

Deep learning–based classification of mesial and distal horizontal projection deviations in intraoral radiographs

Takahiro Sakota

sakota@kdu.ac.jp

Kanagawa Dental University

Masahiro Izumi

Kanagawa Dental University

Motoe Taniguchi

Kanagawa Dental University

Yusuke Kozai

Kanagawa Dental University

Lee TH. Sato

Kanagawa Dental University

Takashi Sakurai

Kanagawa Dental University

Research Article

Keywords: Artificial intelligence, Deep learning, Intraoral radiography, Horizontal angulation, Positioning error

Posted Date: October 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10759584/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Objectives

This study aimed to develop and evaluate a deep learning (DL) model for classifying mesial and distal horizontal projection deviations in intraoral radiographs.

Methods

Images were acquired from a maxillofacial phantom in 8 directions at 6 deviation angles (5° – 30°), yielding 48 images each for the maxilla and mandible. Data augmentation was performed using random translation and cropping. Forty test images were independently acquired from the second phantom (10 images each for the maxillary mesial, maxillary distal, mandibular mesial, and mandibular distal deviations). Accuracy and Wilson's 95% confidence intervals (CIs) were calculated. Five dentists each classified 20 randomly selected test images, and the paired results were compared with the model using two-sided exact McNemar tests. Gradient-weighted class activation mapping (Grad-CAM) was used to visualize the contributing regions.

Results

The DL model correctly classified 36 (90.0%) of 40 test images (95% CI, 76.9%–96.0%). The accuracies were 90% for maxillary mesial and distal deviations, 100% for mandibular mesial deviations, and 80% for mandibular distal deviations. Dentist accuracy ranged from 25% to 95%, whereas the corresponding model's accuracy ranged from 85% to 100%. The model achieved a higher accuracy than 4 of the 5 dentists and significantly outperformed 2 dentists. Grad-CAM highlighted crowns, interproximal surfaces, and periradicular regions.

Conclusions

The DL model accurately classified the mesial and distal horizontal projection deviations in intraoral radiographs from an independent second phantom. This model may support directional correction during repeated radiography.

Introduction

Intraoral radiography is a fundamental examination in dentistry that provides essential imaging information for diagnosing dental caries and diseases that affect the tissues surrounding the teeth. To obtain diagnostically acceptable images, the central X-ray beam must be directed at appropriate horizontal and vertical angles. However, consistently reproducing these acquisition conditions accurately is not easy [1]. In particular, the overlap of interproximal surfaces caused by horizontal angulation errors

may reduce the sensitivity of detecting interproximal caries [2], and inappropriate beam angulation and positioning errors have been reported as major causes of image-quality failure and repeat acquisition in intraoral radiography [1, 3]. Repeat radiography not only reduces clinical efficiency but also increases unnecessary radiation exposure in patients and should therefore be avoided whenever possible [3, 4].

Accurate control of the horizontal projection direction is important not only for diagnosing caries but also for endodontic treatment. Radiographic assessment during root canal treatment can be difficult because of the root morphology and tooth position, and eccentric projections with altered horizontal beam angulation may be required to avoid superimposition of multiple roots or root canals [5].

When an image-quality failure is caused by a positioning error, the operator must determine from the acquired image whether the horizontal projection direction deviated mesially or distally and then correct the X-ray tube head in the appropriate direction to avoid repeating the same error during repeat radiography. However, objectively estimating the direction of the X-ray beam at the time of acquisition from a two-dimensional radiograph containing superimposed anatomical structures is not always straightforward.

In recent years, image analysis techniques using deep learning (DL) have developed rapidly in dental radiology [6]. Previous studies have reported the automated detection of interproximal, occlusal, and secondary caries on bitewing radiographs using YOLOv8 [7] as well as early caries detection using U-Net [8]. Applications of DL have also expanded beyond disease detection to include automated anatomical-region classification and technical quality assessment of intraoral radiographs [6, 9, 10]. For assessment of acquisition positioning, a system combining U-Net–based tooth segmentation with AlexNet classification has been reported for classifying the technical quality of maxillary canine periapical radiographs as acceptable or unacceptable, with a high discriminatory performance (area under the curve, 0.927) [9]. DL models have also been reported for automated assessment of image-quality factors, including positioning and contrast, in panoramic radiographs [10]. More recently, DL models were developed to automatically detect multiple technical quality errors in periapical radiographs, including inappropriate horizontal and vertical beam angulations, insufficient coverage, and cone cuts [11]. In addition, a multitask DL model trained on periapical radiographs collected from multiple institutions was reported to simultaneously classify 6 types of technical errors and assign standardized quality grades [12].

However, most of these studies primarily focused on identifying anatomical regions, detecting the presence of positioning errors, detecting or classifying types of technical errors, and rating images as acceptable or unacceptable or according to a quality grade [9–13]. To avoid repeating the same acquisition error during repeat radiography, it is necessary not only to indicate that an image is unacceptable but also to show whether the horizontal projection direction deviated mesially or distally, thereby informing the operator’s decision regarding the direction of correction. Previous research has also noted that classifying only the overall acceptability of an image cannot clearly identify the cause of acquisition failure and that systems capable of identifying individual causes of failure are needed [9].

However, to the best of our knowledge, no DL model that classifies mesial and distal horizontal projection deviations on intraoral radiographs has been reported. Therefore, this study aimed to develop a DL model for classifying mesial and distal horizontal projection deviations from intraoral radiographs and to evaluate its classification performance.

Materials and methods

Phantom, imaging equipment, and system environment

Two maxillofacial phantoms, each containing an embedded human skull (Rinn; Dentsply Sirona, Charlotte, NC, USA), were used as the imaging subjects. One of the phantoms is presented in Fig. 1. The maxillary and mandibular molar regions were imaged using an intraoral X-ray unit (HD-70; Asahi Roentgen Industry Co., Ltd, Kyoto, Japan). The standard exposure settings were as follows: tube voltage, 70 kV; tube current, 6 mA; exposure time, 25 ms. Image data were acquired from imaging plates (IPs) using a Digora Optime II system (Soredex, Tuusula, Finland). The DL model development, training, and data preprocessing were performed on a PC running Windows 11 Pro (Microsoft Corp., Redmond, WA, USA) with Intel Core i9 CPU and 48-GB RAM (Intel, Santa Clara, CA, USA). An NVIDIA GeForce RTX 3080 graphics processing unit (NVIDIA, Santa Clara, CA, USA) with 10 GB of video memory was used for the training. Visual Studio Code was used as the software development and execution environment, with Python 3.10 as the programming language, PyTorch 2.1.0 as the DL framework, and CUDA 12.1.

Acquisition of training images

One phantom was used for the DL model development (phantom A), and another was used to evaluate classification accuracy (phantom B). For the horizontal direction, the position of the X-ray tube head that produced an orthoradial projection without an interproximal overlap was defined as the reference position. The protractor was positioned such that it read 90° at this reference position, and the deviation from the reference position was defined as 0°. For the vertical direction, the X-ray tube head position at which the projected buccal and lingual cusps of the first molar crown most closely coincided was defined as the reference position, and the deviation angle was similarly defined as 0°. Two dentists confirmed on the acquired images that the horizontally and vertically defined 0° positions met these definitions. The direction of deviation was defined according to the position of the X-ray tube head relative to the reference position for orthoradial projection. Conditions in which the X-ray tube head was positioned mesially or distally relative to the reference position and the central X-ray beam was directed obliquely toward the target region were defined as mesial and distal deviations, respectively. For phantom A, the central X-ray beam deviated from the reference position in 8 directions: mesial, distal, superior, inferior, mesial-superior, mesial-inferior, distal-superior, and distal-inferior. Six deviation angles were used: 5°, 10°, 15°, 20°, 25°, and 30°. For diagonal directions, the horizontal and vertical components deviated by the same angle. For example, in the 5° mesial-superior condition, the horizontal component deviated 5° mesially, whereas the vertical component deviated 5° superiorly. Forty-eight conditions (8

directions $\times$ 6 angles) were established for each jaw, and 1 image was acquired under each condition. Thus, 48 original images were obtained for each of the maxilla and mandible. Images acquired at deviation angles of 10° and 30° are presented with their respective reference images in Fig. 2a and b, respectively.

Preprocessing and data augmentation of training images

Data augmentation was applied to the 48 original maxillary and 48 original mandibular images acquired from phantom A to simulate variations in the intraoral insertion position of the IP. Image data augmentation is a method for artificially increasing the diversity of training images by applying transformations to the original images [14]. Figure 3 provides an overview of data augmentation using random translation and cropping of the original images. For each original image, 499 same-sized crops were generated with random horizontal and vertical translations ranging from -150 to $+150$ pixels. Including the original image, this yielded 500 images per condition and datasets of 24,000 images each for the maxilla and mandible. Image preprocessing was performed in Python using PIL and OpenCV. All the images were converted into three-channel RGB images, resized to 224×224 pixels, and normalized using the mean and standard deviation of the ImageNet dataset.

DL model architecture

Two separate DL models were developed for the maxillary and mandibular molar regions so that each model could learn the respective anatomical structures and projection patterns, rather than requiring a single model to distinguish the target region itself. Both models were implemented using the PyTorch framework, with ResNet-18 as the backbone network [15]. Transfer learning was applied using ImageNet-pretrained weights for initialization. After removing the final fully connected layer of ResNet-18, the 512-dimensional feature vector obtained by global average pooling was used as the shared representation. All network weights, including those of the backbone, were updated during training. Multitask learning has also been investigated for position classification in dental radiographic image analysis [16]. Accordingly, the proposed models implemented multitask learning to learn 2 tasks simultaneously from the shared representation. The network branches into two output heads as follows: the classification head output 8 deviation-direction classes: superior, distal, inferior, mesial, mesial-superior, distal-superior, mesial-inferior, and distal-inferior. The regression head comprised a fully connected layer and a sigmoid function, and its output was multiplied by 30 to produce a continuous deviation-angle estimate ranging from 0° to 30°. The target values for angle regression were acquisition angles of 5°, 10°, 15°, 20°, 25°, and 30°. For the diagonal directions, the same angle was assigned to the horizontal and vertical components, and this assigned value was used as the regression target. Thus, the target value for the diagonal direction did not represent the resultant spatial angle calculated from the horizontal and vertical components; rather, it was the common deviation angle assigned to both components (5°, 10°, 15°, 20°, 25°, or 30°).

DL model training and optimization

The augmented image dataset was randomly divided at the image-file level into a training set (80%; 19,200 images) and a validation set (20%; 4,800 images). The data were split using scikit-learn with random_state set to 42. Because the split was performed at the augmented image-file level rather than at the original-image level, images derived from the same original image may have been included in both the training and validation sets. Adam was used as the optimization algorithm [17]. Cross-entropy loss was used for the classification task and mean squared error for the regression task, and the two losses were summed with a weight of 1 for each to obtain the overall network loss. The batch size was 32, the learning rate was 1×10^{-4} , and the maximum number of epochs was 100. Early stopping was applied when the validation loss failed to improve by at least 1×10^{-4} for 10 consecutive epochs. During the training, the model weights corresponding to the minimum validation loss were saved, and the saved models were used to classify the accuracy-evaluation images.

Evaluation of the DL models

The models were evaluated in three ways: evaluation of DL model accuracy, comparison of classification accuracy between the DL models and dentists, and visualization using gradient-weighted class activation mapping (Grad-CAM).

Evaluation of DL model accuracy

New intraoral radiographs of the left maxillary and mandibular molar regions were acquired using phantom B, which was not used for the model development. The accuracy-evaluation dataset comprised 40 images: 10 each for the maxillary mesial, maxillary distal, mandibular mesial, and mandibular distal deviations. Each image was acquired separately.

For the horizontal direction, similar to phantom A, the position that produced an orthoradial projection without interproximal overlap was used as the reference position. From this reference position, the central X-ray beam was angulated mesially or distally by up to approximately 45° . Unlike the model-development images, fixed 5° increments were not used, and the exact horizontal deviation angle of each test image was neither measured nor recorded. To include conditions with simultaneous horizontal and vertical deviations, the beam was also angulated superiorly or inferiorly by up to approximately 45° from the reference position. However, the exact vertical deviation angle of each image was neither measured nor recorded. The ground-truth label for each image was defined as the mesial or distal deviation according to the horizontal direction intentionally established during image acquisition.

The maxillary model was applied to maxillary test images, and the mandibular model was applied to mandibular test images. For each image, the model saved at the point of minimum validation loss output an 8-class deviation direction and a deviation angle. The class with the highest classification-head output was designated as the predicted direction. The three mesial-component directions (mesial, mesial-superior, and mesial-inferior) were combined as mesial deviation, and the three distal-component

directions (distal, distal-superior, and distal-inferior) were combined as distal deviation, yielding a binary mesial-versus-distal classification. A prediction was considered correct when any of the three directions containing a mesial component was predicted for a mesial-deviation image or when any of the three directions containing a distal component was predicted for a distal-deviation image. Predictions of superior or inferior deviation alone were treated as incorrect because they contained neither a mesial nor a distal component.

The primary outcome of this study was the classification of the mesial and distal horizontal projection deviations. Because the true deviation angle of each test image was neither measured nor recorded, the angle-regression output was not included in the evaluation. The DL model performance was evaluated using accuracy, and the corresponding 95% confidence interval (CI) was calculated using Wilson's method.

Comparison of classification accuracy between the DL models and dentists

Five dentists with experience in acquiring or interpreting intraoral radiographs served as evaluators. Before the evaluation, all evaluators received the same explanation for the definitions of mesial and distal deviations and the classification procedure. For each image, the evaluators classified the horizontal projection direction as deviating either mesially or distally. For each evaluator, 20 images were randomly selected from the 40-image accuracy-evaluation dataset and presented. The image sets were not necessarily identical among the evaluators, and some images were presented to more than one evaluator. The evaluators were blinded to the acquisition conditions, ground-truth labels, and DL model predictions. The DL models classified the same images presented to each evaluator, and the accuracies of the dentist and DL model were calculated. For each evaluator, the correctness of the dentist and DL model on the same images was categorized as both correct, dentist-only correct, DL model-only correct, or both incorrect. These paired binary outcomes were compared using two-sided exact McNemar test.

A supplementary analysis was performed to examine the overall trend across all evaluators by pooling 100 responses from the 5 dentists and the corresponding 100 DL model predictions. In the pooled analysis, each presentation of an image to an evaluator was treated as one observation and compared using two-sided exact McNemar test. Because some images were presented to multiple evaluators, the independence of the observations was not fully assured, and the pooled results may have been affected by correlations among the responses. A two-sided significance level of 5% was used for each test, and no correction for multiple comparisons was applied. All statistical analyses were performed using EZR version 1.60 (Saitama Medical Center, Jichi Medical University, Saitama, Japan), a modified version of R Commander based on R version 4.2.1 [18].

Visualization using Grad-CAM

Grad-CAM was used to examine the image regions that contributed to direction classification [19]. Feature maps and gradient information from the final convolutional layer of ResNet-18 were used to visualize the contributions to the predicted class as heatmaps. Grad-CAM heatmaps were generated for

all 40 images in the accuracy-evaluation dataset, and the locations of the highlighted regions relative to the target tooth, crown, root, interproximal surfaces, and image background were assessed qualitatively.

Results

Accuracy of the DL models

Of the 40 test images acquired from phantom B, which was not used for model development, 36 were correctly classified by the DL models, yielding an accuracy of 90.0% (95% CI, 76.9%–96.0%). By region and direction, the accuracies were 9/10 for maxillary mesial deviations, 9/10 for maxillary distal deviations, 10/10 for mandibular mesial deviations, and 8/10 for mandibular distal deviations. Among the 4 groups, the mandibular distal deviations had the lowest accuracy.

Comparison of classification accuracy between the DL models and dentists

Table 1 presents the classification results for the mesial and distal deviations by the dentist and DL model for the 20 images shown to each evaluator. For each evaluator, the paired classification outcomes of the dentist and DL model for the same images were categorized as both correct, dentist-only correct, DL model-only correct, or both incorrect.

Table 1 Correctness outcomes and comparison of accuracy between each dentist and the DL model							
No.	Both correct	Dentist-only correct	DL model-only correct	Both incorrect	Dentist accuracy (%)	DL accuracy (%)	p Value
1	14	1	3	2	75	85	0.625
2	10	1	7	2	55	85	0.070
3	18	1	0	1	95	90	1.000
4	12	0	8	0	60	100	0.0078
5	5	0	13	2	25	90	0.00024
Total	59	3	31	7	62	90	< 0.001

Values represent the number of images and the accuracy of the dentists and DL model.

The p-values are unadjusted values from the two-sided exact McNemar’s tests.

DL, deep learning.

Among the five evaluators, the DL model achieved a higher accuracy than the dentist for 4 evaluators, whereas the dentist achieved more accurate classifications than the DL model for 1 evaluator. No

significant differences in accuracy between the dentist and the DL model were found for evaluators 1, 2, and 3 ($p = 0.625$, $p = 0.070$, and $p = 1.000$, respectively). For evaluators 4 and 5, DL model accuracy was significantly higher than dentist accuracy ($p = 0.0078$ and $p = 0.00024$, respectively).

In the supplementary pooled analysis of all 100 responses, the dentists correctly classified 62 (62.0%) of 100 responses, whereas the corresponding DL model predictions were correct in 90 (90.0%) of 100 responses. The two-sided exact McNemar test indicated that DL model accuracy was significantly higher than dentist accuracy ($p < 0.001$). However, this supplementary pooled analysis included repeated presentations of the same images, and the independence of the observations was not fully assured.

Visualization of contributory regions using Grad-CAM

Representative Grad-CAM heatmaps are presented in Fig. 4. The regions with relatively high contributions to the predicted class were mainly located over the crowns, interproximal surfaces, and periradicular regions. The image background or borders alone were not consistently emphasized.

Discussion

Models have previously been reported for assessing the technical acceptability of intraoral radiographs and for identifying individual acquisition errors, including inappropriate horizontal or vertical projection angles, insufficient coverage of the crown or apical region, cone cut, open-mouth errors, and interproximal overlap [9, 11–13]. However, to the best of our knowledge, no DL model that determines whether the horizontal projection direction deviates mesially or distally from an intraoral radiograph with directional deviation has been reported. In this study, we developed a DL model to classify mesial and distal horizontal projection deviations relevant to directional correction during repeat radiography. When evaluated using 40 images acquired from a separate maxillofacial phantom that was not used for model development, the model correctly classified 36 images, yielding an accuracy of 90.0% (95% CI, 76.9%–96.0%). The accuracy by region and direction ranged from 80% to 100%. Although the performance was somewhat lower for distal mandibular deviations, each group included only 10 images; therefore, this finding should not be interpreted as evidence of a stable performance difference by region or direction. Although the validation was limited to 2 phantoms, the left maxillary and mandibular molar regions, and a single imaging environment, the findings suggest that the model can classify the horizontal projection direction in images acquired from a separate phantom without relying on the specific images used for model development.

Dentist accuracy varied substantially among the evaluators, ranging from 25% to 95%, whereas the DL model accuracy on the corresponding images ranged from 85% to 100%. Under the conditions of this study, the DL model achieved a higher accuracy than 4 of the 5 dentists, with statistically significant differences for 2. However, because different image sets were presented to the evaluators, these results do not establish that the DL model generally has a higher classification performance than dentists. Nevertheless, the findings suggest that determining the horizontal projection direction during image acquisition from intraoral radiographs is not necessarily straightforward for dentists and that

classifications may vary. Providing the mesial-versus-distal classification output of a trained DL model as supplementary information may complement operator judgment.

The regions relatively emphasized by Grad-CAM indicate only those areas that may have contributed to the model's prediction and do not demonstrate that the model's decision was medically valid [20]. Nevertheless, the regions highlighted in red in the present heatmaps were located mainly over the crowns, interproximal surfaces, and periradicular regions, which may be relevant to the classification of mesial and distal deviations. This finding suggests that the model may have used anatomical image information related to the direction of deviation rather than relying solely on the image background or borders.

If the classification output of the model is presented to the operator, it may provide objective information to support decisions regarding the direction in which the X-ray tube head should be corrected during repeat radiography. It may also be applicable as an educational aid that enables dental professionals and students with limited acquisition experience to review the direction of deviation in acquired images. However, the primary outcome evaluated in this study was the binary mesial-versus-distal classification. Because the exact deviation angles of the test images were not recorded, neither angle-regression performance nor classification performance by deviation angle was evaluated. Therefore, at this stage, the model should be regarded not as one that quantitatively indicates the correction angle for repeat radiography but as one that first indicates the horizontal direction in which the correction should be made.

The number of original images used in this study was limited to 48 for each jaw. Although data augmentation increased the number of images, it did not increase the underlying anatomical diversity. In addition, because the training and validation sets were split at the augmented image-file level, images derived from the same original image may have been included in both sets, potentially leading to an overestimation of the validation performance during model development. However, the final evaluation did not use any of the same original images used for training; therefore, the final direction-classification performance was not evaluated through reproduction of the training images themselves. Future studies should split the data at the original-image level, increase the number of original images, and perform external validation using clinical images acquired at multiple institutions and with multiple devices. The angle-regression performance should also be evaluated using test data with recorded deviation angles. Comparisons with dentists should present the same image set to a larger number of evaluators and use analyses that account for correlations attributable to both evaluators and images.

In conclusion, we developed a DL model for classifying mesial and distal horizontal projection deviations from intraoral radiographs and achieved an accuracy of 90.0% for images acquired from a separate phantom that was not used for model development. Under the conditions of this study, the model demonstrated an accuracy comparable to or higher than that of dentists. Although this evaluation was based on phantom images, the findings suggest that the model may provide objective information that does not rely solely on operator experience and may support correction of the horizontal projection

direction during repeat radiography. In the future, the model may serve as an educational support tool for the objective assessment of radiographic acquisition techniques.

Declarations

Acknowledgments

This work was supported by the Kanagawa Dental University Graduate School Project Research Grant (no. 16)

Funding: This work was supported by the Kanagawa Dental University Graduate School Project Research Grant (no. 16).

Conflict of Interest: The authors declare that they have no conflict of interests.

Data and/or Code Availability: The datasets generated and/or analyzed and the codes used in the current study are available from the corresponding author upon reasonable request.

Ethics Approval: Ethics approval was not required for this study because it used maxillofacial phantom radiographs, and only non-identifiable binary classification responses (mesial or distal) were provided by the participating dentists. No personal, sensitive or identifiable information was collected.

Consent to Participate: Verbal informed consent was obtained from all participating dentists.

Consent to Publish: Not applicable.

Author Contributions: T.S. (Takahiro Sakota) conceptualized the study, developed the methodology and software, performed the investigation and formal analysis, curated the data, prepared the visualizations, and wrote the original manuscript. M.I., M.T., Y.K., L.T.S., and T.S. (Takashi Sakurai) conducted the observer classification test and curated the corresponding data. M.I. and T.S. (Takashi Sakurai) reviewed and edited the manuscript, and T.S. (Takashi Sakurai) supervised the study. All authors reviewed and approved the final manuscript.

References

1. Haghnegahdar A, Bronoosh P, Taheri MM, Farjood A. Common intra oral radiographic errors made by dental students. *Galen Med J*. 2013;2:44–8. <https://doi.org/10.31661/gmj.v2i2.71>.
2. van der Stelt PF, Ruttiman UE, Webber RL, Heemstra P. In vitro study into the influence of X-ray beam angulation on the detection of artificial caries defects on bitewing radiographs. *Caries Res*. 1989;23:334–41. <https://doi.org/10.1159/000261202>.
3. Acharya S, Pai KM, Acharya S. Repeat film analysis and its implications for quality assurance in dental radiology: an institutional case study. *Contemp Clin Dent*. 2015;6:392–5. <https://doi.org/10.4103/0976-237X.161898>.

4. Benavides E, Krecioch JR, Allareddy T, Buchanan A, Keels MA, Mascarenhas AK, Duong ML, O'Brien KK, Ziegler KM, Lipman RD, Connolly RT, Cevdanes L, Cordell K, Elangovan S, Fouad AF, González-Cabezas C, Huja SS, Kademani D, Khan A, Malik A, Pannu D, Peacock ZS, Ramos M, Rios HF, Sedghizadeh P, Romero-Reyes M, Hawkins J, Sarvas EW, Yepes J. American Dental Association and American Academy of Oral and Maxillofacial Radiology patient selection for dental radiography and cone-beam computed tomography: clinical recommendations. *J Am Dent Assoc.* 2026;157:20–e355. <https://doi.org/10.1016/j.adaj.2025.10.013>.
5. Fava LRG, Dummer PMH. Periapical radiographic techniques during endodontic diagnosis and treatment. *Int Endod J.* 1997;30:250–61. <https://doi.org/10.1046/j.1365-2591.1997.00078.x>.
6. Katsumata A. Deep learning and artificial intelligence in dental diagnostic imaging. *Jpn Dent Sci Rev.* 2023;59:329–33. <https://doi.org/10.1016/j.jdsr.2023.09.004>.
7. Karakuş R, Öziç MÜ, Tassoker M. AI-assisted detection of interproximal, occlusal, and secondary caries on bite-wing radiographs: a single-shot deep learning approach. *J Imaging Inf Med.* 2024;37:3146–59. <https://doi.org/10.1007/s10278-024-01113-x>.
8. Lee S, Oh SI, Jo J, Kang S, Shin Y, Park JW. Deep learning for early dental caries detection in bitewing radiographs. *Sci Rep.* 2021;11:16807. <https://doi.org/10.1038/s41598-021-96368-7>.
9. Mori M, Arijji Y, Fukuda M, Kitano T, Funakoshi T, Nishiyama W, Kohinata K, Iida Y, Arijji E, Katsumata A. Performance of deep learning technology for evaluation of positioning quality in periapical radiography of the maxillary canine. *Oral Radiol.* 2022;38:147–54. <https://doi.org/10.1007/s11282-021-00538-2>.
10. Ameli N, Miri Moghaddam M, Lai H, Pacheco-Pereira C. Automated quality evaluation of dental panoramic radiographs using deep learning. *Imaging Sci Dent.* 2025;55:175–88. <https://doi.org/10.5624/isd.20240232>.
11. Chi X, Wang M, Gao Y, Ge Z. Deep learning-based assessment of periapical radiographic image quality. *Sci Rep.* 2026;16:5047. <https://doi.org/10.1038/s41598-026-35100-9>.
12. Fang W, Liu L, Wang X, Wang J, Meng Y, Wu K, Liu T, Feng B. A multi-task deep learning model for quality control of periapical radiographs: simultaneous technical error classification and quality grading. *Dentomaxillofac Radiol.* 2026;twag021. <https://doi.org/10.1093/dmfr/twag021>.
13. Baghdady M, Baskaradoss JK, Prasad S, Bhattacharjee T. Technical error identification in intraoral radiographs using multiple convolutional neural networks: an exploratory study. *Oral Radiol.* 2026. <https://doi.org/10.1007/s11282-026-00941-7>.
14. Shorten C, Khoshgoftaar TM. A survey on image data augmentation for deep learning. *J Big Data.* 2019;6:60. <https://doi.org/10.1186/s40537-019-0197-0>.
15. He K, Zhang X, Ren S, Sun J, Pattern Recognition. Deep residual learning for image recognition. In: *Proceedings of the IEEE Conference on Computer Vision and ;* 2016. pp. 770–8. <https://doi.org/10.1109/CVPR.2016.90>
16. Sukegawa S, Matsuyama T, Tanaka F, Hara T, Yoshii K, Yamashita K, Nakano K, Takabatake K, Kawai H, Nagatsuka H, Furuki Y. Evaluation of multi-task learning in deep learning-based positioning

classification of mandibular third molars. Sci Rep. 2022;12:684. <https://doi.org/10.1038/s41598-021-04603-y>.

17. Kingma DP, Ba J. Adam: a method for stochastic optimization. In: Proceedings of the 3rd International Conference on Learning Representations; 2015.
18. Kanda Y. Investigation of the freely available easy-to-use software 'EZR' for medical statistics. Bone Marrow Transpl. 2013;48:452–8. <https://doi.org/10.1038/bmt.2012.244>.
19. Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D. Grad-CAM: visual explanations from deep networks via gradient-based localization. In: Proceedings of the IEEE International Conference on Computer Vision; 2017. pp. 618–26. <https://doi.org/10.1109/ICCV.2017.74>
20. van der Velden BHM, Kuijf HJ, Gilhuijs KGA, Viergever MA. Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. Med Image Anal. 2022;79:102470. <https://doi.org/10.1016/j.media.2022.102470>.

Figures



Figure 1

Maxillofacial phantom containing an embedded human skull

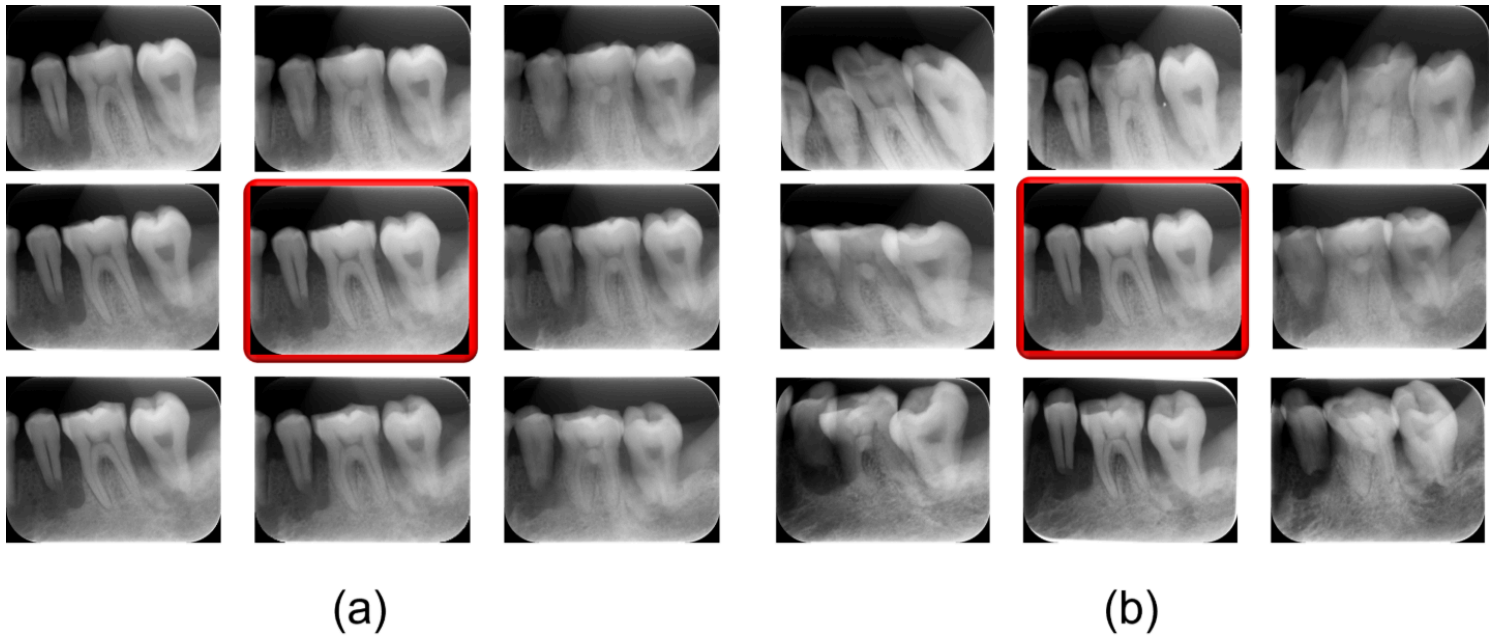


Figure 2

Reference image and images acquired at a deviation angle of 10° (a) and 30° (b). The images are arranged as follows (from left to right): top, mesial-superior, superior, and distal-superior deviations; middle, mesial deviation, reference image, and distal deviation; bottom, mesial-inferior, inferior, and distal-inferior deviations. Red boxes indicate the reference images

Original image

(n = 1)



Random horizontal and vertical translation

(−150 to +150 pixels)

and cropping



Representative augmented images



1 original + 499 augmented images
= 500 images per imaging condition

48 imaging conditions × 500 images
= 24,000 images per jaw

Figure 3

Overview of image data augmentation

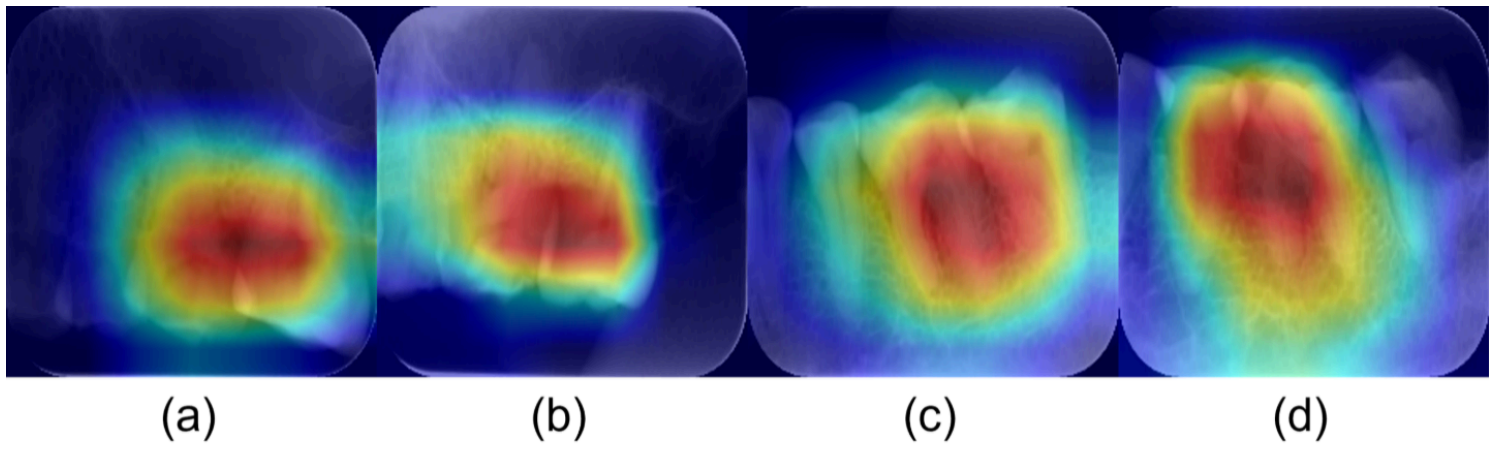


Figure 4

Representative gradient-weighted class activation mapping heatmaps: (a) maxillary mesial, (b) maxillary distal, (c) mandibular mesial, and (d) mandibular distal deviations. Red regions indicate relatively high contributions to the predicted class