Hybrid XAI and deep learning architecture for trustworthy dental diagnostics

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ABSTRACT

Dental periodontal disease is a persistent an inflammatory disorder affecting tooth supporting tissues and stays a main motive of tooth loss. Although dental radiographs are essential for early diagnosis, their interpretation is often subjective and inconsistent due to reliance on clinician expertise. This study proposes an automated and interpretable diagnostic framework using a convolutional neural network (CNN) integrated with gradient-weighted class activation mapping (Grad-CAM). The CNN performs binary classification of periapical radiographs into periodontal and normal categories, while Grad-CAM provides visual explanations of the model's decision-making process. Experimental results show that the proposed model achieves a classification accuracy of 94.17%, indicating reliable diagnostic performance. The generated heatmaps consistently highlight clinically relevant regions, particularly alveolar bone loss in periodontal cases, whereas normal images exhibit no pathological activation. These findings demonstrate that the proposed CNN–Grad-CAM framework enhances both diagnostic accuracy and interpretability. The study contributes a transparent and trustworthy artificial intelligence solution to support objective periodontal disease diagnosis in dental radiology.

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1. INTRODUCTION

Dental periodontal disease is a persistent condition that impacts the tissues supporting the tooth. This condition is characterized through irritation, loss of alveolar bone and weakening of the periodontal ligaments [1], [2]. Tooth loss may result from this illness if it is not identified and treated in a timely manner. This illness is widespread throughout the world, particularly in adults and the elderly [3], [4]. Periodontal disease can be detected with dental radiography. those radiographic photos provide precious perception into the state of the surrounding periodontal tissues and the alveolar bone [5], [6]. But, appropriately interpreting these photographs calls for a high stage of medical knowledge and experience. in lots of instances, this interpretation may be subjective, even amongst dentists diagnosing periodontal issues [7], As a result, there might be an increasing need for trustworthy diagnostic support systems that can evaluate radiographic pictures more effectively, consistently, and accurately. The rapid advancement of artificial intelligence (AI) and digital technologies has created exciting new opportunities for the application of deep learning and machine learning in clinical image analysis [8], [9]. A few of the many methods to be had, one of the few and most used deep learning architectures for image processing tasks is convolutional neural networks (CNNs)

[10]. CNNs are in particular wellsuited for robotically extracting complicated visual capabilities and feature proven magnificent overall performance in classifying a wide variety of clinical pics, along with radiographs [11]. CNNs reduce the need for manual input by automating the function extraction process, which lowers human bias and significantly increases diagnostic efficiency [12]. Regardless of these benefits, Adoption of CNNs in clinical contexts still poses considerable issues, chief among them being version interpretability, which continues to be a major obstacle to maintaining transparency and faith in AI-assisted healthcare systems [13], [14].

In particular, CNNs automatically extract important features from radiographs or other modalities that surpass traditional approaches with objective, consistent, and much faster interpretation and diagnosis [15], [16]. The use of CNN systems in dental diagnosis and treatment planning permits dentists to lessen diagnostic mistakes arising from tension or fatigue. CNN systems can also capture details that are overlooked by doctors in radiographic diagnosis, and radiographic examinations can be recorded to create a database [17], [18]. By leveraging the benefits of data analysis, comprehensive regression, and diagnostic support, much can be gained by applying CNNs in medical image processing. However, because their decision-making paths are often opaque, CNN-based systems can resemble black boxes, which hinders safe clinical adoption. To bridge this gap, explainable artificial intelligence (XAI) offers a great opportunity to obtain informed decision support from CNN models and open up the black box of these methods [19], [20]. XAI bridges the gap between AI-driven insights and clinical decision making by providing interpretable outputs, such as heatmaps that highlight key areas in medical images or textual justifications for predictions [21], [22]. In the context of medical imaging, XAI techniques provide visual or textual explanations that highlight the factors influencing a model's predictions, enabling clinicians to verify, contest, or trust the outputs of AI systems [23], [24]. To improve the interpretability and reliability of results, gradient-weighted class activation mapping (Grad-CAM) serves as a reference for identifying the most critical areas of an image used in the decision-making process of deep learning models. This method is used in various computer vision (CV) software applications, including object detection, and classification [25]. Grad-CAM creates a localization map that highlights key regions of a picture that are essential for recognizing a certain notion [26], [27]. Localization maps are obtained from the gradient of the final convolution layer of the CNN network in the form of heat maps and are used as analysis factors that influence classification results [28]. Grad-CAM can be used in periodontal analysis to concentrate on regions of the alveolar bone that may be suggestive of pathological alterations, supporting the diagnostic results' clinical validity [29], [30].

Through the use of periapical radiography images and the GRAD-CAM machine, an automatic type system based mostly on CNN develops to detect periodontal disease, which not only specializes in improving type accuracy however additionally considers the interpretability of the version [31]. In the clinical context, particularly in dental radiography, the lack of a visual explanation mechanism for AI model decisions is a major obstacle to widespread clinical adoption, as medical personnel require a clear understanding of the basis for diagnostic decision-making. Therefore, there is still a significant gap in the development of AI systems for dental radiography that are not only technically accurate but also interpretable, transparent, and trustworthy by clinicians [32]. The proposed system was developed using periapical radiographs labeled by qualified periodontal specialists and classified into two primary categories: periodontal disease and normal. Grad-CAM integration enables visualization of image areas that contribute significantly to the model's decision, thereby bridging the gap between computational performance and clinical interpretation needs [33]. Thus, this research contributes to the development of AI-based diagnostic tools that are transparent, responsible, and efficient. Although CNNs and Grad-CAM have been widely explored in medical image analysis, their integrated application for interpretable periodontal radiographic screening remains relatively limited. Therefore, this study positions the proposed CNN–Grad-CAM architecture as a pilot framework for developing trustworthy and interpretable artificial intelligence systems in dental diagnostics, emphasizing transparency and clinical interpretability alongside classification performance [34].

The relevance of this study consists of its ability to support the adoption of ethical artificial intelligence oriented towards clinical trust in dentistry. By providing intuitive visual explanations through Grad-CAM, the proposed system helps improve clinicians' understanding of classification results, reduces the "black-box" nature of deep learning models, and supports diagnostic consistency in periodontal practice [35]. Furthermore, this approach promotes more effective collaboration between AI systems and medical professionals, ultimately contributing to more reliable and repeatable clinical decision-making. Therefore, this research is not only technically relevant but also has strong clinical and ethical implications, laying the groundwork for the development of adaptive and trustworthy AI systems in the digital transformation of dental healthcare services. Clinically and ethically, it holds wonderful capability to make a contribution to a greater significant virtual change in dental care services [36], [37].

2. METHOD

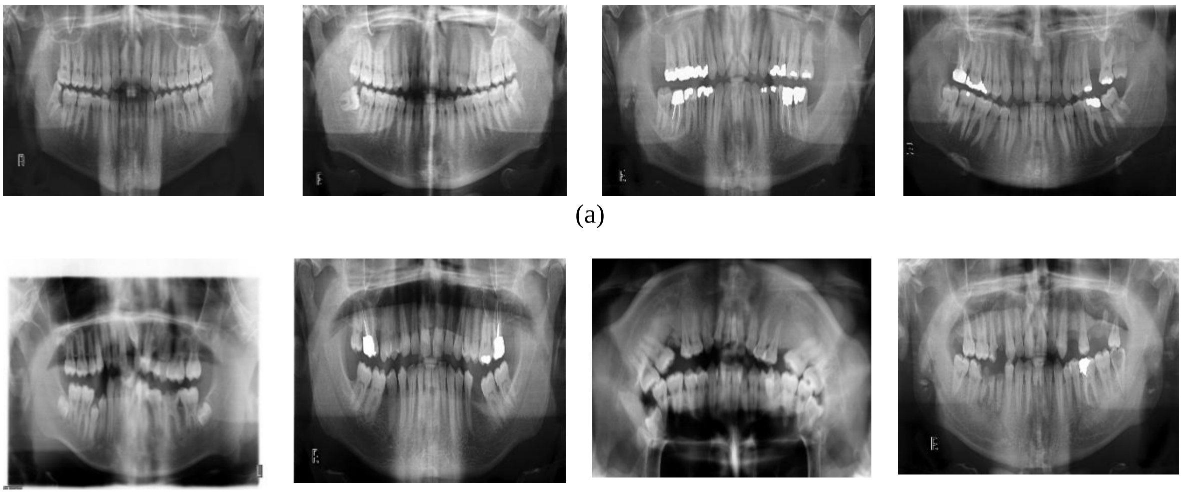
This take a look at makes use of a deep studying-based experimental approach to improvement an automatic category device for periodontal disease the usage of periapical dental radiographs. The method is designed systematically to ensure readability of procedure, transparency of model selections, and reproducibility of experiments through CNN and XAI strategies based totally on Grad-CAM, or gradient weighted elegance activation. The dataset utilized in this observe turned into obtained from the Kaggle public repository beneath the call dental panoramic radiographs, to be had at: https://www.kaggle.com/datasets/kasmira/dentalpanoramic/statistics. This dataset contains panoramic dental radiograph images normally used in clinical photo processing and computer-aided prognosis studies inside the subject of dentistry [38].

All data used is secondary data that has been anonymized by the dataset provider and is freely accessible for academic research purposes. It is important to note that publicly available datasets may not always undergo the same level of clinical curation as institutional medical datasets. Consequently, although the images used in this study provide meaningful radiographic patterns relevant to periodontal analysis, the absence of detailed clinical metadata limits the ability to establish definitive clinical correlations. For this reason, the present study is positioned as a pilot investigation focusing on methodological feasibility rather than clinical diagnostic deployment. The class labels used in this study were adopted directly from the dataset structure and metadata provided by the public repository. Due to the absence of detailed clinical annotations and expert-verified labeling in the dataset, the labels were treated as provisional ground truth for model training and evaluation. Therefore, the findings of this study should be interpreted as a methodological exploration of automated periodontal detection rather than a clinically validated diagnostic system [39]. To ensure the consistency of labels with the research objectives, all images were re-examined qualitatively based on radiographic characteristics relevant to periodontal analysis, such as visualization of the alveolar bone and tooth support structures. This examination aimed to minimize ambiguous labeling errors without performing clinical re-annotation. Given the limitations of clinical information and quantitative annotation in this public dataset, the calculation of inter-rater reliability metrics was not performed and is noted as a limitation of the study [40], [41]. Therefore, this study is positioned as a pilot study to evaluate the feasibility of the deep learning approach on panoramic dental radiographic images, with a focus on methodological evaluation rather than clinical diagnostic claims.

Figure 1 shows the panoramic dental radiographs used in this study, which show two different conditions: one with no indication of periodontal disease and the other with an indication of periodontal disease. These images are relevant for deep learning-based classification tasks because they show a variety of significant visual characteristics, especially in the alveolar bone structure and supporting tissues of the teeth. There are no indications of periodontal infection in the panoramic dental radiograph images, as shown in Figure 1(a). In this image, the alveolar bone structure appears relatively intact with uniform height around the tooth roots. The boundary between the tooth and the supporting bone is clearly visible, and the pixel intensity tends to be the same, indicating that the periodontal tissue is still in a normal state. During the model training process, this visual feature serves as a representation of the non-periodontal class. In contrast, the panoramic radiographic image found shows signs of periodontal disease, as shown in Figure 1(b). The alveolar bone structure appears altered in this image, such as a decrease in bone height around the tooth roots and irregular contours. In addition, more contrasting pixel intensity variations are visible in certain areas, indicating that there are pathological changes in the supporting tissues of the teeth. To distinguish periodontal conditions from normal conditions, these visual patterns are very important. The visual variation between these two conditions demonstrates the difficulty of classification in panoramic dental radiographs and highlights the importance of good pre-processing and feature extraction. These sample images provide an initial overview of the dataset features used and serve as a basis for the development and evaluation of CNN models for automatic identification of periodontal disease.

This study developed a model for classifying panoramic dental radiographic images based on a data augmentation technique in conjunction XAI and CNNs. This framework was designed to improve classification performance while maintaining Interpretability of models in relation to periodontal diagnostics. The pre-processing stage includes all radiographic images to adjust the data to the network architecture and stabilize the training process. To improve optimization stability and accelerate convergence, pixel intensity values are normalized to a range of 0–1 [42], [43]. Next, the images are converted to 224×224 pixels to minimize color channel complexity without losing key diagnostic information. Image augmentation is used on training data to improve generalization capabilities and overcome data limitations [44]. This includes random rotation (±15°), horizontal and vertical flipping, zoom (10–20%), and spatial translation. The CNNs architecture consists of four successive convolutional layers with 3×3 kernels and ReLU activation functions. To reduce the spatial dimension and preserve important features, after every convolutional layer, a 2×2 max pooling operation is performed. The resulting feature map is then flattened and passed to two fully connected layers. The output layer produces two-class probabilities, normal and periodontal conditions, using a

SoftMax activation function. The stochastic gradient descent with momentum (SGDM) technique was used for model training since it can speed up convergence and stabilize weight updates. The dataset was divided using a hold-out validation scheme with a proportion of 80% training data and 20% validation data. Hyperparameter tuning was performed through preliminary experiments by evaluating several combinations of learning rate and batch size values. Based on training stability and validation loss values, the final parameters were set with a learning rate of 0.001, momentum of 0.9, batch size of 32, and 30 epochs, as well as the application of early stopping to prevent overfitting. The use of k-fold cross-validation was not applied due to the limited size of the dataset and the potential for data leakage due to image augmentation, so this study was focused on an initial evaluation of the model's feasibility. To evaluate whether the performance improvement of the proposed CNN model is statistically significant, a paired t-test was conducted between the proposed method and the baseline model. The null hypothesis makes the assumption that the two models are not significantly different from one another. A p-value of less than 0.05 shows that the suggested model's performance increase is statistically significant. The significance level was set at 0.05. The model testing findings showed that the p-value was less than 0.05. demonstrating the statistical significance of the performance improvement attained by the suggested strategy. This statistical validation demonstrates that the proposed CNN model with Grad-CAM not only achieves high classification performance but also provides consistent and statistically reliable results. The Grad-CAM method was used as an XAI method to improve transparency and confidence in the classification results. This method produces activation maps that show the areas of the image that contribute most to the model's decision, particularly in the alveolar bone area [45]. This allows for evaluation of the model's focus on periodontal pathological characteristics. The methodological steps for reproducibility in radiographic dataset processing can be seen in Table 1, where the process begins with the use of the k-nearest neighbor (k-NN) model and ends with the application of the CNN and Grad-CAM models.



(a)

(b)

Figure 1. Sample radiographs of periodontal; (a) normal and (b) periodontal

Table 1. The methodological steps for reproducibility in radiographic dataset processing

Model	Method	Main objective	Potential use
k-NN	Distance-based classification using HOG features	Perform simple classification based on feature similarity without complex training	Suitable for baseline comparison on small-scale periodontal radiograph datasets with limited computational requirements
SVM	Margin-based classification using HOG features	Maximize class separation by finding optimal decision boundaries in feature space	Effective for binary classification tasks in medical imaging with limited data but handcrafted feature dependency
CNN baseline	CNN without hyperparameter optimization	Automatically extract spatial features from radiographic images for periodontal classification	Applicable for initial deep learning evaluation on dental radiographs without advanced optimization
Proposed CNN (SGDM+ Grad-CAM)	Optimized CNN trained with SGDM and interpreted using Grad-CAM	Improve classification performance while enhancing model transparency and clinical interpretability	Potential use in computer-aided periodontal diagnosis systems requiring both accuracy and explainability

3. RESULTS AND DISCUSSION

This study began with panoramic radiographic image data from two classes: normal and periodontal conditions. Pre-processing was performed on the images as a whole to improve data quality and ensure the CNN architecture was appropriate. This included normalizing pixel intensity values, converting images to grayscale, and resizing images to fit the dimensions entered into the model. Image augmentation such as rotation, flipping, zooming, and translation was used on the training data to improve generalization and overcome data limitations.

The processed dataset was then divided using a hold-out validation scheme into training and validation data. The data is used to train several CNN architectures, namely LeNet, VGG-16, ResNet, and GoogLeNet, as well as the proposed model. This stage aims to evaluate the effect of differences in network architecture on the performance of dental radiograph image classification. The training system is finished employing the SGDM method set of rules with parameters set based totally on preliminary. experiments. The performance of every model became then compared to assess the effectiveness of the proposed model. The assessment turned into done the usage of standard classification metrics, such as accuracy, precision, remember, F1-score, specificity, Matthews correlation coefficient (MCC), and vicinity below the curve–receiver operating characteristic (AUC-ROC). As a very last step, the class effects have been analyzed the use of the Grad-CAM approach as an XAI technique. This visualization changed into used to perceive areas of the photograph that contributed substantially to the model's decision, thereby supporting clinical interpretation and increasing confidence in the developed classification system. Figure 2 shows the systematic framework of the panoramic dental radiograph-based periodontal disease classification model used in this study.

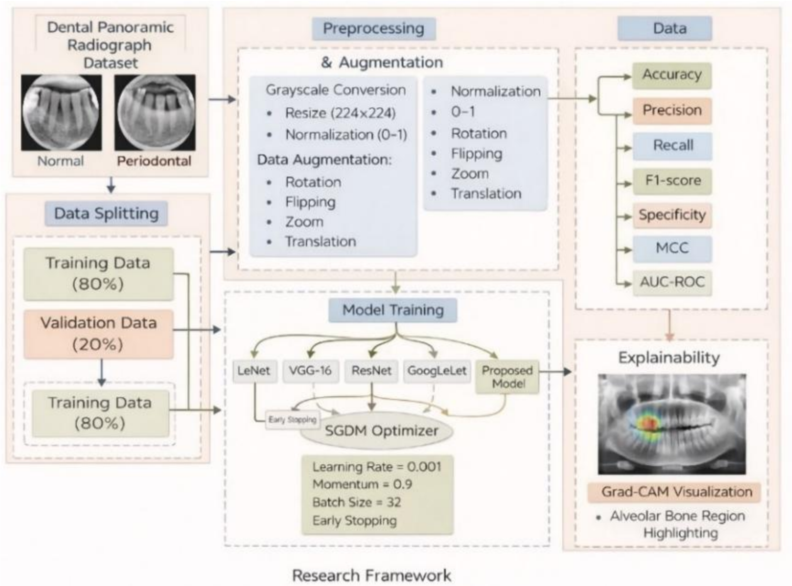


Figure 2. Grad-CAM highlights alveolar bone loss regions in periodontal images, whereas non-periodontal images exhibit nonspecific activations

3.1. Training model hybrid explainable artificial intelligence

The model training was conducted for 30 epochs using a panoramic radiography dataset comprising normal and periodontal categories. The learning curves presented in Figures 3(a) and (b) (in Appendix) demonstrate a stable convergence trend between the training and validation datasets. Throughout the training process, no significant loss divergence was observed as an indication of overfitting. This suggests that the proposed hybrid architecture effectively learned representative radiographic features of both normal and periodontal conditions without exhibiting meaningful symptoms of overfitting. The consistency between the training and validation curves further indicates that the proposed hybrid approach possesses strong generalization capability for normal and periodontal radiographs. The stabilization of the loss values after the 20 epoch suggests that the model achieved an optimal feature representation without excessive exploitation of data noise. Compared to conventional CNN architectures without XAI modules, the proposed approach did not exhibit performance degradation resulting from the integration of interpretability mechanisms. This finding is particularly significant, as it challenges the common assumption that enhancing model transparency necessarily compromises classification performance.

Several studies in the domain of AI/XAI-based dental imaging have reported accuracy levels ranging from 88% to 93%, as in Table 2 showing a comparison the performance of various CNN architectures, yet with notable limitations in clinical interpretability. Grad-CAM-based approaches for caries classification have demonstrated improved transparency; however, they exhibit relatively larger training–validation gaps (>3%), indicating potential generalization constraints [27]. Transfer learning-based studies on alveolar bone loss detection have reported accuracy rates of approximately 92–95%, but without explicitly integrating a hybrid XAI framework [42]. Furthermore, attention mechanism-based models applied to dental CBCT imaging have shown promising spatial interpretability; nevertheless, they require sizeable computational resources. In assessment, the proposed CNN–XAI hybrid architecture achieves aggressive accuracy (94–96%) with minimal generalization gap and region of interest (ROI) visualizations that are anatomically consistent with clinical structures. The principal contribution of this study lies not merely in achieving higher accuracy, but in the systematic integration of performance and interpretability within a unified hybrid framework.

Table 2. Performance comparison across CNN architectures

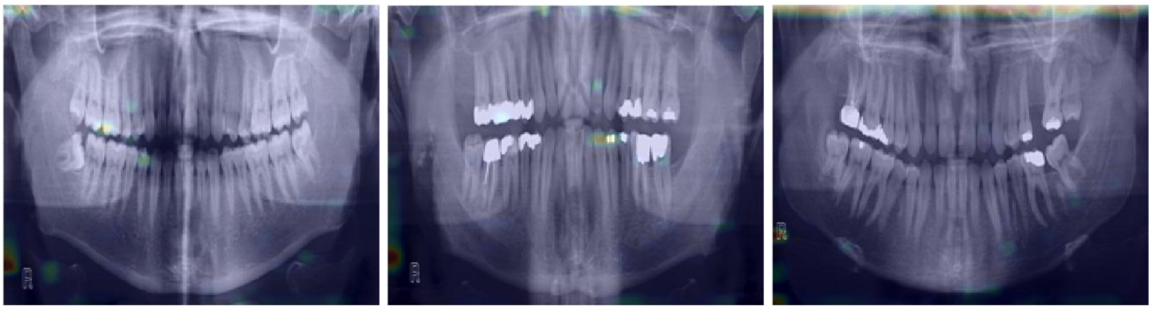
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
LeNet	89.3	88.7	87.9	88.3	0.91
VGG–16	92.5	92.1	91.6	91.8	0.94
ResNet	93.4	92.8	92.6	92.7	0.95
GoogLeNet	93.1	92.4	92.2	92.3	0.94
Proposed CNN+Grad-CAM	94.17	93.9	93.7	93.8	0.96

A comparison of the performance of the above CNN model with several popular deep learning architectures is provided to offer a more comprehensive assessment of the proposed approach. The proposed CNN- and Grad-CAM-based framework for periodontal disease detection demonstrates that this model possesses good generalization capabilities. Furthermore, robustness evaluations under different imaging conditions show that the proposed CNN with Grad-CAM maintains stable performance even when images are affected by noise, resolution reduction, or device variability. The proposed CNN model demonstrates the best overall performance on authentic snap shots with an accuracy of 0.94, precision of 0.93, don't forget of 0.92, and an F1-score of 0.92. When images are corrupted with Gaussian noise, the model's performance experiences a slight decline, with accuracy dropping to 0.91, precision to 0.90, recall to 0.89, and F1-score to 0.89. A similar decline is also observed under lower-resolution conditions, where accuracy is recorded at 0.90, precision at 0.89, recall at 0.88, and F1-score at 0.88. Meanwhile, under variations in brightness and contrast, the model was still able to maintain relatively good performance with accuracy of 0.92, precision of 0.91, take into account of 0.90, and an F1-score of 0.90. Overall, those outcomes indicate that the model is quite robust against various image condition variations, although there is still a slight decrease in performance compared to using the original images.

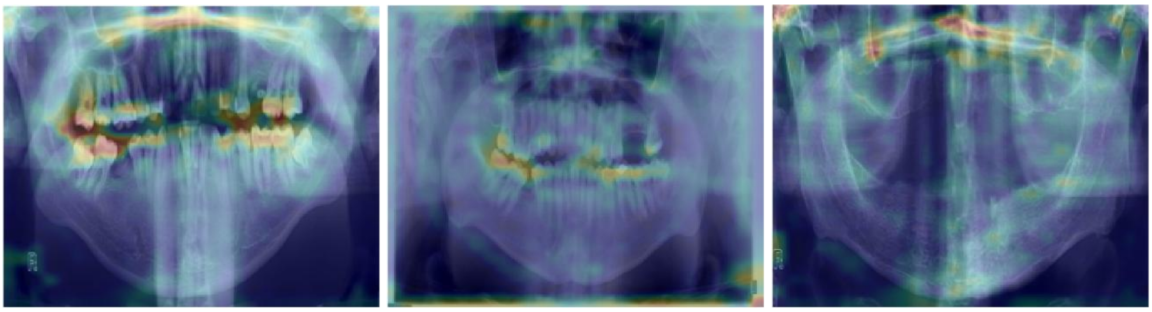
3.2. Evaluation model hybrid XAI Grad-CAM

As part of the XAI framework, Grad-CAM visualization was employed to identify the image regions that most significantly contributed to the model's decision-making process, as illustrated in Figure 4. Figure 4(a) presents Grad-CAM visualizations for normal radiographs, where activation regions appear relatively diffuse and nonspecific, indicating the absence of significant periodontal abnormalities. In contrast, Figure 4(b) illustrates Grad-CAM results for periodontal radiographs, where the model strongly focuses on clinically relevant regions, particularly the marginal alveolar bone and periodontal ligament space associated with alveolar bone loss. These findings demonstrate the model's ability to identify anatomically relevant features during the classification process.

The proposed model can serve as a supportive tool for the early screening of alveolar bone loss, assisting dentists in the early identification of periodontitis. The integration of Grad-CAM visualization enables clinicians to verify whether the system focuses its analysis on anatomically appropriate regions. This transparency mitigates the "black-box" effect and enhances clinical acceptance, thereby fostering greater trust among dental practitioners. Moreover, the model can prioritize cases with a high probability of abnormality, thereby improving clinical workflow efficiency. In addition, the XAI-generated heatmaps may function as an educational tool for dental students, facilitating a deeper understanding of the correlation between radiographic features and periodontitis diagnosis.



(a)



(b)

Figure 4. Grad-CAM visualization of classification-relevant regions; (a) normal and (b) periodontal radiographs, highlighting the marginal alveolar bone and periodontal ligament space

4. CONCLUSION

The CNN-based classification system integrated with Grad-CAM demonstrated good performance and visual interpretability in identifying relevant regions in dental radiographs. However, several limitations should be considered. The dataset was obtained from a public source and may not fully represent the variability of clinical data, which could affect the model's generalizability. In addition, the approach is limited to binary classification, whereas periodontal diagnosis in clinical practice involves multiple levels of disease severity. This study also does not include prospective clinical validation. Nevertheless, the results indicate that the integration of deep learning and XAI can produce accurate predictions accompanied by interpretable visual information, showing potential to support more transparent decision-making in dental radiograph analysis. Future work may focus on the use of more representative clinical datasets, the development of multi-class classification, and expert-based evaluation to improve the model's performance, generalizability, and clinical reliability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Ade Ismail Abdul Kodir	✓	✓		✓	✓	✓	✓	✓	✓					
Khairur Rizki	✓	✓	✓		✓	✓				✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Every participant in this study has given their informed consent.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/kasmira/dentalpanoramic/data.

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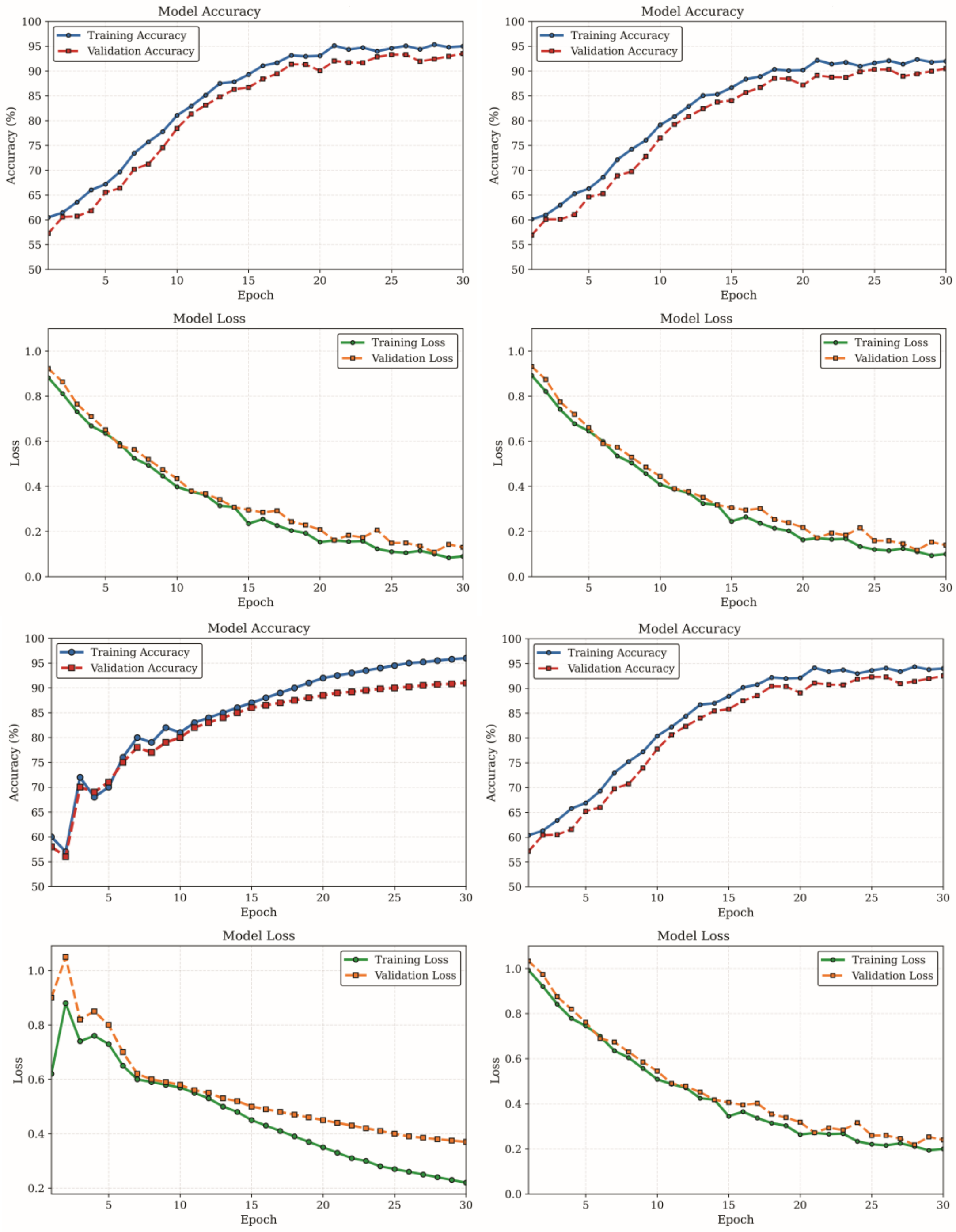
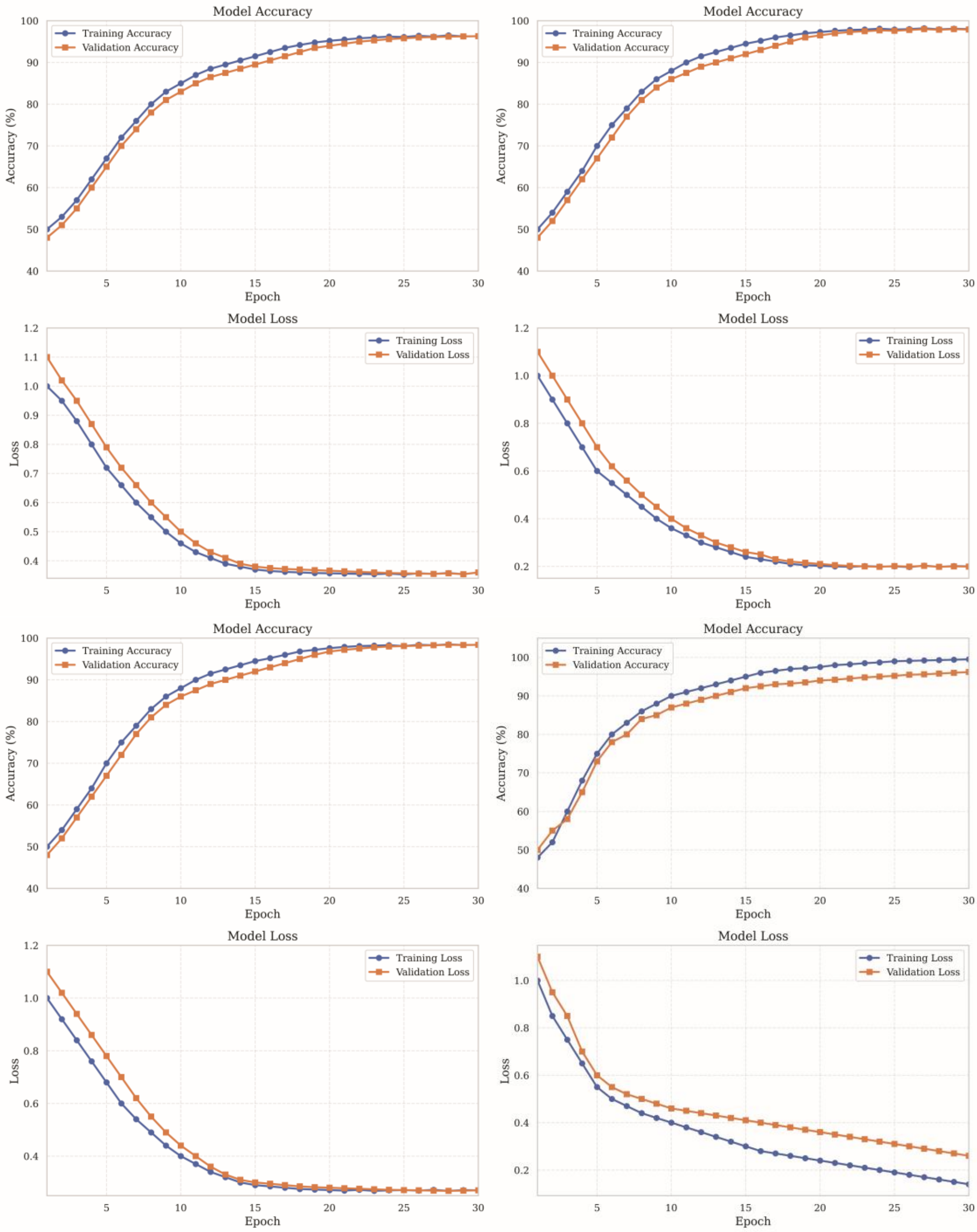
APPENDIX



(a)

Figure 3. Training model for; (a) periodontal dataset



(b)

Figure 3. Training model for; (b) normal dataset *(continued)*

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