Dental Materials Journal 2022; 41(6): 889–895

Analysis of the feasibility of using deep learning for multiclass classification of dental anomalies on panoramic radiographs

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The aim of the feasibility study was to construct deep learning models for the classification of multiple dental anomalies in panoramic radiographs. Panoramic radiographs with single supernumerary teeth and/or odontomas were considered the "case" group; panoramic radiographs with no dental anomalies were considered the "control" group. The dataset comprised 150 panoramic radiographs: 50 each of no dental anomalies, single supernumerary teeth, and odontomas. To classify the panoramic radiographs into case and control categories, we employed AlexNet, which is a convolutional neural network model. AlexNet was able to classify whole panoramic radiographs into two or three classes, according to the presence or absence of supernumerary teeth or odontomas. The performance metrics of the three-class classification were 70%, 70.8%, 70%, and 69.7% for accuracy, precision, sensitivity, and F1 score, respectively, in the macro average. These results support the feasibility of using deep learning to detect multiple dental anomalies in panoramic radiographs.

Keywords: Artificial intelligence, Deep learning, Convolutional neural network, Dental anomalies, Panoramic radiograph

INTRODUCTION

Artificial intelligence (AI) solutions are rapidly becoming integrated into daily clinical practice. According to a recent survey, various AI-based medical devices have been approved by regulatory bodies worldwide[1,2]. From 2015 to March 2020, the United States Food and Drug Administration approved 222 AI-equipped medical devices, including three dental devices[1]. AI research related to dentistry is actively underway[3-7].

Developmental anomalies that involve tooth number are common conditions. Typical cases include missing or supernumerary teeth, which affect the subsequent growth of healthy dentition. For instance, there is a strong correlation between the absence of a primary tooth and the absence of its permanent tooth successor[8]; supernumerary teeth may also cause impaction of permanent teeth[9]. Therefore, early diagnosis and appropriate treatment are essential for avoiding unnecessarily long treatment periods; they are also necessary to achieve optimal final outcomes.

Although odontomas are not regarded as teeth, they are associated with developmental anomalies that involve tooth number[10]. Odontomas are dental hamartomas that comprise irregularly grown dental tissue[11]. There are two types: a compound type that consists of many small tooth-like structures together and a complex type that consists of a single amorphous mass. Both types may interfere with normal tooth eruption; they may be associated with the absence of permanent teeth, formation of dentigerous cysts, and (rarely) calcification of odontogenic cysts[10,12].

Although panoramic radiography is a common imaging modality in dental practice and plays an important role in the diagnosis and treatment planning of dental and maxillofacial diseases, intraoral and panoramic radiographs alone are insufficient for the diagnosis of supernumerary teeth and odontomas[13-15]. It was noted that the prevalence of supernumerary teeth is likely to be underestimated due to differences in the training levels of dentists[13]. Cone beam computed tomography is used as a supplementary diagnostic tool[15,16]. However, routine examination *via* panoramic radiography remains important for the early detection of supernumerary teeth and odontomas, as well as the prevention of adverse events[17,18]. AI is expected to contribute to the construction of a system that will help clinicians achieve accurate and rapid diagnosis; AI will detect anomalies on panoramic radiographs, enabling treatment by referral to a specialized institution.

We previously reported that a convolutional neural network (CNN)-based deep learning technique demonstrated good performance in the binary classification of supernumerary teeth during the early mixed dentition stage[19]. The binary classification is the task of classifying given data into one of two classes. Deep

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Received Apr 25, 2022: Accepted Jun 23, 2022
doi:10.4012/dmj.2022-098 JOI JST.JSTAGE/dmj/2022-098

learning models are currently sought that can identify the presence of multiple dental anomalies (rather than supernumerary teeth alone) from a single panoramic radiograph. Therefore, the aims of the present study were to construct deep learning models for the detection of multiple dental anomalies in panoramic radiographs, and to evaluate the feasibility of such detection. Multiclass classification is the task of classifying given data into three or more categories. Unlike binary classification, multiclass classification focuses on the type of dental anomalies in addition to detecting disease. In general, multiclass classification is considered a more difficult task than binary classification[20]. Hence, in the first part of this study, we constructed binary classification models. The deep CNNs could use images to distinguish between no dental anomalies and odontomas, and between no dental anomalies and dental anomalies (comprising a mixed dataset of supernumerary teeth and odontomas). In the second part of this study, we constructed and evaluated a more challenging task, a multiclass classification model. The deep CNN model can use images to distinguish among supernumerary teeth, odontomas, and no anomalies.

MATERIALS AND METHODS

This retrospective study protocol was approved by the Ethical Committee for Epidemiology of Hiroshima University (Approval Number: E-1357-2). The requirement for informed consent was waived by the Ethical Committee because we obtained consent using an opt-out method. Of the diseases included in this study, odontomas were the most difficult cases from which to collect panoramic radiographs. Therefore, 50 cases of odontomas were selected for this feasibility study, together with panoramic radiographs of 50 patients with no dental anomalies and 50 patients with supernumerary teeth, for retrospective analysis.

Patients

The panoramic radiographs and medical records of 150 patients aged 6 to 17 years (51 female, 99 male), acquired at Hiroshima University Hospital (Hiroshima, Japan) between April 2011 and September 2021, were retrospectively analyzed after anonymization that involved the removal of personal information.

All panoramic radiographs were recorded using Hyper-X or SOLIO XZ systems (Asahi Roentgen Industries, Kyoto, Japan). The dataset used in this study consisted of panoramic radiographs of patients with no dental anomalies, patients with single supernumerary teeth, and patients with odontomas. In this study, patients with single supernumerary teeth and/or odontomas were designated as the "case" group. The supernumerary teeth used in the dataset were located in the region from the maxillary midline to the incisors. The odontomas used in the dataset were located in the maxilla (26 patients, 52%), mandible (23 patients, 46%), and "maxillamandible" (1 patient, 4%). A location in the "maxillamandible" indicates that one odontoma was present in the maxilla, while another odontoma was present in the mandible. Patients who exhibited anomalies in other teeth were excluded from the study. Medical records were searched to identify panoramic radiographs formatted as JPEGs; then, an experienced pediatric dentist (14 years of experience) performed conclusive re-diagnosis and re-classification of the panoramic radiographs. If the experienced dentist could not accurately determine a diagnosis by panoramic radiograph alone, the image was excluded from diagnosis. Patients who exhibited no dental anomalies were designated as the "control" group. Finally, the dataset consisted of 150 panoramic radiographs: 50 each of no dental anomalies, single supernumerary teeth, and odontomas (Figs. 1A–C).

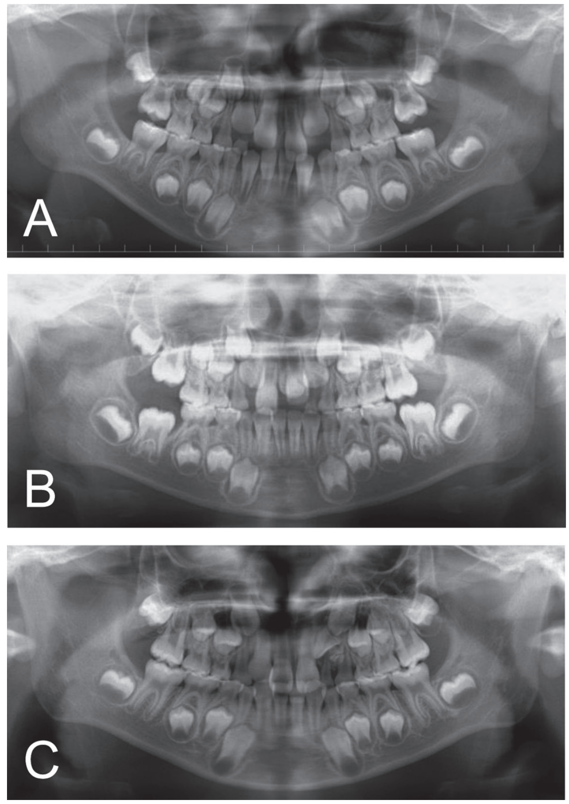

Fig. 1 Representative panoramic radiographs of (A) no dental anomalies (control group), (B) single supernumerary tooth (case group), and (C) odontomas (case group) used in this study.

Dataset preparation

All panoramic radiographs were manually cropped in the area containing the whole mandible and the maxillary teeth (Figs. 1A–C); the images were automatically resized to 150×150 pixels *via* Python algorithms, then used as input data.

To evaluate the classification performances of the deep CNN model, three datasets were created using these panoramic radiographs (Fig. 2).

- Dataset 1 consisted of 100 panoramic radiographs: 50 images with no dental anomalies (control group) and 50 images of odontomas (case group). The deep CNN trained using Dataset 1 classified no dental anomalies and odontomas. This is a binary classification algorithm.
- Dataset 2 consisted of 150 panoramic radiographs: 50 images with no dental anomalies (control group) and 100 mixed images of supernumerary teeth and odontomas (case group). The deep CNN trained using Dataset 2 classified no dental anomalies and dental anomalies (including both supernumerary teeth and odontomas). This is a binary classification algorithm. The purpose of this model was to classify the presence or absence of dental anomalies, not to identify the type of disease.
- Dataset 3 consisted of 150 panoramic radiographs: 50 images with no dental anomalies (control group), 50 images of supernumerary teeth (case 1 group), and 50 images of odontomas (case 2 group). The deep CNN trained using Dataset 3 classified no dental anomalies, supernumerary teeth, and odontomas. This is a multiclass classification algorithm and identifies the type of dental anomalies.

To train the models and evaluate their performance, a holdout method was used. Each dataset was randomly split into two parts: 40% of the overall data were used as the test dataset, while the remaining 60% of overall data were used as the training dataset (Fig. 2). The training and test datasets did not contain images from the same patients.

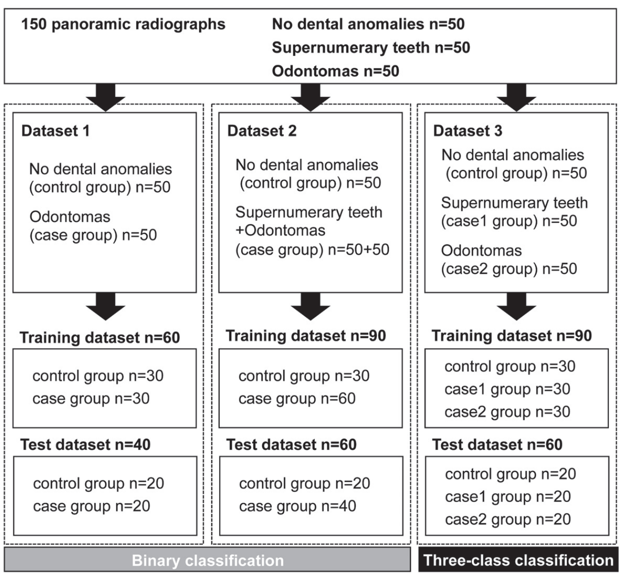

Fig. 2 Flowchart of the experimental workflow.

Deep learning architectures

All procedures were performed with Intel Core i7-11700K 3.60 GHz CPU (Intel, Santa Clara, CA, USA), 32 GB RAM and NVIDIA GeForce RTX 3090 24 GB GPU (NVIDIA, Santa Clara, CA, USA). All deep CNNs were constructed using Python (3.8.11) and were implemented using Keras (2.4.3), with TensorFlow as the backend. A schematic illustration of the learning and classification approach is shown in Fig. 3. To classify the panoramic radiographs into case and control categories, we employed AlexNet, which is a deep CNN model[21].

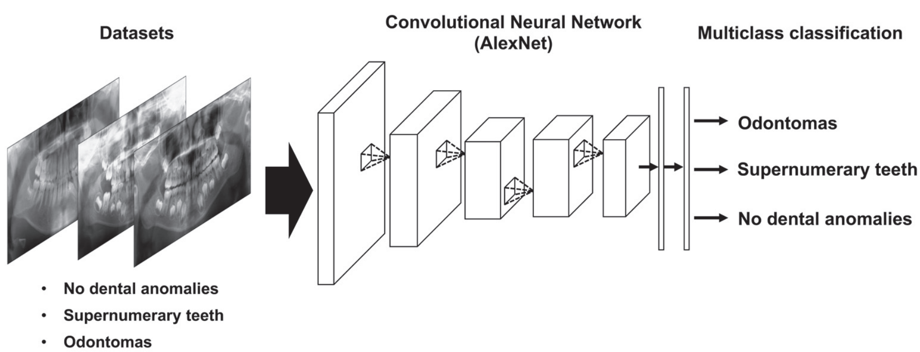

Fig. 3 Schematic overview of classifying images of dental anomalies using deep learning. Illustration of learning and classification with AlexNet.

Table 1 Hyperparameters of AlexNet used in the study

	Learning rate	Epochs
Dataset 1	4.7×10^{-6}	500
Dataset 2	1.5×10^{-6}	650
Dataset 3	1.3×10^{-6}	450

AlexNet has five convolutional and three fully connected layers with a final Sigmoid or Softmax. Three max-pooling layers were placed after the first, second, and fifth convolutional layers. The images in the training datasets were input into AlexNet and trained using the RMSProp optimizer. Model training was performed using the learning rates and epochs shown in Table 1. The number of epochs used to construct each model was determined by monitoring the loss function; all numbers of epochs were within the range where overfitting did not occur.

Performance metrics

The performance of AlexNet was assessed in terms of accuracy, precision, sensitivity, and F1 score. For binary classification, receiver operating characteristic (ROC) curves and areas under the ROC curves of the test datasets were also evaluated. The performance metric values were calculated using the following formulas:

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

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

$$Sensitivity=\frac{TP}{TP+FN}$$

$$F1\ score=\frac{2(Sensitivity\times Precision)}{Sensitivity+Precision}$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative (all positive and negative determinations are made using counts for case detection)[19].

RESULTS

Three datasets were used to evaluate the model's ability to classify panoramic radiographic images with dental anomalies. To assess whether each model could be properly trained, the training loss and validation loss were traced. Furthermore, each model was also evaluated with accuracy up to the maximum number of epochs employed in each dataset. Training loss and validation loss of the model decreased with each dataset, whereas the accuracy of the model tended to improve with each dataset as the epoch progressed (Fig. 4). The performance metrics of models trained on Datasets 1 and 2 are shown in Table 2. When trained using Dataset 1, which contained images of no dental anomalies and odontomas, the model's performance metrics were 80%, 87.5%, 70%, and 77.8% for accuracy, precision, sensitivity, and F1 score, respectively. When trained using Dataset 2, which contained images of no dental anomalies and mixed images of supernumerary teeth and odontomas, the model's performance metrics were 83.3%, 87.5%, 87.5%, and 87.5% for accuracy, precision, sensitivity, and F1 score, respectively. The ROC curves and areas under the ROC curves of each of the obtained models in these binary classifications are depicted in Fig. 5.

The three-class classification results are shown in Fig. 6 as a confusion matrix. The performance metrics are shown in Table 3, along with the macro average

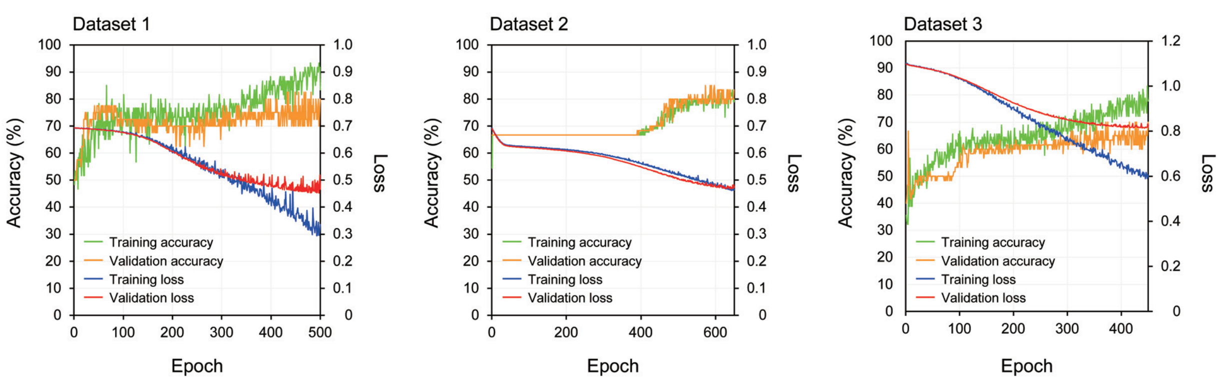

Fig. 4 Loss and accuracy of each model.
For binary classification, Dataset 1 contained images of odontomas; Dataset 2 contained images of single supernumerary teeth and odontomas. For three-class classification, Dataset 3 contained images of single supernumerary teeth and odontomas.

Table 2 Performance metrics of models trained on Datasets 1 and 2

	Accuracy (%)	Precision (%)	Sensitivity (%)	F1 score (%)
Dataset 1	80.0	87.5	70.0	77.8
Dataset 2	83.3	87.5	87.5	87.5

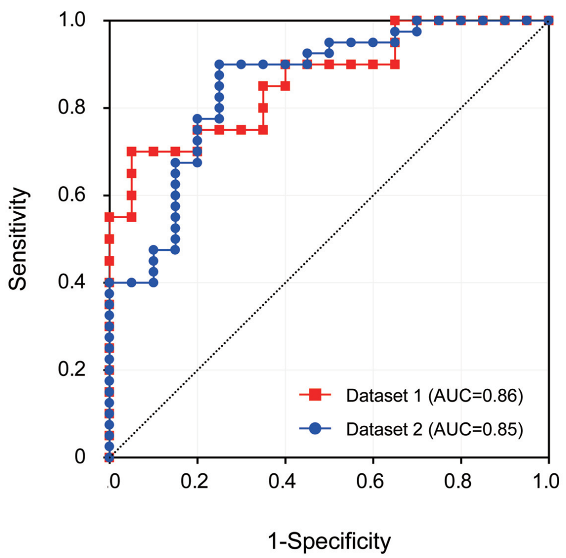

Fig. 5 ROC curves and areas under the ROC curves (AUCs) of the two AlexNet models to which each test dataset was applied.
Dataset 1 contained images of odontomas; Dataset 2 contained images of single supernumerary teeth and odontomas.

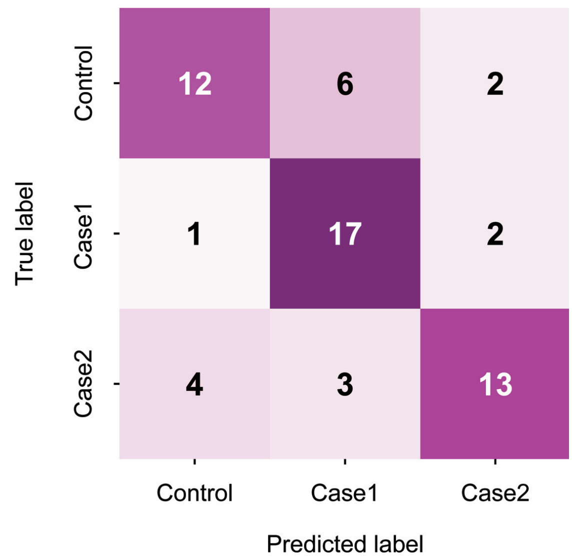

Fig. 6 Confusion matrix for the AlexNet model tested on Dataset 3.
Control, no dental anomalies; Case 1, single supernumerary teeth; Case 2, odontomas.

Table 3 Performance metrics of the model trained on Dataset 3

	Class	Precision (%)	Sensitivity (%)	F1 score (%)	Accuracy (%)
Dataset 3	Control	70.6	60.0	64.9	—
	Case 1	65.4	85.0	73.9	—
	Case 2	76.5	65.0	70.3	—
	Macro average	70.8	70.0	69.7	70.0

scores for three-class classification to indicate overall performance across classes in Dataset 3. When trained using Dataset 3, the model's performance metrics were 70%, 70.8%, 70%, and 69.7% for accuracy, precision, sensitivity, and F1 score, respectively, in the macro average.

DISCUSSION

In the past 10 years, there has been increasing interest in the application of deep learning to dental treatment[3-7,22-24]. Medical images are regarded as the primary input for AI applications in healthcare. Because imaging is important for examination and diagnosis during dental treatment, dental images are expected to become suitable input for AI. Specifically, bitewing radiographs[25], cone beam computed tomography[26], and cephalograms[6] have been suggested as input for deep learning-based diagnosis; studies that involve panoramic radiographs have also been reported[13,27-30].

In this study, we demonstrated that AlexNet was able to classify whole panoramic radiographs into two or three categories, according to the presence or absence of supernumerary teeth or odontomas; the model's performance metrics were promising. The results of three-class classification showed that the model's performance metrics values were approximately 70% in the macro average. We previously compared the performance of three deep CNN models (*i.e.*, AlexNet, VGG16, and InceptionV3) on the classification of supernumerary teeth. In this previous study, the classification of supernumerary teeth by these three deep CNN models yielded similar performance metrics[19]. AlexNet is an epoch-making deep CNN model that was published in 2012[21]. Since then, various deep CNN models have been proposed; however, AlexNet remains in use and has undergone continuous improvement[19,28,31,32].

The potential for application of deep learning to dental anomalies in panoramic radiographs has only recently been explored in terms of supernumerary tooth diagnosis. In two studies, the authors attempted to develop a deep learning system that classified the presence or absence of mesiodens (*i.e.*, the supernumerary tooth located between the two maxillary central incisors) in panoramic radiographs[28,29]. For the classification task in these studies, the authors performed manual cropping of the maxillary incisor area as a region of interest in panoramic radiographs. Ha *et al*. reported that an object detection CNN model based on YOLOv3 was able to detect the presence of a single impacted mesiodens on panoramic radiographs of primary, mixed, and permanent dentitions[30]. When it comes to AI diagnosis, sensitivity is a crucial metric because high sensitivity means few false negatives (*i.e.*, if a person has a negative test, they are likely to be free of the disease). However, previous studies have shown that any algorithm's performance (sensitivity) for both object detection and classification tasks for supernumerary teeth is in the 80% to low 90% range, and is not perfect for other metrics as well[19,28-30]. Therefore, we presume that more stable results might be achieved by combining classification and object detection CNNs. To our knowledge, our study is the first to apply deep learning to the detection of odontomas. In binary classification to distinguish between no dental anomalies and odontomas, the AlexNet performance metrics values ranged from 70% to 87.5%. Odontomas may occur in areas of the jaw where teeth are located; the compound type occurs more frequently in the anterior maxilla, while the complex type occurs more frequently in the posterior mandible[33]. Although our dataset included both compound and complex types of odontomas, along with varying sites of occurrence, AlexNet demonstrated good performance metrics in binary classification.

Although our findings demonstrate the potential for deep learning to identify multiple dental anomalies in panoramic radiographs, there were several important limitations in this study. First, our datasets included small numbers of samples; Dataset 2 had imbalance with regard to the number of control and case images. Importantly, datasets in healthcare applications are frequently small and imbalanced across classes because diseases, adverse events, and emergencies are inherently less common, compared with normal and/or healthy situations[34]. Second, we used a holdout method to randomly split the initial datasets into training and test datasets. The construction of a robust model will require considerable effort and ingenuity to collect large datasets for analysis in future studies.

CONCLUSION

We constructed AlexNet models using three datasets that included images of single supernumerary teeth and odontomas; these models were used for multiclass and binary classification tasks. Our results support the feasibility of using deep learning to detect multiple dental anomalies in panoramic radiographs.

ACKNOWLEDGMENTS

This study was partially supported by grants-in-aid from the Ministry of Education, Culture, Sports, Science and Technology of Japan to Y.M. [20K18604]. We thank Ryan Chastain-Gross, Ph.D., from Edanz (https://jp.edanz.com/ac) for editing a draft of this manuscript.

CONFLICTS OF INTEREST

All authors declare no conflicts of interest.

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