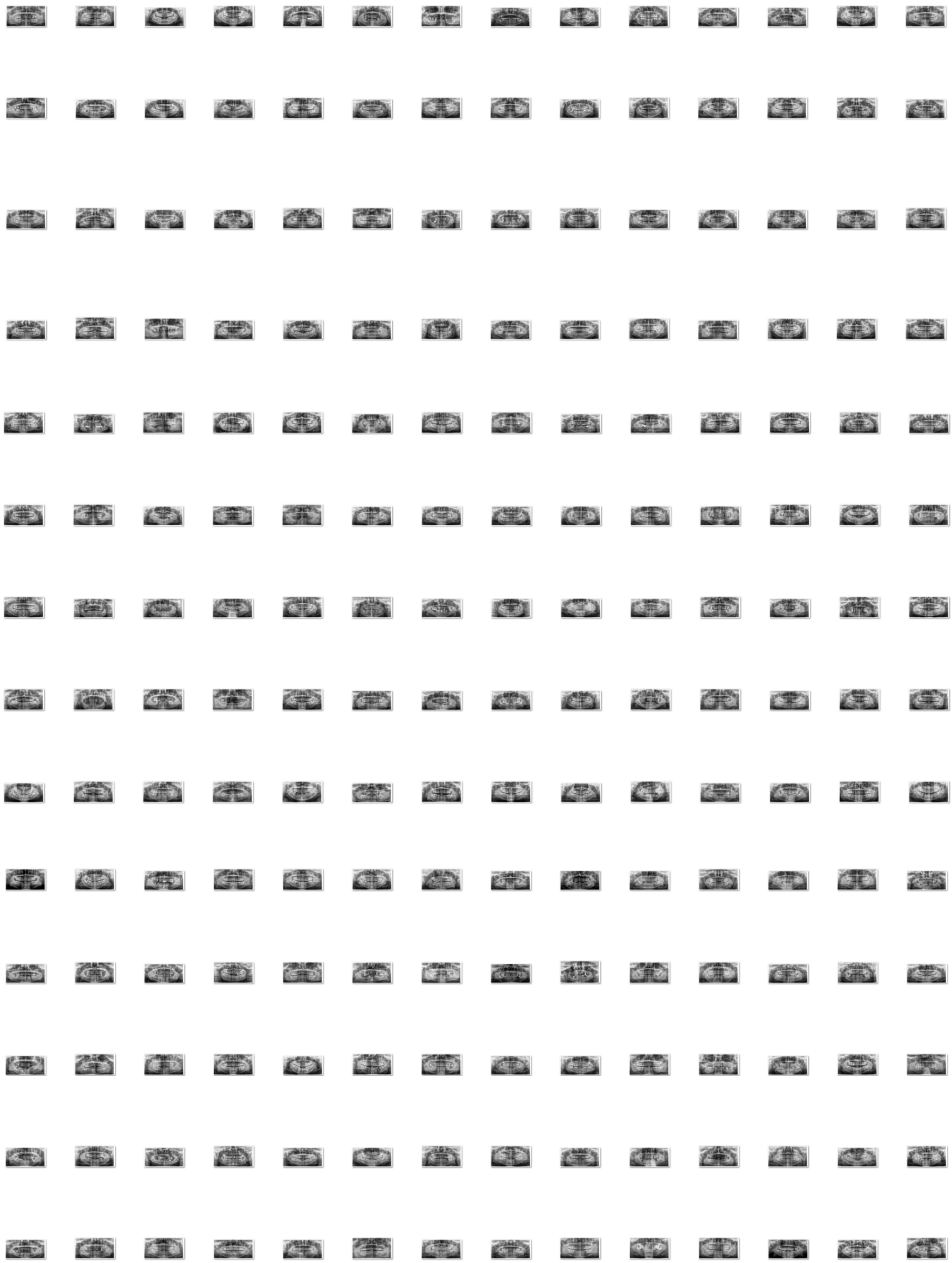


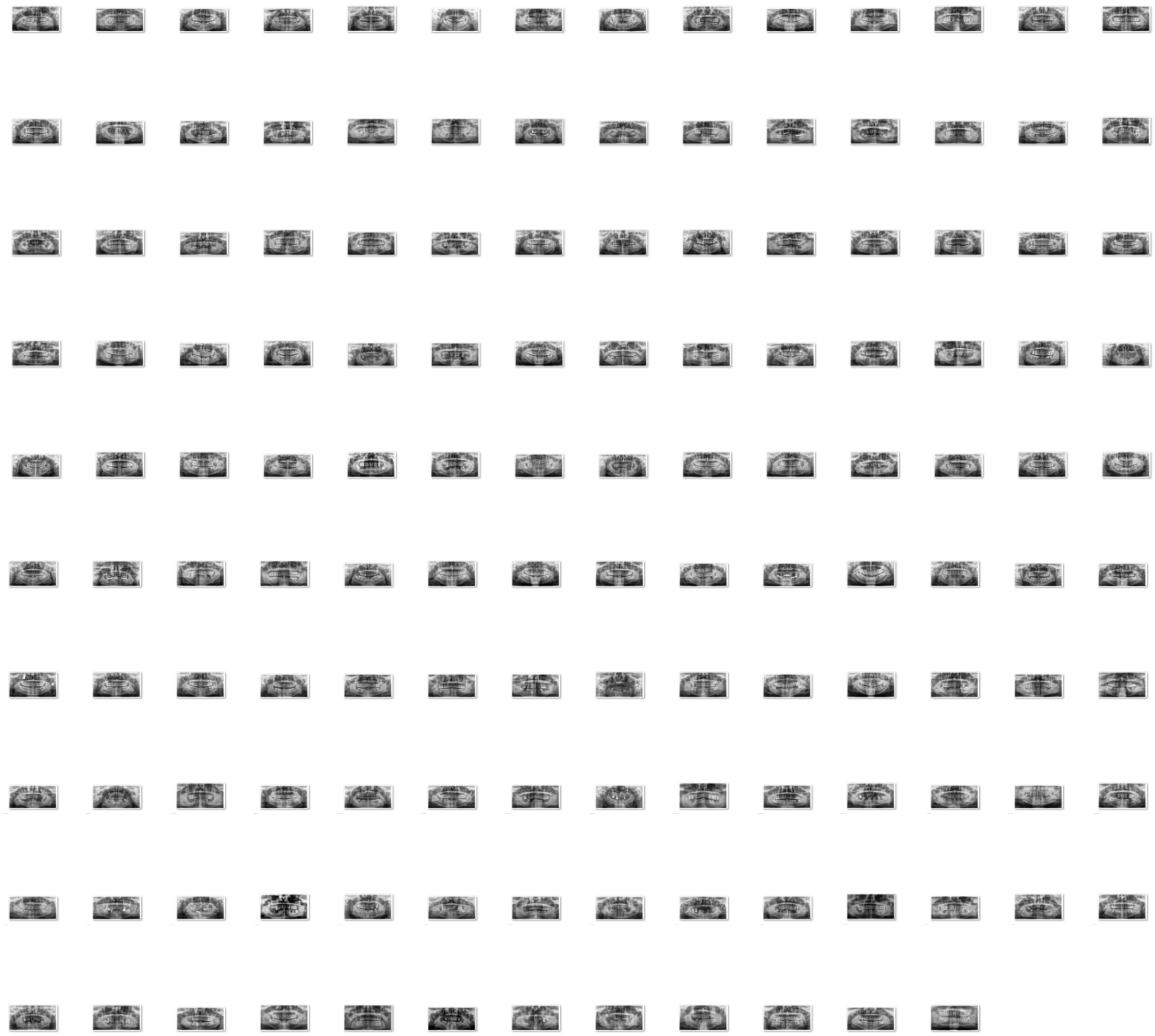




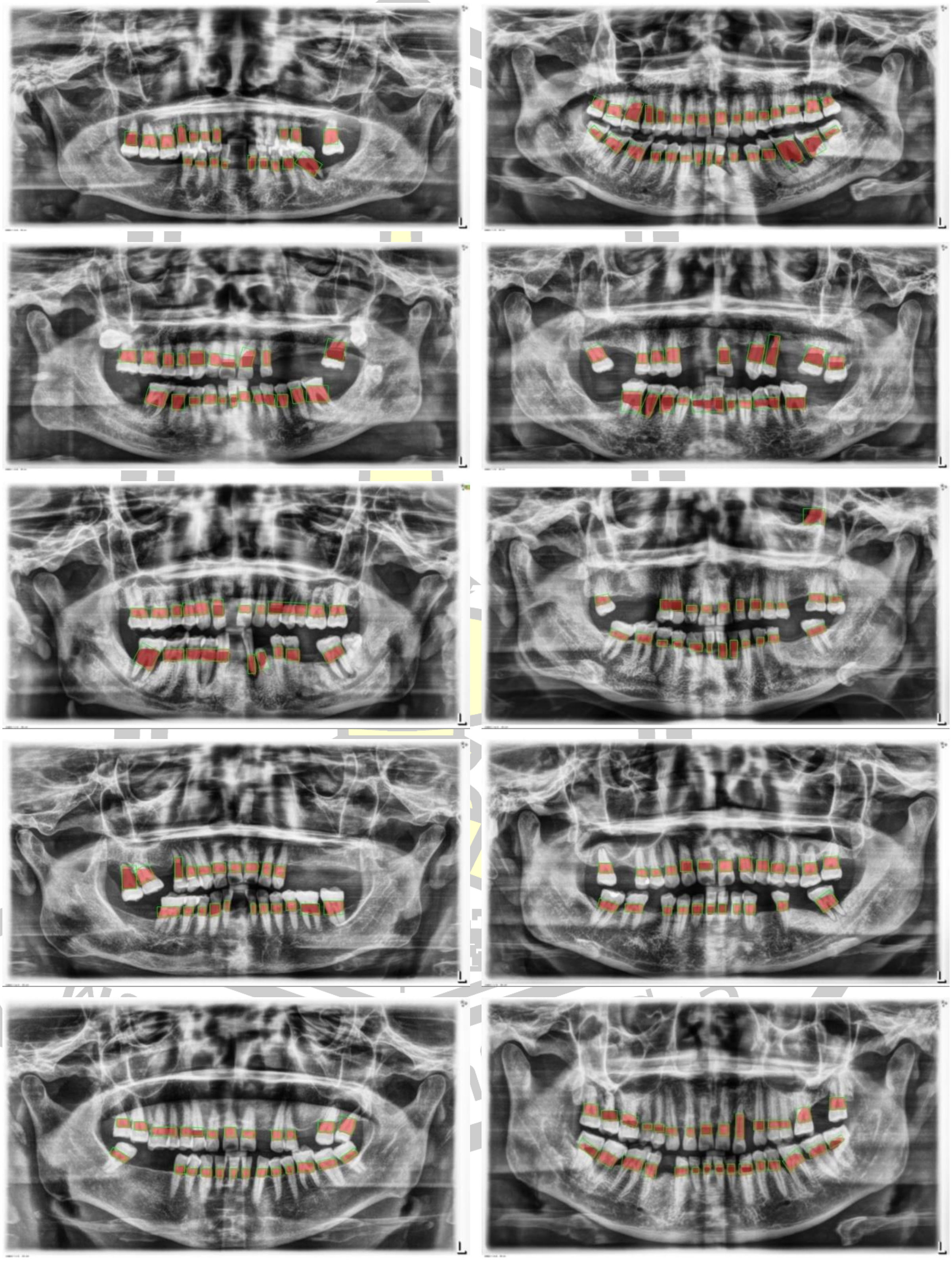


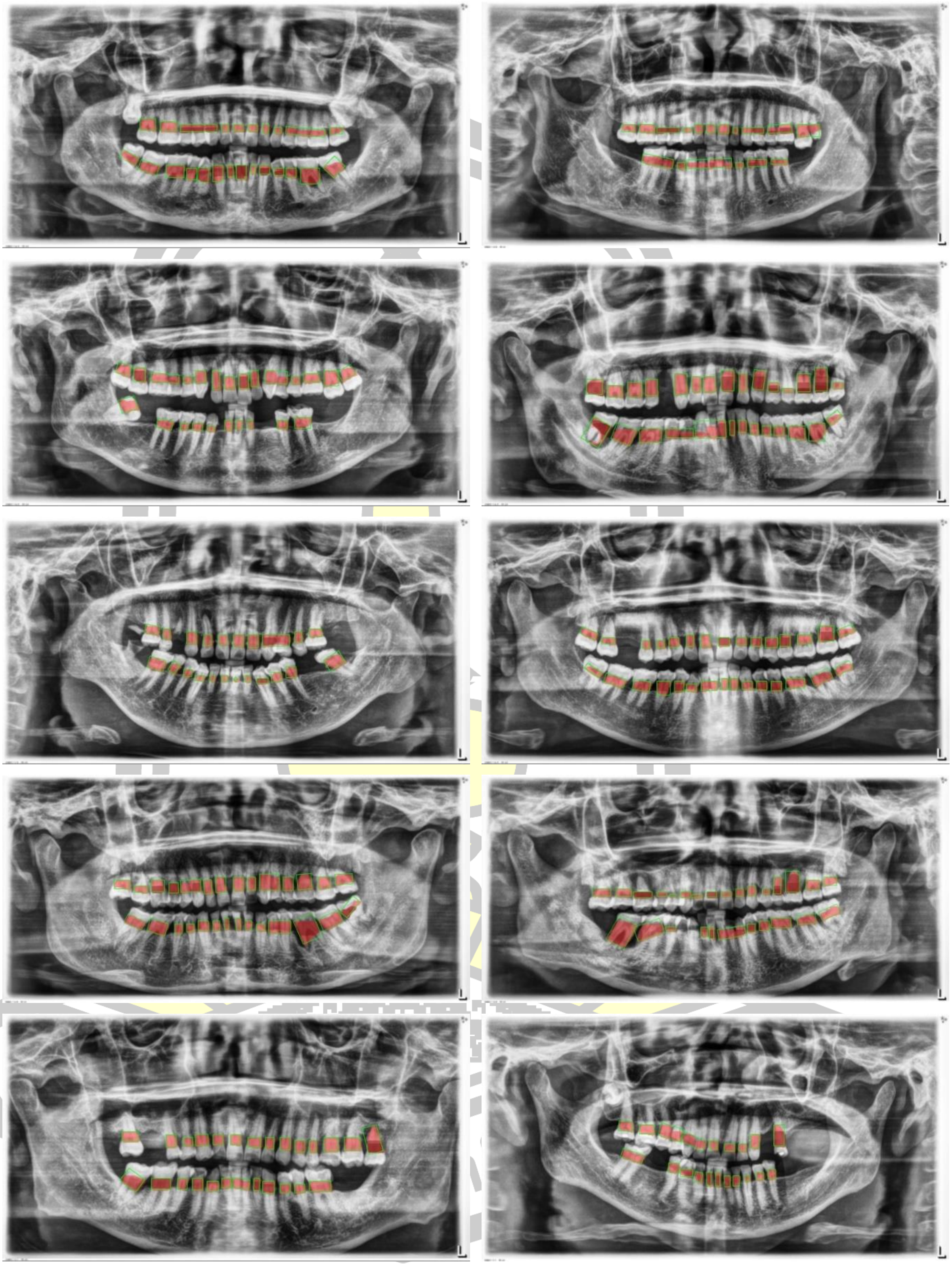


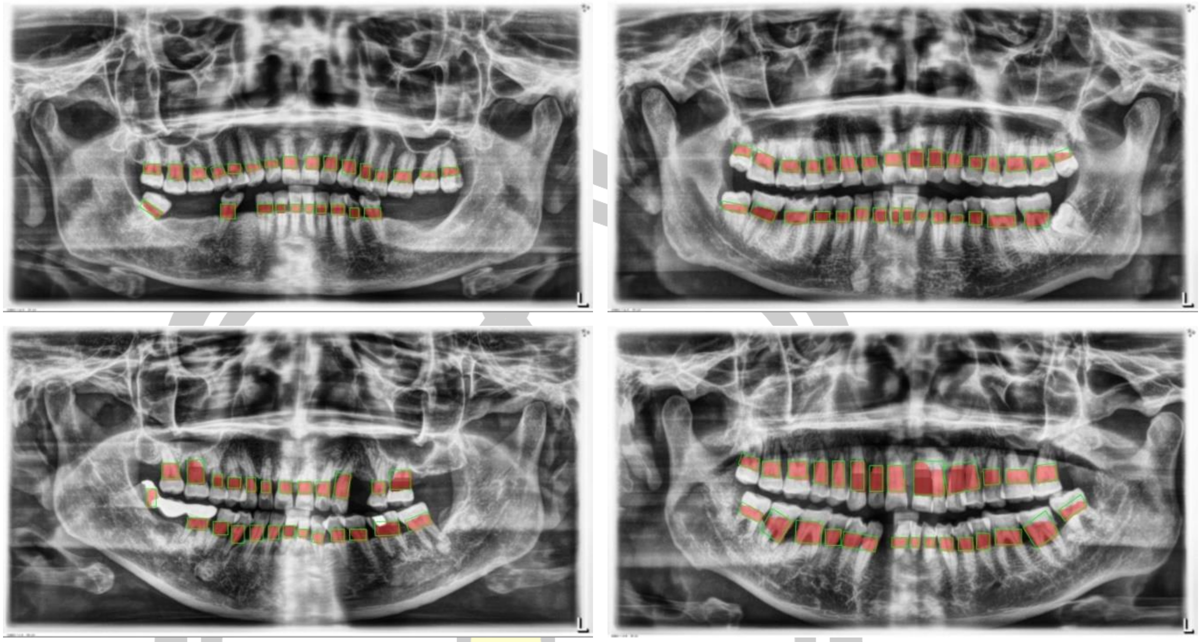




Examples of AI results in detecting the distance from the CEJ to crestal bone







A total of 90 images were used in the clinical implementation to compare the accuracy of periodontitis diagnosis between the AI model, general practitioners (GPs), and periodontists against expert periodontists.

ID	HN	Code	Sex	Age	Periodontist	GPs	AI	Expert
1	60143	1	1	18	0	0	2	0
2	60170	2	1	23	0	0	2	0
3	60381	3	1	45	3	3	2	3
4	330377	4	1	44	0	1	2	2
5	60682	5	1	22	0	0	1	1
6	66150	6	2	38	3	2	2	2
7	61196	7	2	19	0	0	2	2
8	61351	8	1	18	0	1	3	3
9	56862	9	2	54	3	4	3	3
10	199709	15	2	41	2	2	2	2
11	120959	19	2	60	3	3	4	3
12	67506	23	2	59	2	2	3	3
13	67783	25	1	27	0	0	2	2
14	67887	25	1	42	3	3	3	3
15	69235	27	1	38	2	1	2	2
16	110450	27	1	66	3	2	2	3
17	69258	28	1	39	2	1	2	2
18	236897	28	2	63	3	2	3	3
19	15893	30	1	51	2	3	2	2
20	71353	31	1	24	0	0	2	2
21	164875	35	1	41	3	3	3	3
22	439251	37	2	61	2	2	3	3
23	440567	39	2	53	2	3	3	3
24	441900	40	2	32	1	0	2	2
25	187435	41	2	57	3	3	3	3

ID	HN	Code	Sex	Age	Periodontist	GPs	AI	Expert
26	442741	42	2	45	3	3	3	3
27	445491	44	2	23	1	0	3	1
28	44708	45	2	28	1	1	2	2
29	447490	47	2	57	2	2	2	2
30	165557	48	2	48	3	3	3	3
31	447725	49	2	42	3	3	3	3
32	447798	50	2	76	4	4	3	4
33	447841	51	1	28	1	1	2	2
34	448319	53	2	19	2	0	2	2
35	448945	54	1	44	1	2	2	2
36	449991	55	2	48	2	3	3	3
37	451129	58	1	60	2	1	3	2
38	452657	59	1	69	2	2	2	2
39	456846	62	2	26	2	1	3	2
40	460024	64	1	68	3	4	2	3
41	462094	65	2	19	0	0	2	2
42	465008	67	2	55	3	2	2	3
43	465631	68	2	28	3	1	3	3
44	466578	69	1	34	3	3	3	3
45	466602	70	1	63	3	3	3	3
46	467098	71	1	34	1	1	3	1
47	467099	72	1	54	3	3	3	3
48	468491	73	2	67	2	2	3	3
49	468673	74	2	52	3	1	2	3
50	471611	75	2	40	2	1	2	2
51	472466	76	2	33	2	1	2	2
52	473563	77	2	20	1	1	2	2
53	473726	78	1	25	1	0	3	1

ID	HN	Code	Sex	Age	Periodontist	GPs	AI	Expert
54	474492	79	1	40	2	2	3	2
55	173676	79	1	58	3	2	3	3
56	480322	80	2	47	3	2	3	3
57	484910	81	1	57	3	2	2	3
58	489081	82	1	44	3	3	3	3
59	490238	83	1	24	1	0	3	1
60	49316	84	1	39	2	2	2	2
61	160737	84	1	39	3	2	3	3
62	493573	85	2	38	2	0	3	2
63	496926	86	2	51	3	3	3	3
64	498691	87	1	31	2	2	3	3
65	501425	88	1	60	3	3	3	3
66	503182	89	1	24	1	2	2	2
67	503203	90	1	57	2	1	3	2
68	503694	91	2	51	3	1	2	2
69	505894	92	1	64	2	2	3	2
70	18872	92	2	59	3	3	3	3
71	508204	93	1	57	3	3	3	3
72	113087	93	2	58	2	2	3	3
73	512236	94	2	36	1	1	2	2
74	181505	94	2	53	2	1	2	2
75	53268	95	1	54	3	3	3	3
76	106120	96	2	18	0	0	2	0
77	106545	97	1	80	2	3	4	2
78	107410	98	1	20	0	0	3	0
79	10783	99	2	22	1	0	2	2
80	107916	100	1	58	2	2	2	2
81	105554	100	2	48	3	2	3	3

ID	HN	Code	Sex	Age	Periodontist	GPs	AI	Expert
82	10898	101	1	28	0	3	2	2
83	144873	101	2	68	3	4	4	3
84	109191	102	1	61	3	3	3	3
85	109545	103	1	18	0	0	2	0
86	18885	110	1	49	3	3	3	3
87	118857	124	1	37	3	2	3	3
88	52749	229	1	59	3	3	3	3
89	53302	236	2	48	2	2	2	2
90	53416	241	1	56	2	2	3	3

Legend: 0 represents Non-periodontitis, 1 represents Periodontitis Stage I, 2 represents Periodontitis Stage II, 3 represents Periodontitis Stage III, and 4 represents Periodontitis Stage IV.

A total of 90 images represented the AI model's results in diagnosing periodontitis during clinical implementation.

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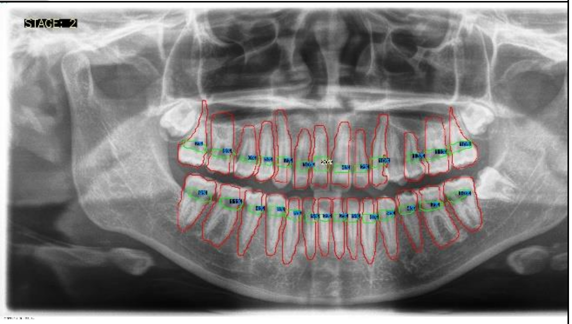
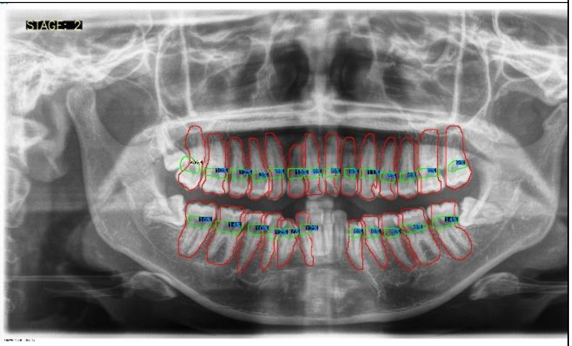
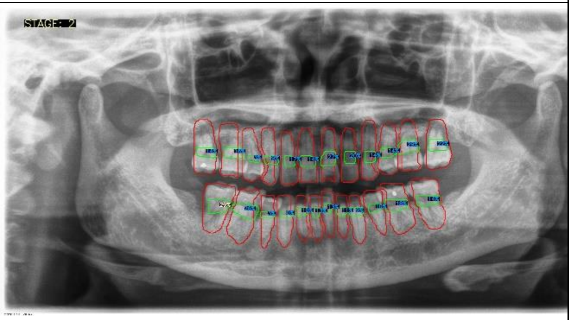
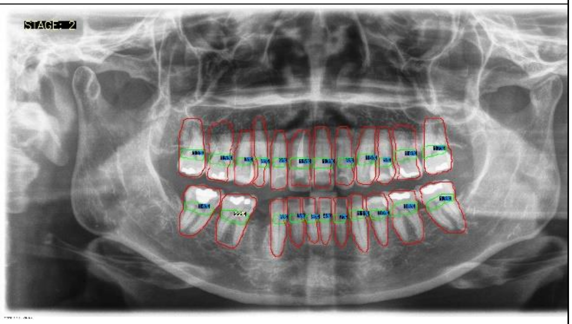
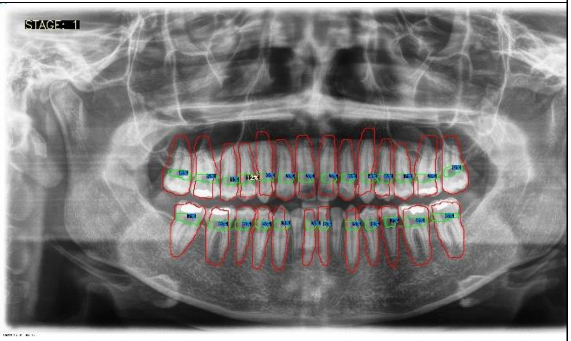
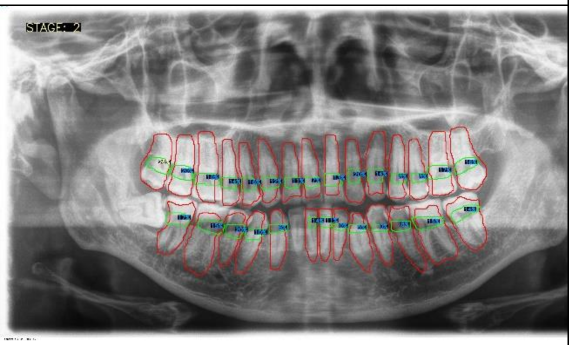
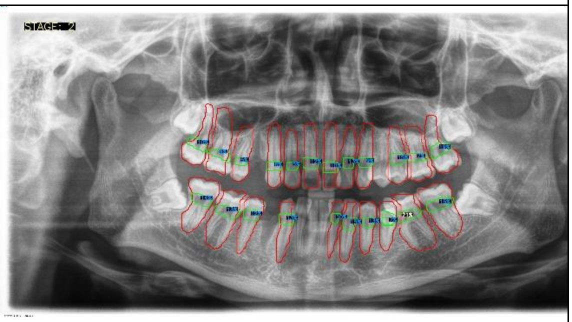
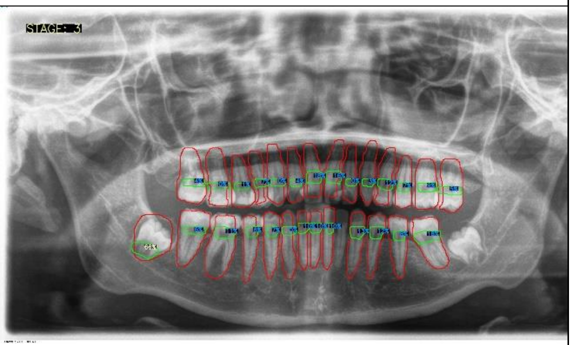
1		
2		
3		
4		

Id	Original images	Results
5		
6		
7		
8		
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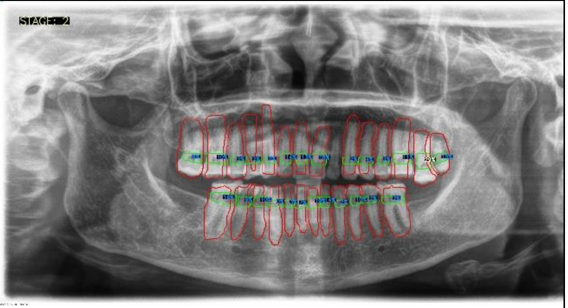
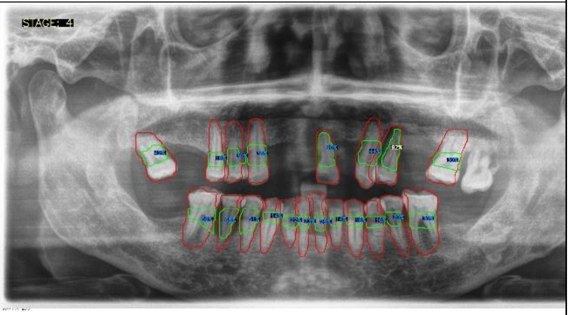
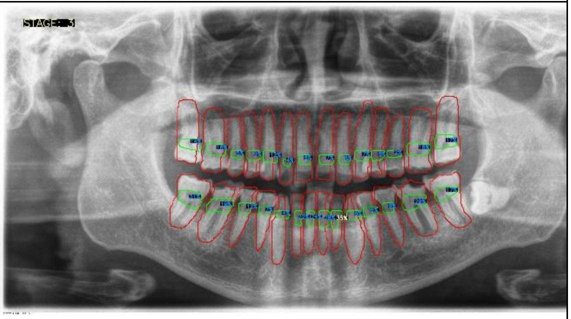
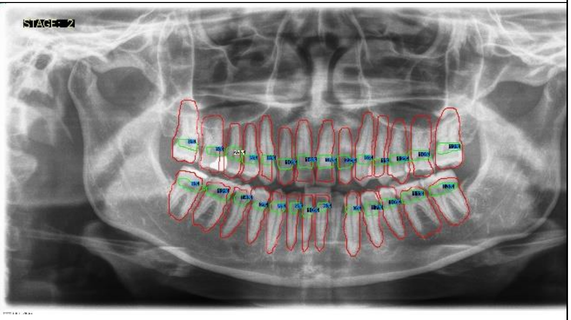
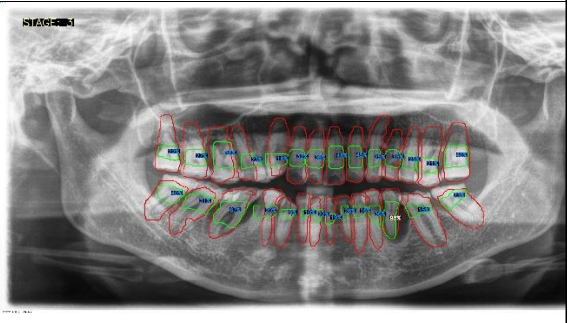
Id	Original images	Results
10		
11		
12		
13		
14		

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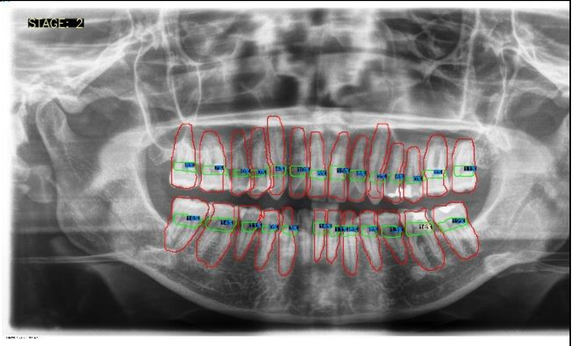
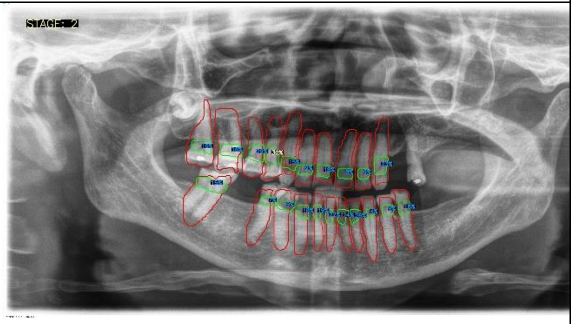
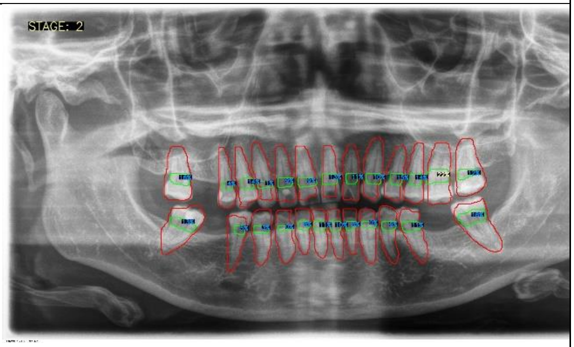
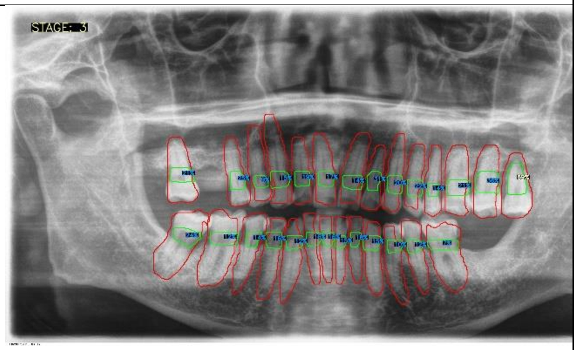
15		
16		
17		
18		

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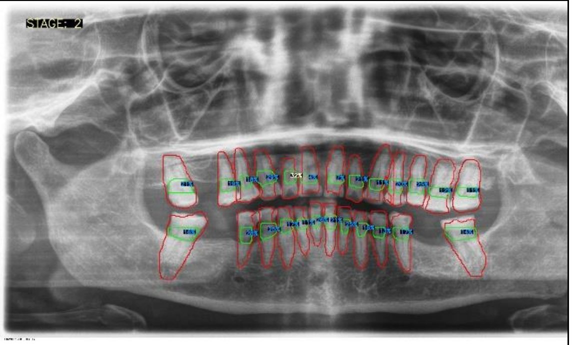
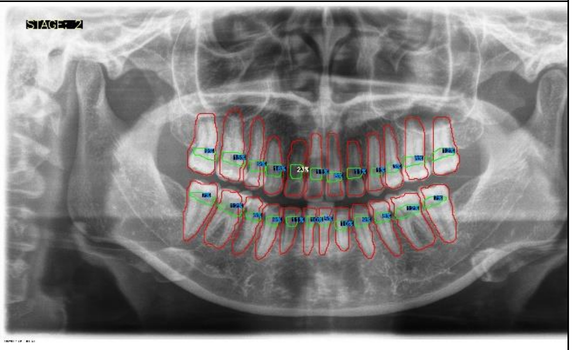
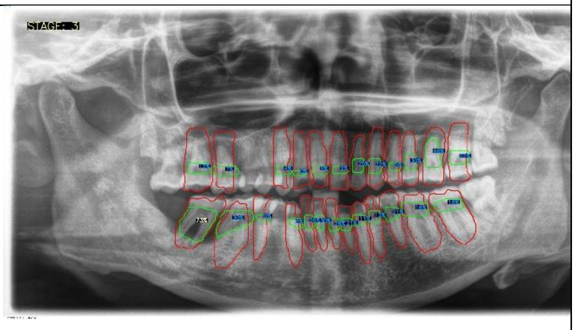
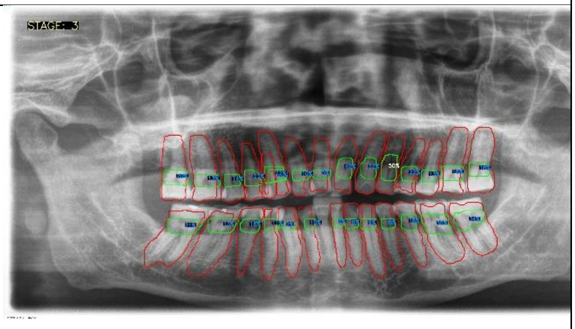
19		
20		
21		
22		

Id	Original images	Results
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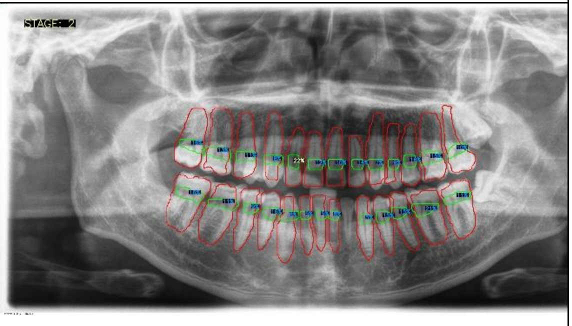
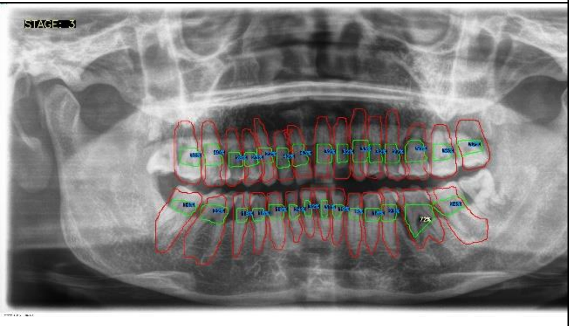
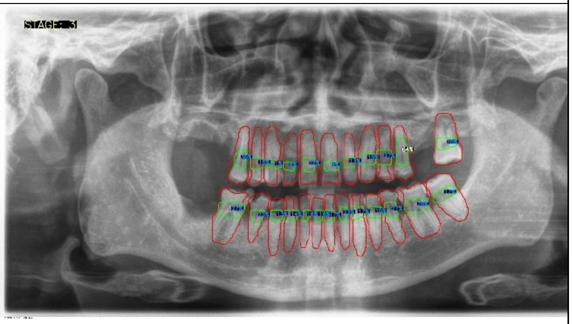
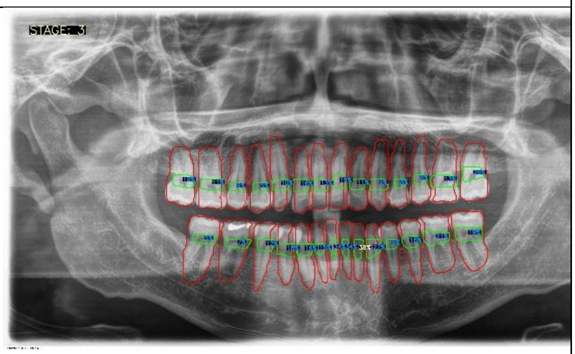
24		
25		
26		
27		

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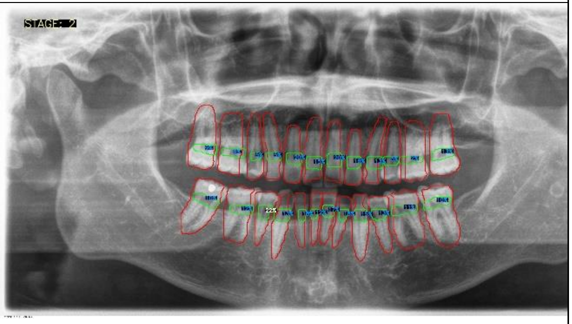
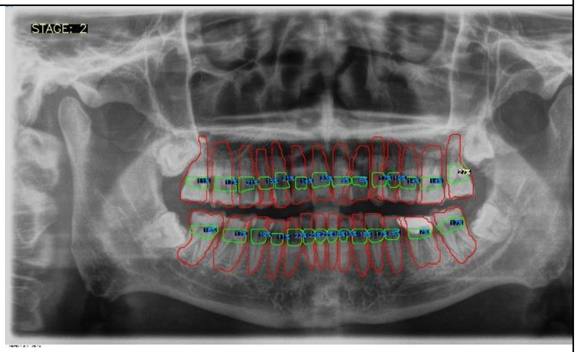
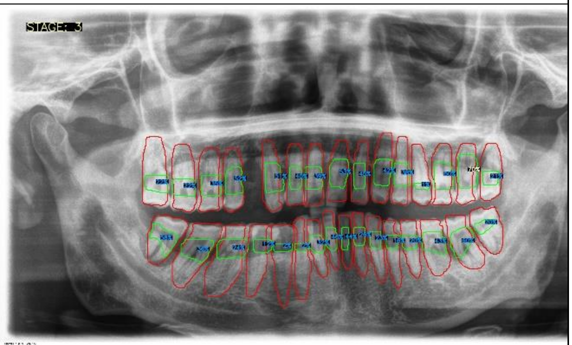
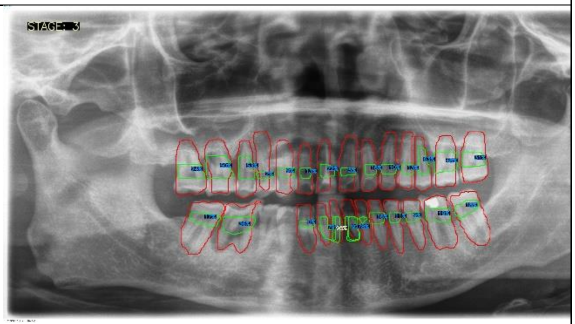
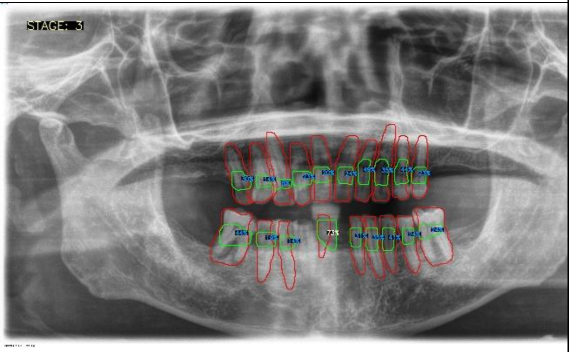
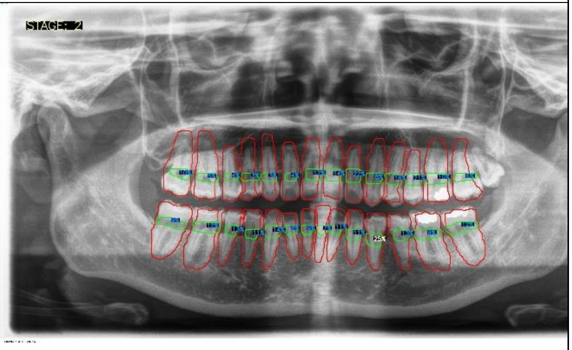
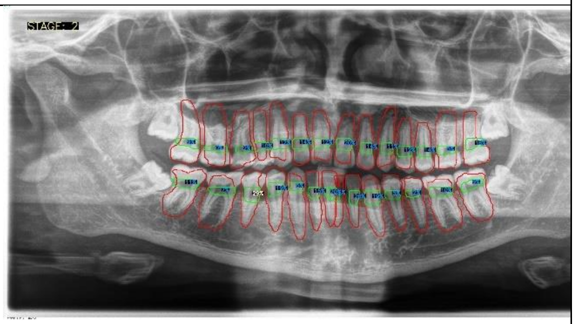
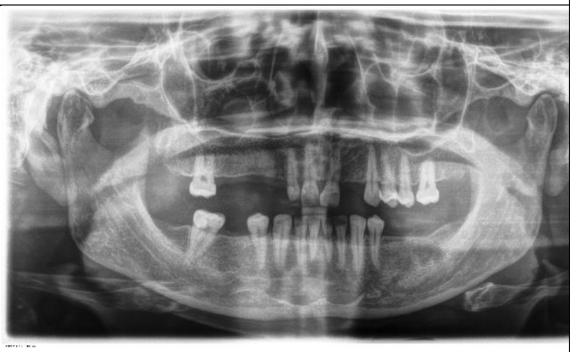
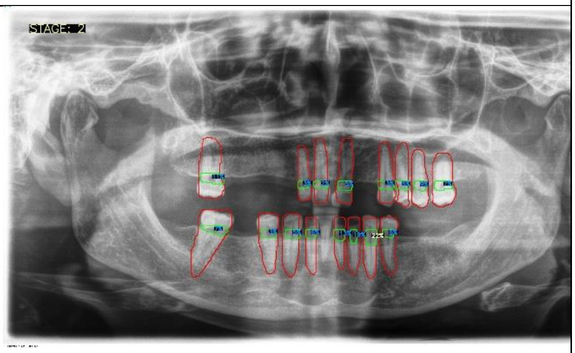
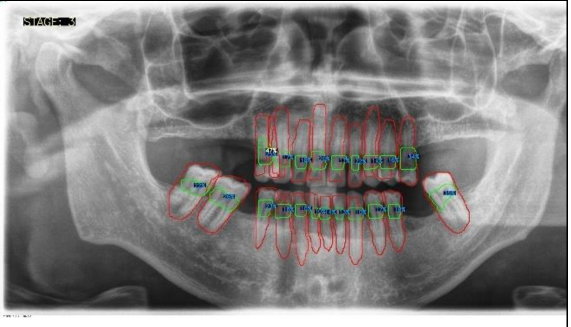
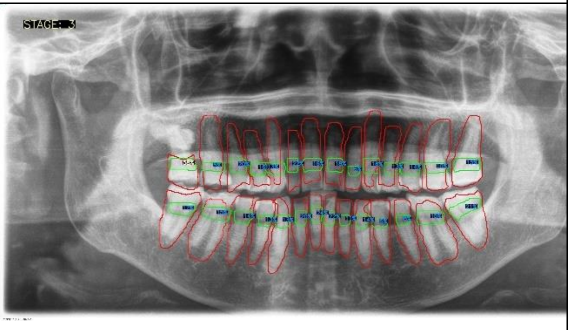
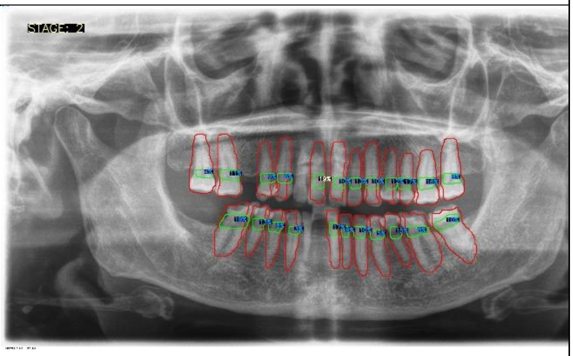
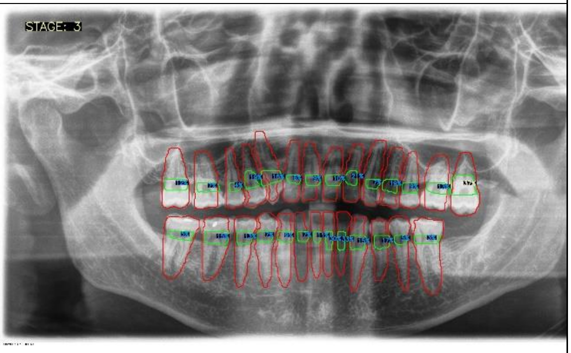
28		
29		
30		
31		

Id	Original images	Results
32		
33		
34		
35		

Id	Original images	Results
36		
37		
38		
39		

Id	Original images	Results
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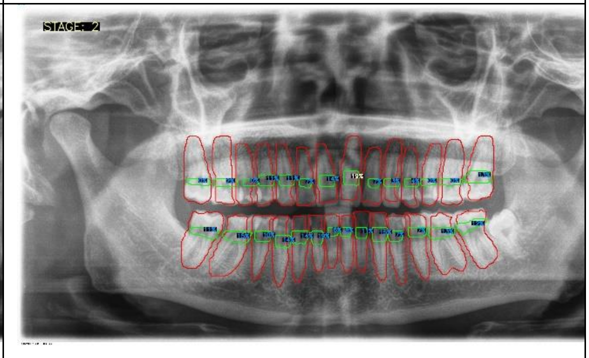
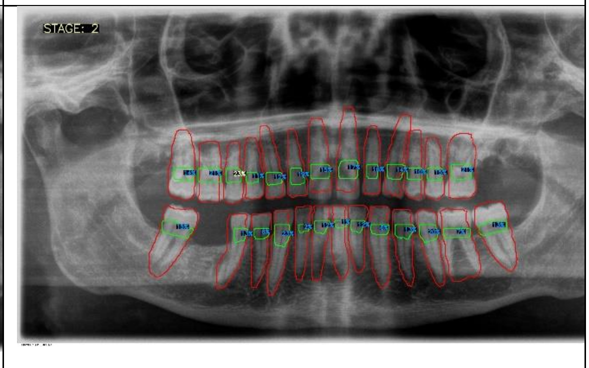
41		
42		
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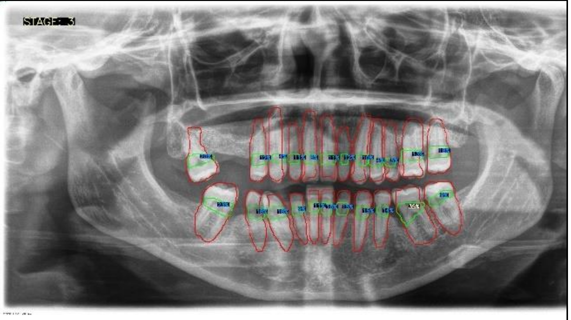
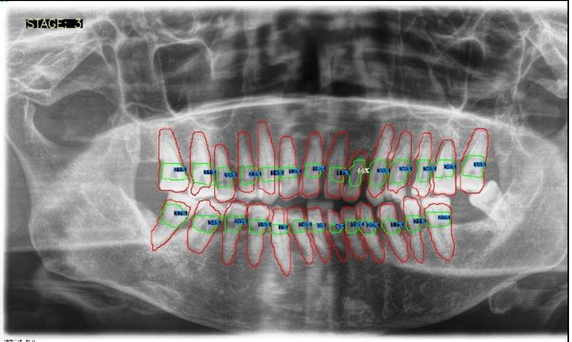
Id	Original images	Results
44		
45		
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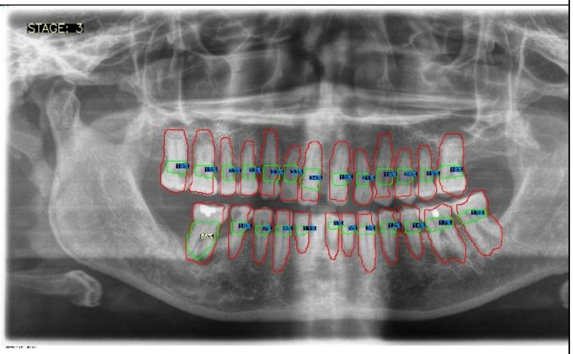
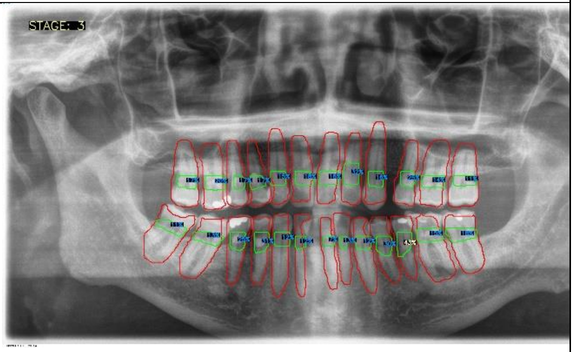
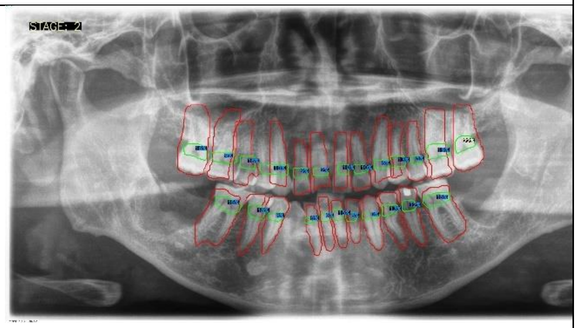
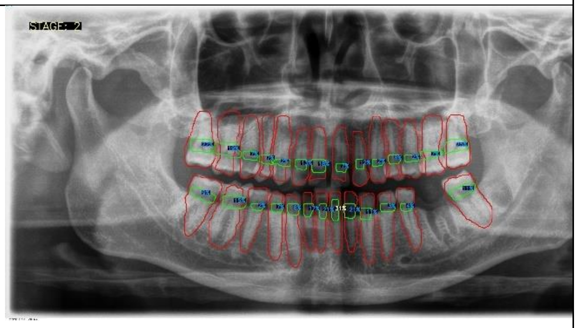
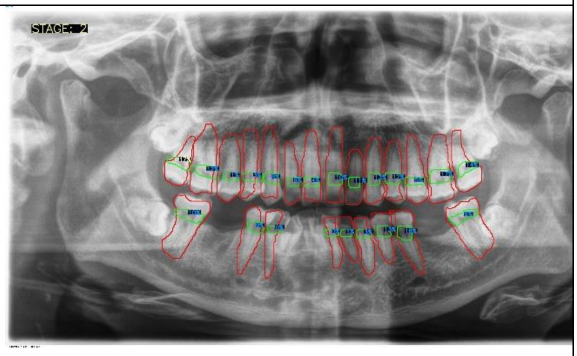
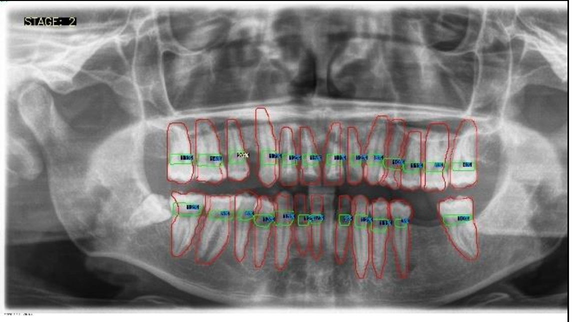
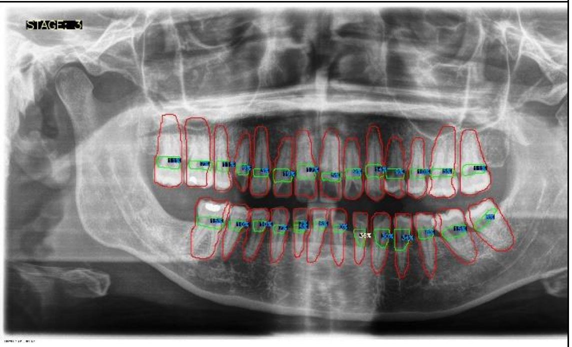
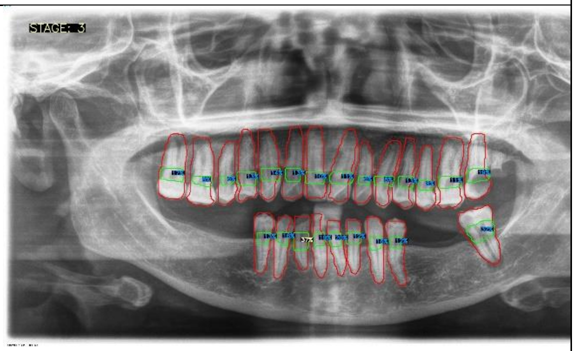
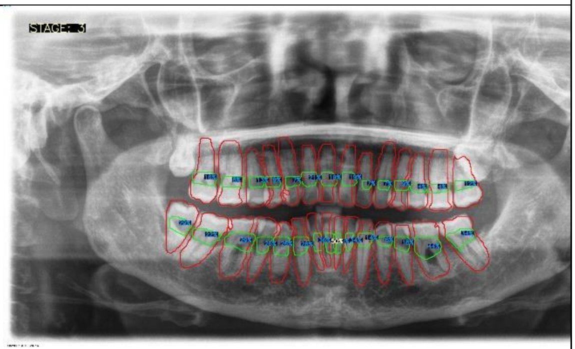
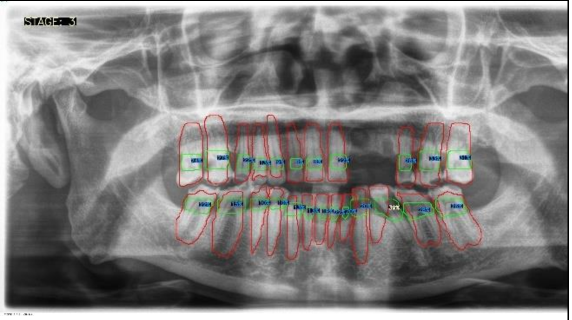
47		

Id	Original images	Results
48		
49		
50		
51		

Id	Original images	Results
52		
53		
54		
55		

Id	Original images	Results
56		
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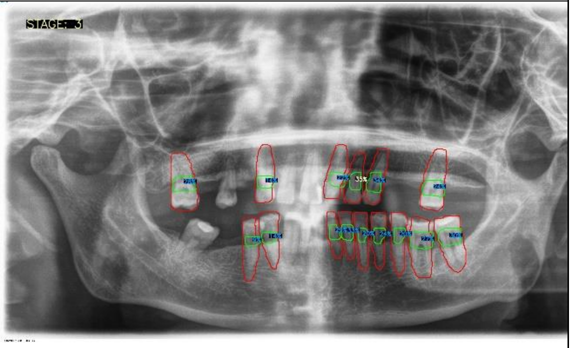
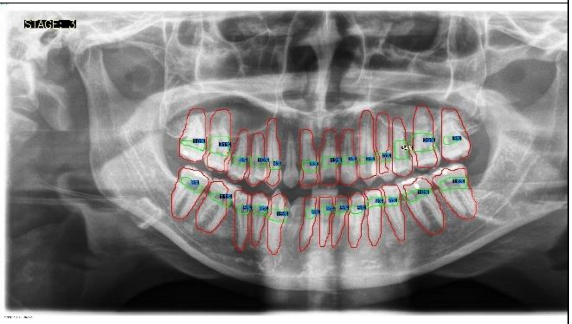
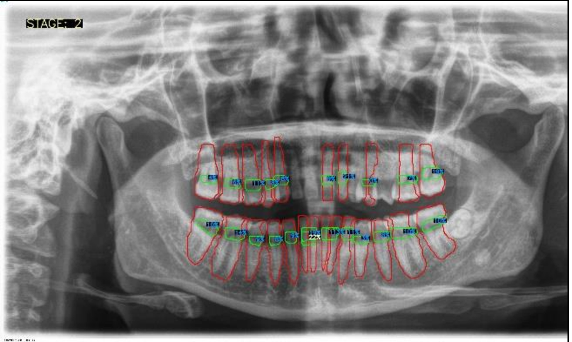
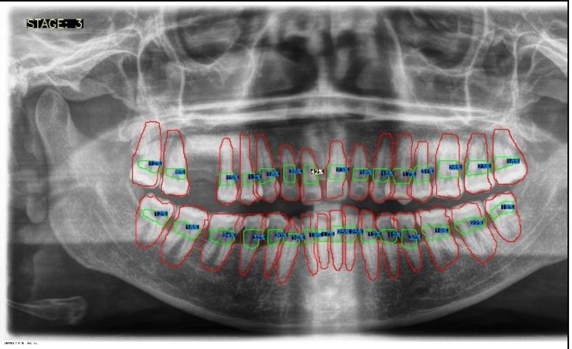
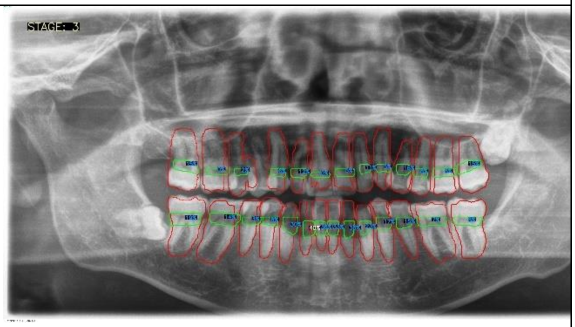
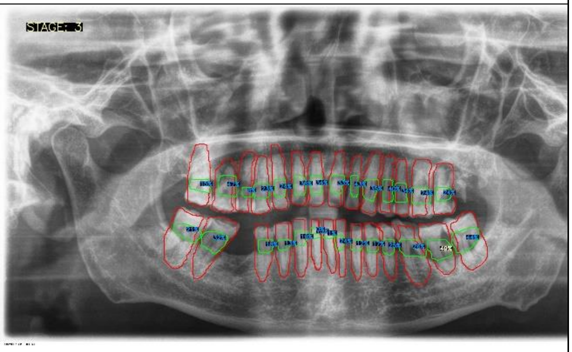
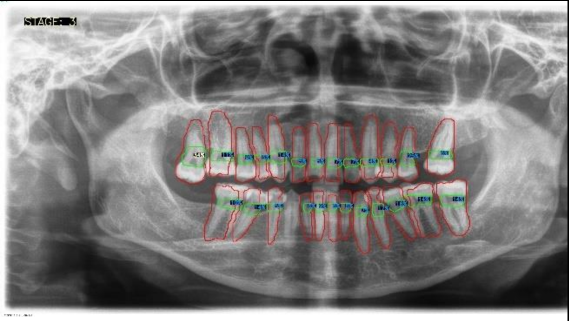
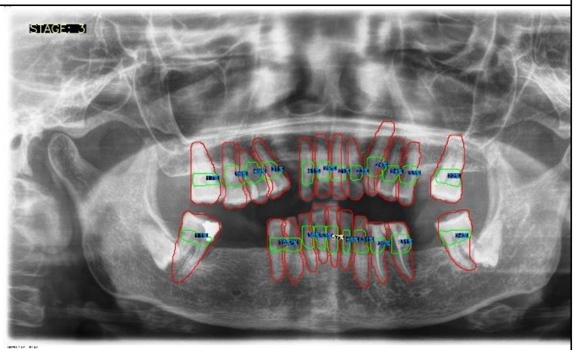
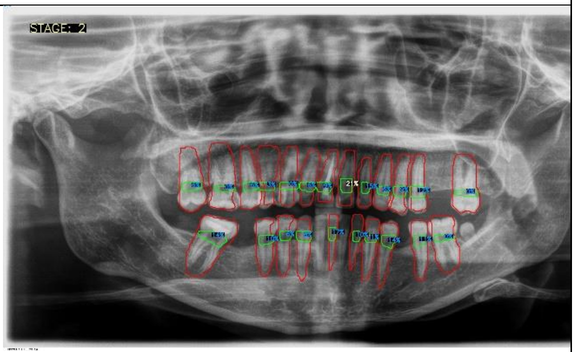
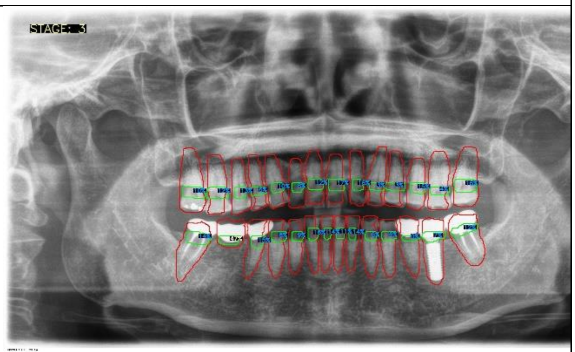
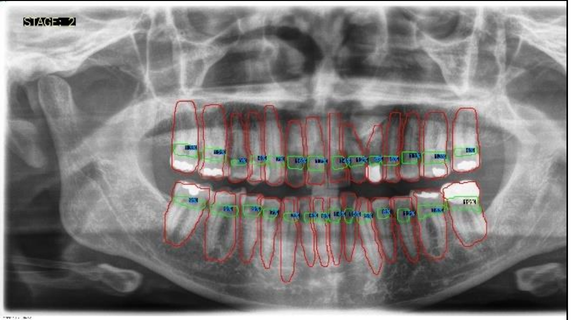
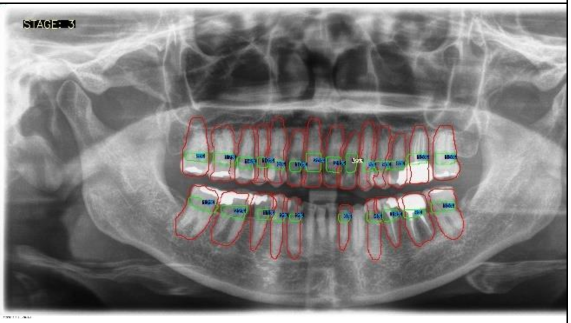
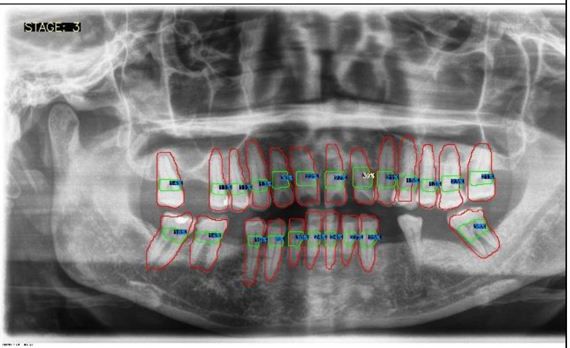
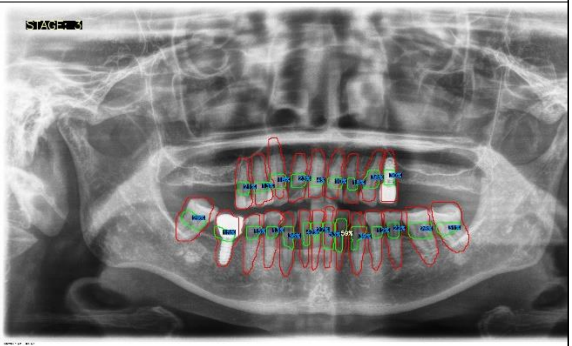
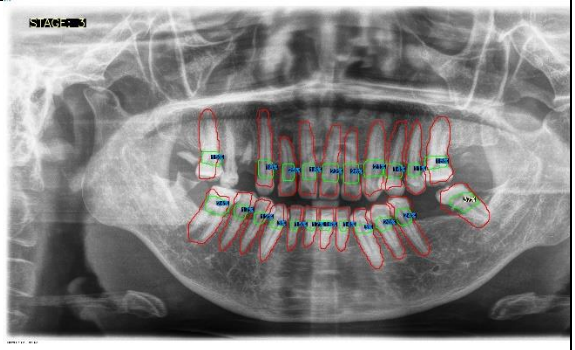
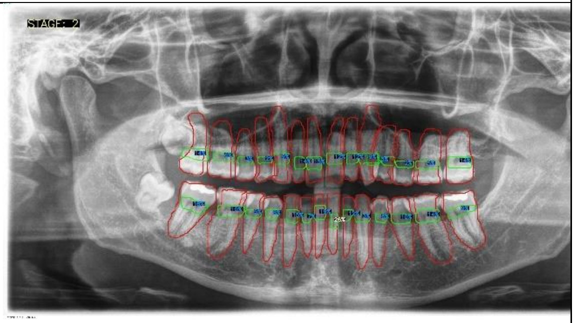
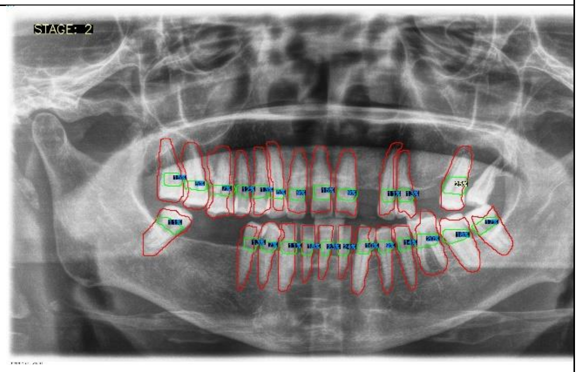
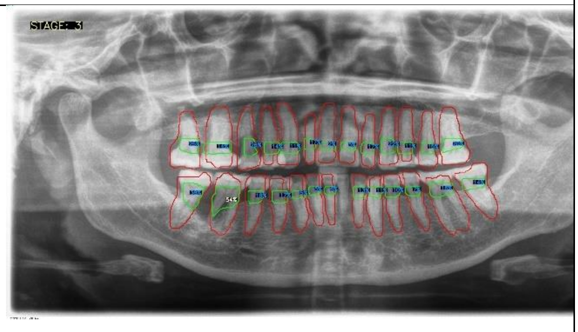
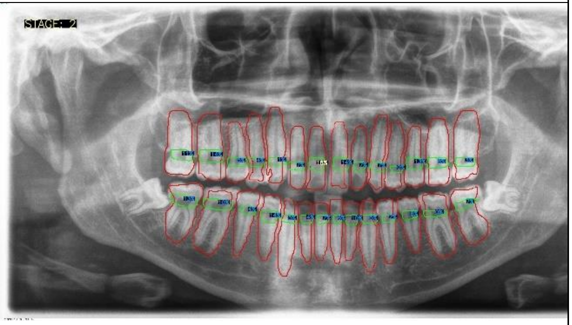
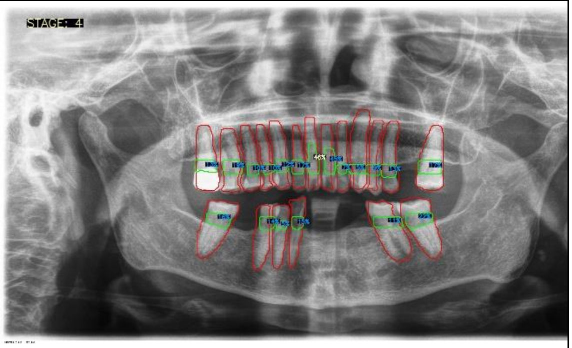
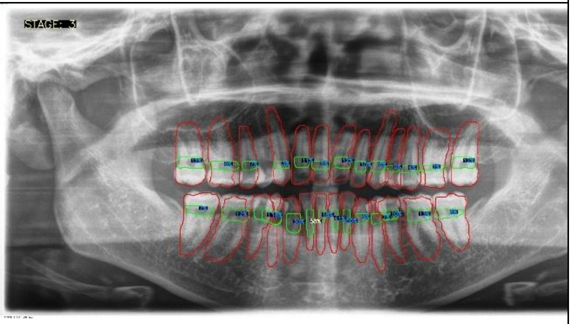
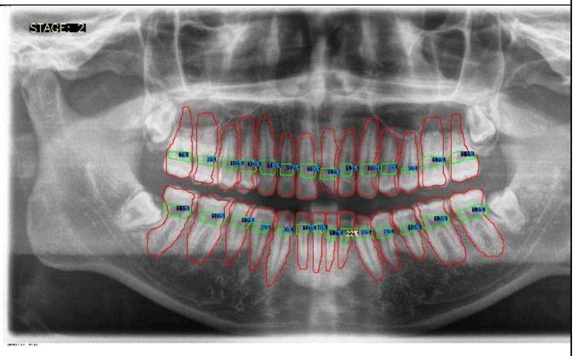
58		
59		

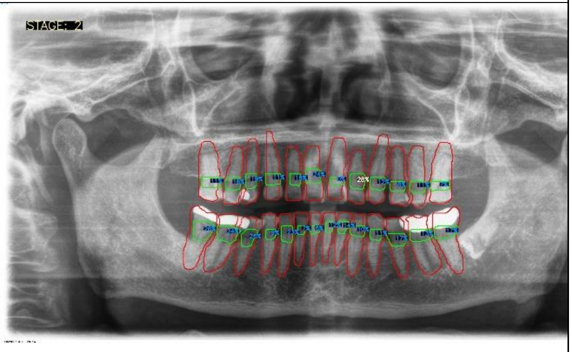
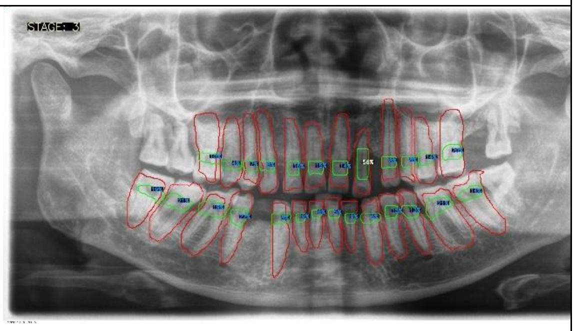
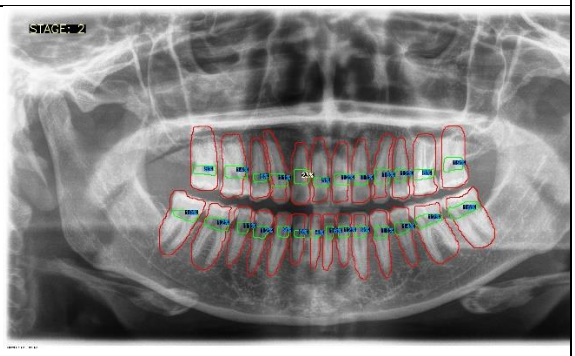
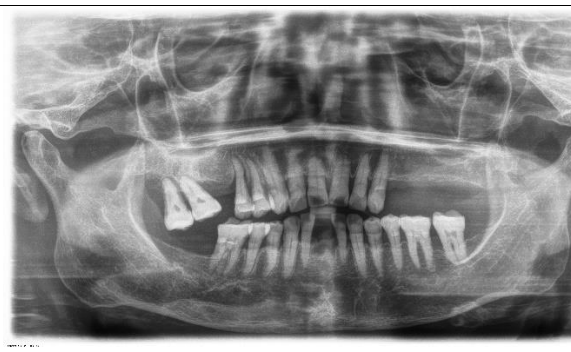
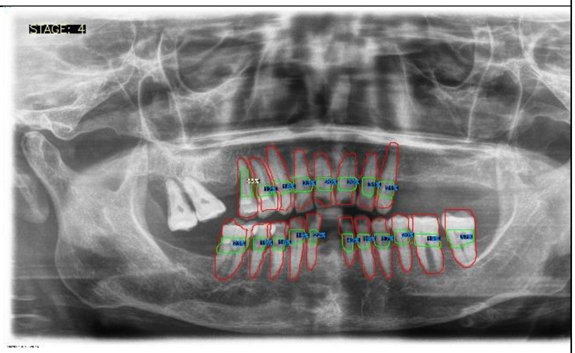
Id	Original images	Results
60		
61		
62		
63		

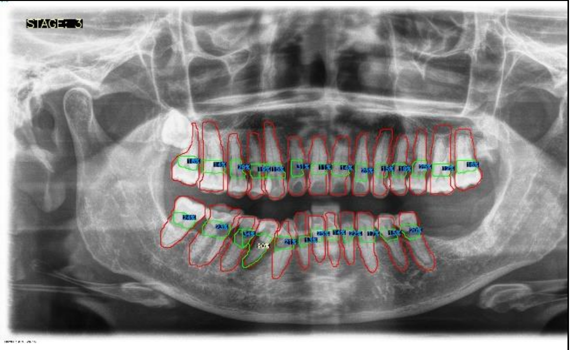
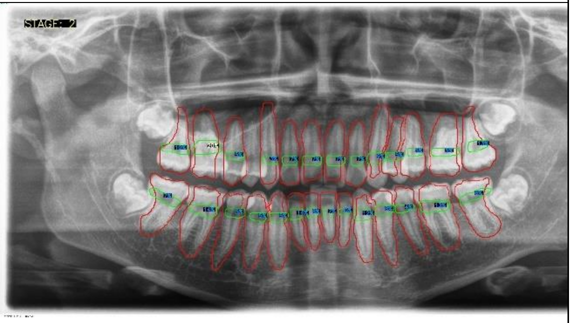
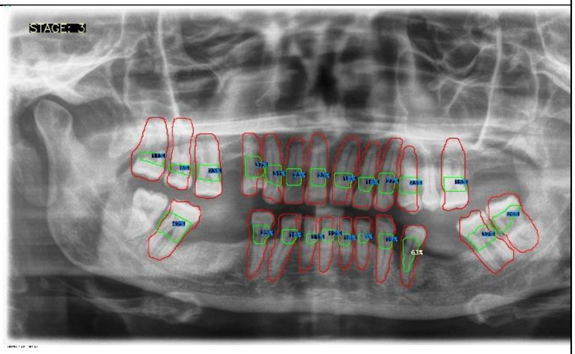
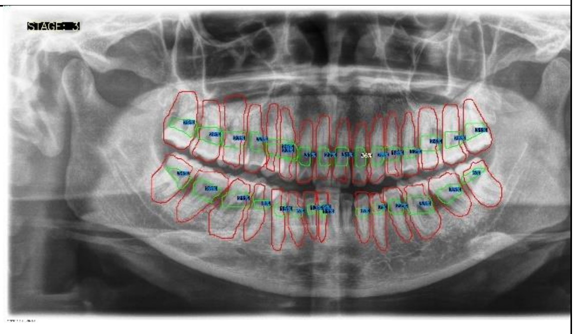
Id	Original images	Results
64		
65		
66		
67		

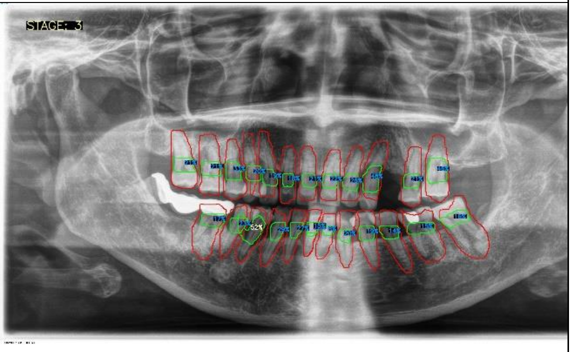
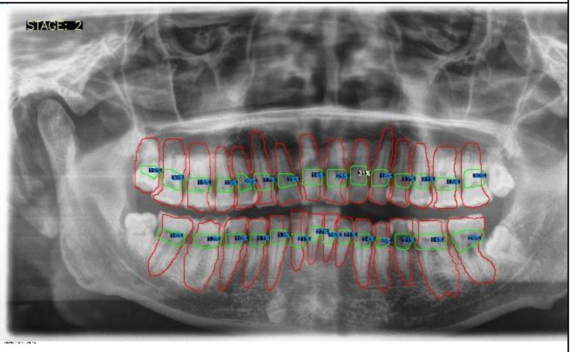
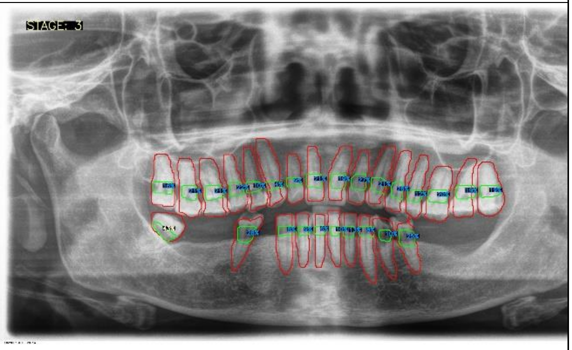
Id	Original images	Results
68		
69		
70		
71		

Id	Original images	Results
72		
73		
74		
75		

Id	Original images	Results
76		
77		
78		
79		

Id	Original images	Results
80		
81		
82		
83		

Id	Original images	Results
84		
85		
86		
87		

Id	Original images	Results
88		
89		
90		

A total of 300 previously unseen panoramic images were utilized in the clinical implementation to evaluate the accuracy of periodontitis diagnosis. This comparison focused on the performance of the AI model and periodontists against expert periodontists, ensuring a comprehensive assessment of diagnostic efficacy, as shown in the table below.

ID	HN	Sex	Age	Periodontist	AI	Expert
1	233863	1	18	2	2	2
2	48385	2	40	2	2	2
3	114993	2	27	2	2	2
4	100066	2	26	1	2	2
5	100432	2	48	3	2	3
6	10285	1	64	2	2	2
7	102981	2	70	2	3	3
8	103643	2	64	3	3	3
9	10380	2	51	2	3	2
10	104194	2	80	2	3	3
11	105865	2	30	2	2	2
12	105973	1	24	2	2	2
13	107446	1	40	1	2	1
14	107580	2	24	2	2	2
15	107937	1	42	3	2	3
16	108375	2	71	2	3	3
17	108756	2	24	1	2	1
18	10898	2	29	2	2	2
19	1096	2	55	2	2	2
20	111407	2	49	2	2	3
21	111968	2	24	2	3	3
22	112837	2	69	2	2	3
23	113901	2	26	2	2	2
24	114326	2	48	3	3	3

ID	HN	Sex	Age	Periodontist	AI	Expert
25	114993	2	27	2	2	2
26	116690	2	65	3	3	3
27	117056	2	71	3	3	3
28	117392	1	63	3	2	3
29	119558	2	56	3	2	2
30	119863	2	32	2	2	2
31	120935	2	23	2	2	1
32	121444	2	23	1	2	1
33	390228	2	38	2	3	2
34	1229	2	63	3	3	3
35	12365	2	64	3	2	2
36	124044	2	63	3	3	3
37	124192	2	53	2	2	2
38	125359	2	45	3	2	3
39	125360	1	51	3	3	3
40	12564	2	69	3	2	3
41	129490	2	57	3	3	3
42	12979	2	49	2	2	2
43	130494	2	67	3	2	3
44	130637	1	64	3	3	3
45	130687	2	23	2	3	3
46	137093	1	32	2	2	1
47	137179	1	22	2	2	2
48	137439	2	38	2	2	2
49	137764	1	22	2	2	2
50	138718	1	18	1	2	0
51	13931	2	65	3	3	3
52	140767	2	32	2	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
53	220396	2	18	1	3	0
54	486648	1	39	1	2	2
55	178879	2	36	2	2	2
56	88660	1	58	3	2	3
57	101665	2	59	2	2	2
58	490873	1	26	0	2	1
59	143093	2	64	3	2	2
60	143125	1	34	3	3	3
61	143318	2	40	2	2	2
62	200613	2	20	1	0	0
63	204111	2	46	3	3	3
64	204145	2	19	2	2	2
65	204189	1	41	2	2	2
66	204249	1	65	3	3	3
67	204369	2	66	3	3	3
68	20443	2	35	2	2	2
69	204441	1	52	2	2	3
70	20451	2	33	2	2	2
71	205167	1	62	3	3	3
72	205451	2	31	3	3	3
73	205929	2	18	1	2	1
74	206030	1	19	1	2	0
75	206089	2	77	3	3	3
76	206240	2	43	2	3	3
77	20632	2	52	2	3	2
78	206328	2	18	0	3	1
79	206393	2	24	0	2	2
80	206408	2	44	2	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
81	206420	2	39	3	2	3
82	20649	2	18	2	2	2
83	206707	2	45	2	2	2
84	206853	1	49	2	2	2
85	207048	2	67	1	2	2
86	207180	2	23	1	2	2
87	207212	1	18	0	2	1
88	207275	2	68	3	3	3
89	207329	2	42	3	3	3
90	20735	2	33	3	3	3
91	20759	1	31	1	2	2
92	20766	2	64	2	3	2
93	207723	2	27	1	1	1
94	207806	2	45	3	3	3
95	207819	2	58	3	3	3
96	207860	2	38	1	2	1
97	208080	1	66	2	3	2
98	208115	2	48	3	3	3
99	300446	2	25	2	2	2
100	300727	2	34	2	2	2
101	300794	1	29	1	3	2
102	301100	1	41	2	2	2
103	301179	1	29	2	2	2
104	301361	1	35	3	3	3
105	301500	1	25	0	2	2
106	301630	1	27	0	2	2
107	301724	2	25	0	2	2
108	3019	1	65	2	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
109	31000	2	22	3	3	3
110	310014	2	27	2	2	1
111	310089	2	26	2	2	2
112	310102	2	27	0	1	1
113	150736	1	51	4	4	4
114	150770	1	29	0	2	2
115	152552	2	71	3	3	3
116	152906	2	69	3	3	3
117	153020	2	26	2	3	2
118	153065	2	31	2	2	2
119	153068	1	57	2	3	2
120	1532	2	59	2	2	2
121	153258	1	18	0	2	1
122	153398	2	20	0	2	0
123	153471	2	32	2	2	2
124	153523	1	32	1	2	2
125	153683	1	63	3	3	3
126	153736	2	24	3	2	3
127	153921	2	25	1	1	1
128	15395	2	24	1	2	2
129	154047	2	30	0	3	3
130	154169	1	45	3	3	3
131	15423	2	62	3	3	3
132	154241	1	54	2	2	2
133	15429	1	45	3	2	3
134	154302	1	40	2	3	3
135	154473	1	22	2	3	3
136	154656	2	25	2	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
137	154666	1	30	2	2	2
138	154702	1	62	2	2	3
139	154869	1	51	2	3	3
140	154911	2	26	2	2	3
141	4001	1	26	2	2	2
142	400287	2	23	2	2	1
143	400293	2	25	0	2	1
144	400315	2	33	1	3	1
145	40041	2	22	0	2	2
146	400458	2	22	0	2	2
147	400498	2	22	2	2	2
148	401660	1	23	2	2	2
149	410626	2	56	2	3	2
150	410937	2	31	2	2	2
151	41177	2	37	2	2	2
152	412065	2	21	1	2	2
153	412437	2	29	0	2	2
154	41325	2	28	1	3	2
155	41348	2	52	2	3	2
156	413530	1	38	3	3	3
157	413862	2	21	1	3	2
158	414015	1	34	0	1	1
159	414111	2	19	0	3	3
160	41426	1	46	3	2	3
161	414691	1	28	0	2	2
162	4147	2	57	3	3	3
163	41504	1	39	2	3	3
164	415073	2	20	0	1	1

ID	HN	Sex	Age	Periodontist	AI	Expert
165	415198	1	66	2	3	3
166	415876	2	22	2	2	2
167	416797	2	18	0	2	2
168	41744	1	28	1	2	2
169	420004	2	26	1	2	1
170	420111	2	29	1	2	2
171	420266	1	20	1	2	2
172	420440	2	24	2	2	2
173	340026	2	25	2	2	2
174	340260	2	54	3	3	3
175	3141	2	26	1	2	2
176	34153	2	60	3	3	3
177	341570	2	21	1	2	2
178	34168	2	25	0	2	2
179	341703	2	20	0	2	2
180	342202	2	21	1	3	1
181	342206	2	31	2	3	3
182	34271	1	27	1	2	2
183	343703	2	53	3	2	2
184	34374	1	34	2	2	2
185	344066	1	24	2	2	1
186	344261	2	33	2	2	2
187	344388	2	19	1	2	2
188	344720	2	45	3	3	3
189	344944	2	19	1	2	1
190	344958	2	34	1	2	2
191	345366	2	18	0	2	1
192	345603	2	32	1	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
193	34572	2	54	2	2	2
194	34588	2	26	0	2	2
195	346123	2	28	1	2	2
196	346367	2	36	2	2	3
197	346440	2	20	2	2	2
198	346522	1	18	0	3	2
199	346539	2	47	2	2	3
200	347364	1	22	0	2	1
201	50010	2	61	3	3	3
202	34791	2	54	2	3	3
203	143041	2	32	2	2	2
204	207287	2	54	2	3	3
205	371397	1	45	2	2	3
206	371450	2	45	3	3	2
207	37220	2	62	3	2	2
208	346733	2	36	2	2	3
209	346350	1	29	2	2	3
210	344901	2	36	2	2	2
211	60143	2	18	0	2	0
212	60170	2	23	0	2	0
213	60381	2	45	3	2	3
214	330377	2	44	0	2	2
215	60682	2	22	0	1	1
216	66150	1	38	3	2	2
217	61196	1	19	0	2	2
218	61351	2	18	0	3	3
219	56862	1	54	3	3	3
220	199709	1	41	2	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
221	120959	1	60	3	4	3
222	67506	1	59	2	3	3
223	67783	2	27	0	2	2
224	67887	2	42	3	3	3
225	69235	2	38	2	2	2
226	110450	2	66	3	2	3
227	69258	2	39	2	2	2
228	236897	1	63	3	3	3
229	15893	2	51	2	2	2
230	71353	2	24	0	2	2
231	164875	2	41	3	3	3
232	439251	1	61	2	3	3
233	440567	1	53	2	3	3
234	441900	1	32	1	2	2
235	187435	1	57	3	3	3
236	442741	1	45	3	3	3
237	445491	1	23	1	3	1
238	44708	1	28	1	2	2
239	447490	1	57	2	2	2
240	165557	1	48	3	3	3
241	447725	1	42	3	3	3
242	447798	1	76	4	3	4
243	447841	2	28	1	2	2
244	448319	1	19	2	2	2
245	448945	2	44	1	2	2
246	449991	1	48	2	3	3
247	451129	2	60	2	3	2
248	452657	2	69	2	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
249	456846	1	26	2	3	2
250	460024	2	68	3	2	3
251	462094	1	19	0	2	2
252	465008	1	55	3	2	3
253	465631	1	28	3	3	3
254	466578	2	34	3	3	3
255	466602	2	63	3	3	3
256	467098	2	34	1	3	1
256	467099	2	54	3	3	3
258	468491	1	67	2	3	3
259	468673	1	52	3	2	3
260	471611	1	40	2	2	2
261	472466	1	33	2	2	2
262	473563	1	20	1	2	2
263	473726	2	25	1	3	1
264	474492	2	40	2	3	2
265	173676	2	58	3	3	3
266	480322	1	47	3	3	3
267	484910	2	57	3	2	3
268	489081	2	44	3	3	3
269	490238	2	24	1	3	1
270	49316	2	39	2	2	2
271	160737	2	39	3	3	3
272	493573	1	38	2	3	2
273	496926	1	51	3	3	3
274	498691	2	31	2	3	3
275	501425	2	60	3	3	3
276	503182	2	24	1	2	2

ID	HN	Sex	Age	Periodontist	AI	Expert
277	503203	2	57	2	3	2
278	503694	1	51	3	2	2
279	505894	2	64	2	3	2
280	18872	1	59	3	3	3
281	508204	2	57	3	3	3
282	113087	1	58	2	3	3
283	512236	1	36	1	2	2
284	181505	1	53	2	2	2
285	53268	2	54	3	3	3
286	106120	1	18	0	2	0
287	106545	2	80	2	4	2
288	107410	2	20	0	3	0
289	10783	1	22	1	2	2
290	107916	2	58	2	2	2
291	105554	1	48	3	3	3
292	10898	2	28	0	2	2
293	144873	1	68	3	4	3
294	109191	2	61	3	3	3
295	109545	1	18	0	2	0
296	18885	2	49	3	3	3
297	118857	2	37	3	3	3
298	52749	2	59	3	3	3
299	53302	1	48	2	2	2
300	53416	2	56	2	3	3

BIOGRAPHY

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