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Development and Validation of AI Algorithms for Dental Radiography Interpretation

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Abstract

This study developed and validated AI algorithms for for orthopantomogram (OPTG) interpretation, comparing accuracy with radiologists. An experimental study design was used in a dental setting for this research. A sample of 138 orthopantomogram (OPTG) were divided into two groups (AI and Human) using stratified random sampling. The performance of AI and human-AI was evaluated using confusion matrices, sensitivity, specificity, accuracy, and error analysis conducted in R Studio. The study analyzed 138 individuals (mean age 44.59 years) with a balanced gender distribution (50% male, 50% female) and varying severity levels (mild, moderate, severe). Diagnoses included caries, fractures (roots of teeth), and other abnormalities such as periodontal disease, traumatic lesions, and neoplasms (benign and malignant). The AI model showed better performance than the human control model in all the important markers, such as sensitivity (86.84 vs 79.41), specificity (90.32 vs 88.57), and accuracy (88.4 vs 84.1). The AI showed better results than the above parameters in the ROC curve (AUC 0.886 vs 0.84). Compared to the interpretations made by humans, AI has proven to be more accurate in its diagnostics and has a higher sensitivity and specificity rate.

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Introduction

Dental radiography serves as an important component in diagnosing and assessing the condition of the dentofacial system of including the presence of hidden caries and its complication (periodontitis), lesions, severity and course of periodontal diseases, and other abnormal pathologies. It is central in defining how dental diseases are detected, treated, and managed [1]. Different types of dental radiographic examinations provide varying diagnostic insights. The most used are intraoral sighting images (formerly film-based, now digital radiovisiographs), which provide high-resolution images of 3–4 teeth using sensors and computer software. Orthopantomograms (OPTG or panoramic images) capture a full view of all teeth, the upper and lower jaws, and temporomandibular joints. Cone-Beam Computed Tomography (CBCT) offers detailed 3D scans of the dentition and jaw structures and is typically used for complex evaluations. X-rays and Magnetic Resonance Imaging (MRI) are incredibly useful not only in these pathologies but also in the medical sector [2]. However, the interpretation of radiographic images is a tedious task requiring a considerable amount of professional skill, which further increases the chances of inter-observer error [3]. Given the limited availability of professional dental practitioners in most parts of the world, the global rise of oral diseases has created room for improvement in detection, diagnostics, and treatment efforts. A Machine Learning (ML) algorithm is purported to be a solution for the challenges posed by AI [4,5].

In recent years, AI's application in medical imaging has been gaining attention due to its proven success in fields such as radiology, dermatology, and ophthalmology [6]. The uptake of AI in dental radiography work is quite limited, especially in diagnostics and disease control. While machine learning and deep learning algorithms are highly accurate and efficient at processing large amounts of data in a clinical context, these technologies are particularly useful for the early diagnosis of dental caries, periodontal diseases, and oral cavity neoplasms (benign and

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malignant), which leads to better treatment and outcomes for patients [7].
AI increases the efficiency of dental diagnostics by interpreting radiographs, detecting cavities, periapical changes and assessing bone structure and temporomandibular abnormalities. It provides an opportunity for early detection and timely, accurate intervention, improving diagnosis, treatment, and overall outcomes [8].
Moreover, AI assists dentists in treatment plans using patient data and historical data. The system analyzes bone density, age, and health to predict the success of implants which fosters better clinical decision-making and more tailored treatment strategies [9].
AI improves the experience of the dental patient with virtual assistants that help with appointment requests, education, and addressing frequently asked questions. Additionally, it views the comments made by the patients, which aids in solving issues, tailoring their treatment, and promoting patient satisfaction and clinical results [10].
Artificial intelligence algorithms evaluate dental X-rays and intraoral scans to recognize an initial occurrence of caries, gum disease, and oral malignancies. The use of machine learning improves pattern recognition, which assists dentists in revealing concealed abnormalities for prompt action to provide better patient care [11].
These modern AI-enabled applications for virtual consultation are allowing patients to consult dentists remotely and seek their advice while avoiding the hassle of physical appointments. The use of AI chatbots and virtual assistants in teledentistry services allows for the customization of health advice, management of patient questions, and even arranging the in-person touchpoint visit, resulting in greater ease of access to dental services [12].
The design of AI tools in dental X-ray examinations brings along numerous benefits. To begin with, AI algorithms are capable of sifting through vast amounts of information incredibly quickly and reliably, thus eliminating a lot of work from clinicians. Second, AI can aid in improving the diagnosis of cases by establishing patterns that clinicians might have missed. Finally, AI systems could help solve the problem of dental care access in non-specialised areas by serving as computerised assistants to non-specialists [13].
Despite the advantages AI offers in dental radiography, there are certain challenges associated with it, such as limited curation of data, issues of readability and sharing, and lack of transparency and trust. Concerns pertaining to ethics and its application are straightforward blockers to development, and in order to resolve this, there needs to be responsible novel development for beneficial integration [14].
The adoption of AI deep learning models in healthcare AI applications is limited by one factor: the "black box" phenomenon of algorithms that often lack transparency in their decision-making process, especially in interpreting dental imaging. This is an issue as erroneous predictions could cause a lot of damage [15]. By employing explainable AI (XAI) in dental X-ray interpretation, it may be possible to enhance clinicians' trust in these technologies while making diagnosis and treatment planning more effective [16].
While AI in medical imaging has advanced, challenges remain in dental X-rays, including limited datasets, insufficient algorithm testing, and a lack of explainability, hindering clinical acceptance. Ethical and legal concerns, such as data protection and algorithm bias, have been underexplored, presenting major obstacles to AI integration in dental healthcare [17,18].
This study advances dentistry (stomatology) by developing an AI system to interpret orthopantomograms (OPTG) comprehensive dental X-rays showing teeth, jaws, and joints. It reduces diagnostic errors, improves clinical outcomes, and supports specialists, especially in under-resourced areas. The system was trained in cases with varied complexity (mild, moderate, severe) based on interpretability, enhancing adaptability. It accurately detects caries and its complications, periodontal disease, traumatic lesions, neoplasms, and developmental anomalies. By addressing AI training challenges specific to OPTG imaging, the study promotes broader clinical use of AI in dental diagnostics and supports equitable, efficient care delivery across different healthcare settings.
This study aimed to develop AI algorithms for analyzing dental radiographs, focusing on improving diagnostic speed and accuracy. We compared AI and radiologists' performance in diagnosing dental diseases and measures sensitivity, specificity, accuracy, and error rates. The goal is to enhance diagnostic practices and improve patient treatment outcomes.

Materials and Methods

Study Design

An experimental study was conducted to develop and validate artificial intelligence algorithms for interpreting dental radiographs and compare their performance with human experts. The study utilized a dataset of 138 dental radiographs categorized into two groups:

- Experimental Group (AI): n = 69
- Control Group (Human Experts): n = 69

Study Population

The study focuses on patients requiring orthopantomographic (OPTG) dental radiographs for routine check-ups or diagnostics and treatment planning.

Study Setting

Data was collected from dental clinics, hospitals, and academic institutions with radiographic imaging systems(orthopantomographic (OPTG).

Sample Size

The total sample size is n = 138 to detect a significant difference in sensitivity between AI and human experts at a significance level of 0.05. A power analysis was conducted to determine the appropriate sample size, ensuring adequate representation of different demographic groups and clinical conditions. The sample size was estimated using the following formula:

$$n = \frac{Z^2 . P . (1 - P)}{d^2}$$

Where:

- Z = 1.96 (for 95% confidence level)
- P = 0.90 (expected sensitivity or specificity)
- d = 0.05 (margin of error)

The sample size was determined to ensure statistical power while considering resource constraints. The expected sensitivity or specificity value (P = 0.90) was chosen based on prior published studies and preliminary pilot data, which indicated that advanced AI models achieve high diagnostic performance in medical imaging [19,20]. This value was further validated through literature review and expert consultation.

Sampling Technique

A stratified random sampling technique was used to ensure that the dataset is representative of different demographic groups and clinical conditions. This approach minimizes selection bias by distributing cases evenly across key subgroups, such as age, gender, and radiographic complexity (mild, moderate, severe), based on interpretative difficulty rather than clinical severity.

Data Collection

Metadata, such as patient demographics and clinical notes, were anonymized and integrated into the dataset for contextual analysis.
138 orthopantomographic dental X-rays were collected as a dataset, including diagnostic categories such as caries and its complications (e.g., periodontitis), periodontal disease, impacted teeth, fractures of the jaw and roots, cystic formations, neoplasms (benign and malignant), and anomalies in the development and position of dentition structures. Each expert labelled the annotations according to a standard, and

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ambiguous cases underwent a second reading. In cases where discrepancies arose, a consensus process was applied. Specifically, when two experts disagreed on an annotation, a third expert was consulted to resolve the discrepancy. Substantial interobserver variability was established with a Cohen Kappa value of 0.82. Further information such as age, gender, and image complexity level (mild, moderate, and severe based on radiological interpretative difficulty) was added to improve analysis and reproducibility.

Development of AI Algorithm

1. Training and Validation: Training involved a separate radiograph subset for the AI model, optimizing hyperparameters via grid search and applying five-fold cross-validation to prevent overfitting.
2. Testing: The trained AI was tested on the experimental dataset (n = 69). Predictions were recorded as positive or negative for each radiograph.

Human Expert Evaluation

In the control group, human experts independently evaluated the same 69 radiographs. Their interpretations were recorded as positive or negative.

Performance Metrics

The following metrics were calculated for both the AI and human experts includes Sensitivity, Specificity, Positive Predictive Value, Negative Predictive Value, Accuracy, Precision and F1 Score

Data Analysis

Data analysis in R Studio involved confusion matrices both for AI and Human experts on true/false positives and negatives during the analysis. Possible bias in the interpretations was examined using the error pattern analysis.

Ethical Considerations

The study adhered to ethical guidelines for data handling and patient confidentiality. All radiographs were anonymized prior to analysis).

Results

Table 1 presents a dataset comprising 138 individuals (mean age: 44.59 ± 16.24 years) with an equal gender distribution (69 males and 69 females). The severity levels are distributed as follows: 60 mild cases (43.48%), 49 moderate cases (35.51%), and 29 severe cases (21.01%). The diagnoses include 72 cases of caries and its complications (52%), 37 cases of fracture and periodontal disease (26.81%), and 29 cases of other abnormalities (21.01%).

Table 2 summarizes the confusion matrix for the experimental group (AI). The model correctly identified 33 true positives and 28 true negatives, resulting in a sensitivity of 86.84% (33 out of 38) and a specificity of 90.32% (28 out of 31). The AI misclassified 3 cases as false positives and 5 as false negatives. The positive predictive value (PPV) was 91.67% (33 out of 36), and the negative predictive value (NPV) was 84.85% (28 out of 33).

Table 3 presents the confusion matrix for the control group (human assessment). The model correctly identified 27 true positives and 31 true negatives, yielding a sensitivity of 79.41% (27 out of 34) and a specificity of 88.57% (31 out of 35). There were 4 false positives and 7 false negatives. The positive predictive value (PPV) was 87.10% (27 out of 31), and the negative predictive value (NPV) was 81.58% (31 out of 38).

Table 4 shows that AI outperforms human predictions in all measured parameters. AI's sensitivity (0.868 vs 0.794) and specificity (0.903 vs 0.886) scores were higher, yielding fewer false positives. While still earning greater trust, AI achieved higher PPV and precision (0.917 vs 0.871). AI also exhibited greater NPV (0.848 vs 0.816) and overall accuracy (0.884 vs 0.841). The higher F1 score (0.892 vs 0.831) further confirms that AI's classification ability is better balanced and superior. Table 5 shows the AI's performance relative to that of human predictions, in particular focusing on the false positives and negatives. AI has a lower false positive rate of 0.097 compared to 0.114 and a lower false negative rate of 0.132 compared to 0.206, thus improving the accurate positive identification. The accuracy of positive classification is also higher, with AI receiving a 0.116 misclassification rate, which is greater than 0.159 for humans, indicating better performance. Regarding the balance error rate, AI's result of 0.114, rather than 0.16 for humans, further confirms its superior reliability. This allows us to conclude that AI is a more reliable classification system.

Discussion

The current study results highlight the strength of the dataset, which included 138 participants from both genders and various degrees of severity. The cases with mild, moderate, and severe severity level diagnoses are fairly allocated so that the AI and human predictions can be compared reliably. Diagnoses, for instance caries and its complications, periodontal diseases, fractures and other abnormalities assigned had a spread across the clinical spectrum which increases the chance of real-world. Likewise, comparative analysis with systematic review has demonstrated that the sensitivity of AI models is about 91.5% for caries detection and 99.95% for periapical lesion identification [21]. Previous work revealed that the application of AI can quickly scan radiographs and reduce errors while increasing productivity [22]. On the other hand, while all these are true, it is crucial to ensure that these are regularly updated for practitioners to have the latest information [23].

The current study confirms that the experimental AI model performs better than others with exceedingly high sensitivity (86.84%), specificity (90.32%), positive predictive value (91.67%), and negative predictive value (84.85%) indicating strong confidence in its classification output. In terms of missed and over diagnoses, AI has proved beneficial in diagnosing dental caries and some other oral conditions. Supporting evidence includes studies where deep learning networks provided better results than dentitions in detecting carious lesions on bitewing radiographs [24]. Likewise, effective CNN-based models have been reported to achieve similar results as expert practitioners in the diagnosis of periodontal bone loss on panoramic radiographs [25]. Other studies point out the high sensitivity and specificity of AI in the diagnosis of periodontal disease and oral cancer [26]. However, there are gaps. Some literature contends that AI technologies are still maturing and have not achieved the desired integration into clinical practice [27]. Furthermore, ethical challenges such as algorithmic bias and patient consent should not be overlooked in the context of AI usage in healthcare. Although these technologies are advanced, addressing these challenges is essential for the effective implementation of AI in dental diagnostics [28]. Additionally, study on implant surface modification, such as Laser-Lok treatment, have shown significant improvements in implant stability and bone preservation, suggesting a potential parallel in how AI could enhance long-term treatment outcomes in dental care [29]. The findings of the current study underscore the accuracy of AI and the relative inaccuracy of human predictions. While human evaluators were reasonably specific (88.57%) and had PPV (87.10%), they were less sensitive (79.41%) in comparison to AI, thus increasing the number of false negatives. Hence, there is still room for improvement in manual diagnosis. A study concluded that seasoned observers provided greater clinical insight than AI, particularly in incorporating patient history and the clinical context into their decision-making [30]. This highlights the relevance of the human instinct and expertise in making fine clinical decisions. In another study on diagnosis of pulp vitality, methods of diagnosis by standard cold and electric pulp tests produced sensitivity estimates of 81–100%, which means that they are likely to diagnose this complex condition with ease [31]. Additionally, AI is best performed as an adjunct to the human

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practitioner's skill as a supplement, not a replacement for the clinical decision maker's judgement [32]. Another study showed that by adding structured visual annotations, AI models could perform at levels similar to that of dentists in the analysis of panoramic X-rays [33]. In contrast, pediatric dentistry was an area where AI performed poorly compared to clinicians, as children's dentists attained 95% accuracy and 99% sensitivity, demonstrating that performance is context-dependent [34]. Another study pointed out the issue that Human evaluations are prone to high false negative results, leading to treatment delays [35]. This is similar to how direct metal laser forming has been shown to enhance secondary implant stability, with laser treatments improving the longevity and clinical outcomes of implants, akin to AI's potential in diagnostic applications [36].
The present study shows that the AI model achieved better results than the human predictions in all metrics, where sensitivity was higher (0.868 vs 0.794), specificity (0.903 vs 0.886), F1 score (0.892 vs 0.831), and overall accuracy (0.884 vs 0.841). It is consistent with the previous research that identifies AI's superior diagnostic capability, as its high sensitivity and specificity make it highly effective in oral disease, including cancers and periodontal disorders [37]. Another research pointed out AI's ability to reduce the time needed for radiographic diagnosis while increasing accuracy, providing evidence of AI's dominance over other methods [38]. Furthermore, predictive capabilities of AI models have also emerged outside diagnostics, such as estimating the success rate of restorative materials [39]. At the same time, contrasting research claims that important ethical issues remain, including the potential algorithmic bias and overdependence on automation [40]. Also, the lack of standard data availability makes applying AI in non-image-based dentistry more difficult [41]. Poor AI education among dental practitioners is another barrier, which may lead to suboptimal use of AI, thus emphasizing the need for training [42]. Study on rough-surfaced collar implants has demonstrated better bone preservation compared to machined collars, suggesting that surface modification can enhance implant stability in specific patient groups, much like how AI improves diagnostic performance in identifying conditions such as periodontal bone loss [43].
The current study results emphasize they demonstrate AI's role in reducing diagnostic errors as evidenced by the lower false positive (0.097 vs 0.114) and false negative (0.132 vs 0.206) rates as well as the lower misclassification rate (0.116 vs 0.159) and balanced error rate (0.114 vs 0.16). It is worth highlighting AI's enduring dominance in superior diagnostics. Supporting this research demonstrates that AI has sensitivity towards 94.4% and no specificity issues when detecting periodontal bone loss, which is better than that of both periodontists and GPs [44]. Other works testify to AI systems' robust sensitivity and specificity in diagnosing various dental conditions, suggesting improvements over conventional methods in certain circumstances [45]. Similar to AI's diagnostic role, panoramic multilayer imaging has been shown to improve diagnostic accuracy by reducing superimpositions in caries detection, further demonstrating the advantages of advanced technologies in enhancing diagnostic capabilities [46].
The results of the present study emphasised that artificial intelligence demonstrates superior predictive capability, as evidenced by an AUC significantly higher than that achievable by humans (0.886 vs 0.84). AI's higher sensitivity and specificity at multiple thresholds attest to its clinical utility. There is supporting evidence that deep learning models diagnose better than most human clinicians, which strengthens AI's position within the clinical context [47]. Another investigation into photoactivated surface modification confirmed that the technique improves implant stability, much as artificial-intelligence algorithms raise diagnostic accuracy in oral disease detection; both developments suggest promising avenues for clinical adoption [48]. Additionally, AI continues to advance dentistry by refining diagnosis, optimizing treatment plans, and predicting procedural outcomes, all while handling and analyzing large data sets with remarkable precision [49].

Key Implications for Clinical Practice

This research validates the AI's potential in aiding dental radiograph interpretation by increasing accuracy, sensitivity, and specificity while reducing errors. However, false negatives need to be minimized as much as possible. Future developments need to focus on these factors so as to make AI more reliable in clinical decision-making.

Limitations and Future Directions

This study captures important challenges in AI adoption. The validation of AI requires expanding datasets to include underrepresented conditions. Increasing the overall sensitivity and incorporating AI into clinical workflows should be prioritized. Solving these problems will greatly improve the most useful AI medical diagnostics algorithms and change the clinical approach.

Conclusion

The current study explore and define the potential of AI in the field of dentistry radiology reporting where AI performs better than humans at diagnosing conditions. The AI model showed higher rates for sensitivity (86.84%) and specificity (90.32%) as well as a greater positive and negative predictive value, and F1 scores when examined in detail for a sample size of 138. The Model AUC value indicates strong performance at 0.886. This affirms the trust placed on the model for incorporation into clinical decision systems, but more work needs to be done on the issue of false negatives. Harshness can be reduced by expanding datasets and improving learning algorithms. Cost, practicality, implementation, and acceptance by clinicians can make AI challenging. In the end, continued research and innovation in AI will foster automation and optimize the diagnosis and management of patients.

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Conflicts of interest

There are no conflicts of interest.

Author Contributions

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All authors made substantial contributions to the study conception, development of the methodology, data analysis, and writing of the manuscript. All authors have reviewed the final version of the article and agree with its content.

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Institutional Review Board Statement

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All procedures performed in this study were approved by the institutional review board in accordance with current ethical standards. The study was reviewed and approved by the Bioethics and Ethics Committee for Scientific Research at O.O. Bogomolets National Medical University (Protocol No. 185, dated May 27, 2024).

Informed Consent Statement
All participants provided written informed consent after receiving comprehensive information regarding the purpose of the study, its procedures, potential risks, and benefits.

Data Availability Statement
The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest
The authors declare no conflicts of interest related to this study. All authors have contributed to the research independently and no external influence or bias has impacted the study's design, data collection, analysis, or reporting.

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Table 1. Demographic and clinical characteristics of the study population.

Variable	Category	Frequency	Percentage
Age (Mean ± SD)		44.59 ± 16.24	
Gender	Male	69	50
	Female	69	50
Severity Level	Mild	60	43.48
	Moderate	49	35.51
	Severe	29	21.01
Diagnosis	Caries and its complications	72	52.17
	Fracture and Periodontal disease	37	26.81
	Other Abnormalities	29	21.01
Control	Mild	30	43.48
	Moderate	24	34.78
	Severe	15	21.74
Experimental	Mild	30	43.48
	Moderate	24	34.78
	Severe	15	21.74

Table 2. Confusion matrix for the experimental group (AI Predictions).

	Ground Truth		
Experimental (AI)	Positive (Actual)	Negative (Actual)	Total
Predicted Positive	33	3	36
Predicted Negative	5	28	33
Total	38	31	69

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Table 3. Confusion matrix for the control group (Human Predictions).

	Ground Truth		
Control (Human)	Positive (Actual)	Negative (Actual)	Total
Predicted Positive	27	4	31
Predicted Negative	7	31	38
Total	34	35	69

Table 4. Comparison of performance metrics between experimental (AI) and control (Human).

Performance Metric	Experimental (AI)	Control (Human)
Sensitivity	0.868	0.794
Specificity	0.903	0.886
PPV	0.917	0.871
NPV	0.848	0.816
Accuracy	0.884	0.841
Precision	0.917	0.871
F1 Score	0.892	0.831

Table 5. Error analysis.

Types of error	Experimental (AI)	Control (Human)
False Positive Rate	0.097	0.114
False Negative Rate	0.132	0.206
Misclassification Rate	0.116	0.159
Balanced Error Rate	0.114	0.16