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Evaluation of Clinical Application Potential based on a Deep Learning Technique with Real-Size Dental Panoramic Radiography: A Preliminary Study

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With the recent advancement of artificial intelligence (AI), data-based research is being actively conducted in the dental medical field. However, there is a limited amoun of research yet based on algorithms using panoramic radiography. This study was conducted to find the standard AI reading that distinguishes the young from the elderly using panoramic radiographic images, and to confirm the applicability of the method as a means of increasing the reliability of a diagnosis. A total of 117 panoramas in A dental clinic were used. The selected radiographic images were classified into two groups: the old group and the young group. To load the classified images into the suggested and designed multi-layer neural network model (modified DarkNet), they were split into 70 % training data and 30 % testing data using the 'SplitEachLable()' Matlab function. To identify the old group, the focal class activation mapping or CAM (the height of the alveolar bone and the major places where other treatment actions took place) area was estimated. To identify the young group, a wide CAM area over the entire area was estimated as a feature. These data could be important quantitative indicators of the health of the alveolar bone and of the overall dental condition. Significant results and features were derived to show the potential of quantitative indicators for dental care. The results of this study confirmed the possibility of estimating the alveolar bone age based on AI.

Keywords : Artificial Intelligence (AI), Electromagnetic radiation (X-ray), dental panoramic radiography, dark-net, class activation map

1. Introduction

Artificial intelligence (AI) began in the 1940s and 1950s when scientists from various fields discussed the potential of artificial brains [1]. With the growing interest in AI due to the Fourth Industrial Revolution, it is being used not only in the engineering field but also in the medical field [2]. In particular, computer-aided diagnosis is increasing the accessibility of digital medical data [3].

Deep learning is a field of machine learning wherein machines automatically learn how to solve a given problem using a deep learning neural network. It is defined as a set of machine learning algorithms that extract features of key data by combining several nonlinear transformations and attempt a high level of abstraction [4]. Deep learning is designed based on the structure of an artificial neural network, but it has been developed into a simple and excellent form by supplementing the disadvantages of the existing artificial neural network, such as overfitting and a slow learning time. Representative deep learning algorithms are convolutional neural networks (CNNs), which show good performance in the video and audio fields, and recurrent neural networks (RNNs), which show good performance in character recognition such as handwriting recognition [5-7]. In particular, CNNs improve the performance of artificial neural networks by automatically extracting features from input images to solve problems [2]. When the problem is defined by the user, the performance limit of the algorithm is determined by the user. When a feature is automatically extracted from an input image, the optimum performance to solve the problem based on data can be achieved, so the reliability is excellent. Excellent reliability and accuracy are being studied as collaborative tools, which is the role of com-

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puter-assisted diagnosis in the medical field. Therefore, the development of AI improves work efficiency and reduces human errors. This is why manual human work is rapidly being replaced by digital labor [8]. Although AI is not a substitute for medical experts, it is a tool for increasing the accuracy and reliability of diagnoses in various medical fields.

This application has been reported to show excellent performance in deep learning models for diagnosing dental caries in periapical radiographic images in the dental field [9]. Several algorithm-based studies have been conducted to increase the accuracy of the diagnosis of caries [10, 11]. Recently, a CNN, an artificial neural network, has shown excellent performance in detecting dental caries in periapical radiographic images [12]. In addition to the diagnosis of dental caries, active studies on the diagnosis of periapical lesions, maxillary sinusitis, vertical fracture teeth, etc. are being conducted [13-15]. However, there is no progress in algorithm-based research using dental panorama radiographic images.

Periodontal disease is accompanied by the destruction of the alveolar bone, leading to tooth loss [16]. If dental caries invades the dentin or pulp, invasive and surgical treatments should be performed, such as extensive dental structure removal, root canal treatment, and post-extraction prosthetic treatment [17]. Therefore, as one ages, the number of prostheses and implants to replace the lost teeth in the oral cavity inevitably increases due to the loss of the alveolar bone [18].

Therefore, this study was conducted to find a standard AI reading that can distinguish the young from the elderly based on dental panorama radiographic images, and to assess the potential of AI for such application.

2. Materials and Methods

2.1. Datasets

In this study, the data of 117 patients who agreed to the academic use of their images were utilized among patients who visited A dental clinic. PaX-i3D Green of Vatech mcis was used for panoramic radiography. For imaging, the arch was fixed so that it was not twisted by aligning the mid-sagittal plane laser beam while the patient wore the bite block. The head was fixed by aligning the Frankfurt plane beam with the Canine laser beam. The images were taken with 74 kVp and 8.0 mA for men, and 73 kVp and 8.0 mA for women.

2.2. Preprocessing

A total of 117 radiographic images were finally selected, and the original images were cropped from 2880 × 1504 units to 1827 × 1200 units to remove the extra area, as shown in Fig. 1. The selected radiographic images were classified into two groups: the old group and the young group. To load the classified images into the suggested and designed multi-layer neural network model (modified DarkNet), all the radiographic images were split into 70 % training data and 30 % testing data using the 'SplitEachLable()' Matlab function. To apply image processing techniques including CNNs, the Matlab 2020a (Mathworks, USA) software was employed with a deep learning toolbox.

2.3. Modified DarkNet

For image analysis, there are many kinds of deep learning models such as Densenet, Googlenet, Inception-resnet, Resnet, Squeezenet, and DarkNet [19-27]. DarkNet is one of the widely used deep learning models for radiographic image analysis [25]. The conventional DarkNet is composed of CNNs that are 53 and 19 layers deep (called DarkNet-53 and DarkNet-19, respectively). However, the conventional DarkNet required an input size of 256 × 256 units. To apply the input size of a 1827 × 1200-unit image, the customized DarkNet model was designed and tested with 117 radiographic images. For the analysis, the modified DarkNet was designed as shown in Fig. 2. For the

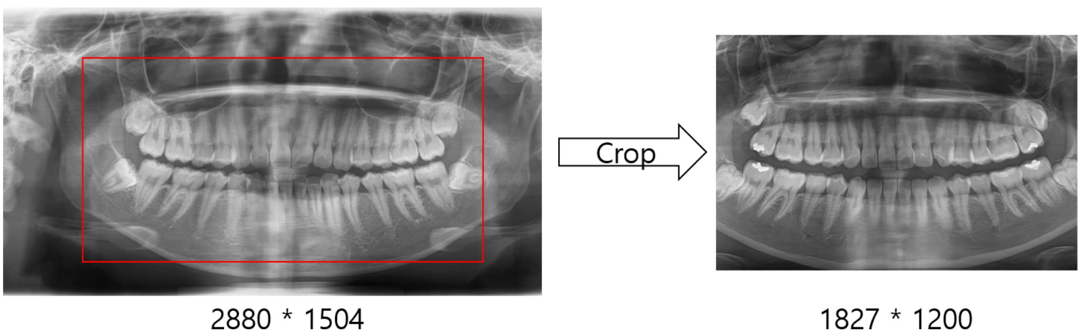

Fig. 1. (Color online) Original image and cropped image for deep learning. The original radiographic images include useful information outside the red line (left). The image on the right is the cropped image from the original image.

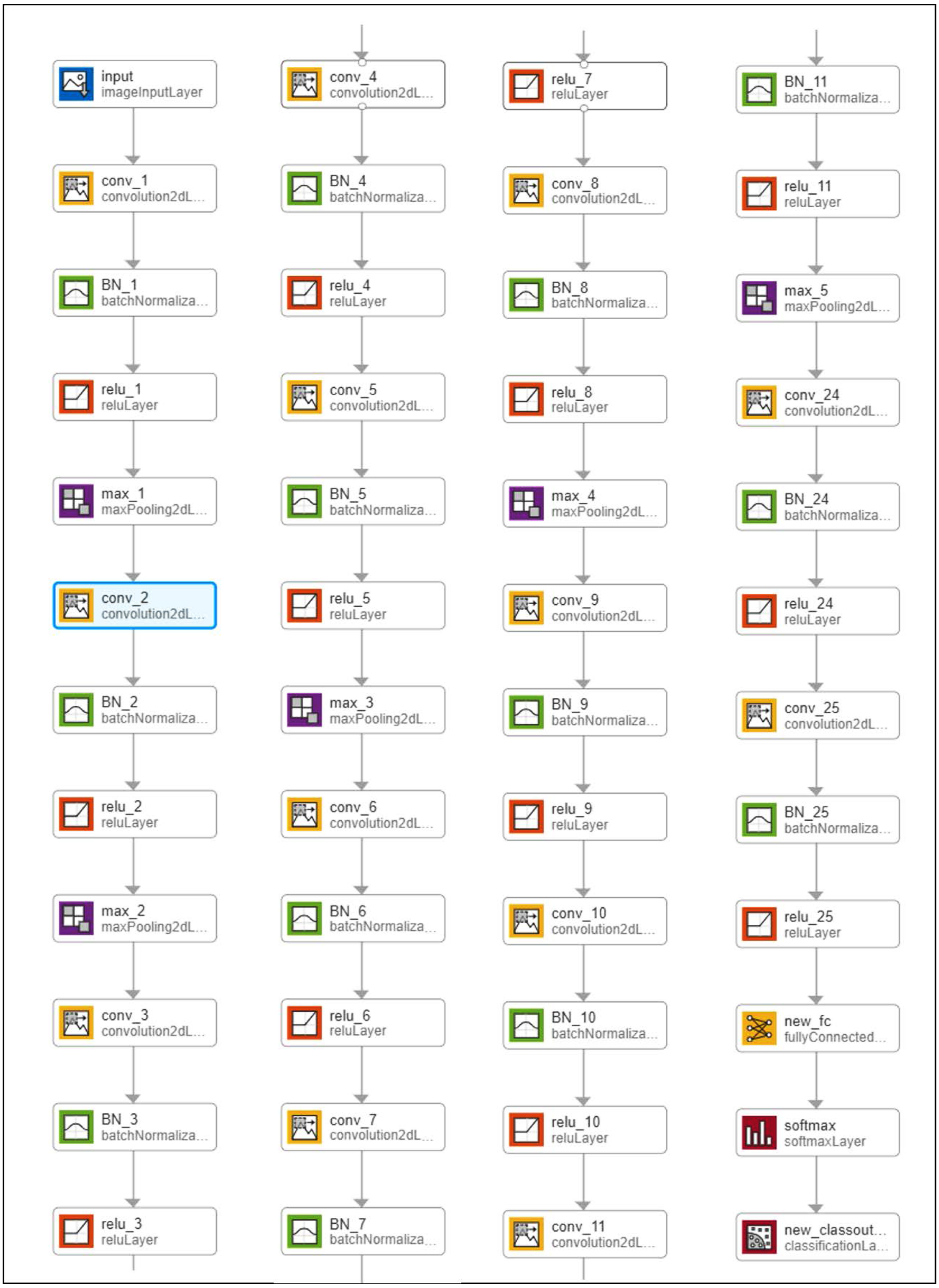

Fig. 2. (Color online) The modified DarkNet. The designed model had 48 deep layers. It required the customized input size of 1827 × 1200 units.

training and validation using the TrainNetwork() function, the following option parameters were used: MiniBatchSize: miniBatchSize, MaxEpochs: 20, InitialLearnRate: 3e-4, Shuffle: every-epoch, ValidationFrequency, and valFrequency. The valFrequency was calculated using the formula (number of train data)/miniBatchSize, and the miniBatch-

Size was set at 12. A personal computer system with an Intel i7-8700K processor, 64 GB RAM, RTX2080 (12GB vRAM), Windows 10 operating system, and MATLAB 2020a environment was used for the training and validation study with modified-DarkNet. It took around 100 seconds to finish the training and validation with miniBatchSize = 12.

2.4. Class Activation Mapping

Class activation mapping (CAM) is a useful technique for getting the discriminative image regions used by a CNN to determine a specific class in a radiographic image. In other words, CAM demonstrates which regions in the radiographic image are relevant to the determined class. The design of the CAM technique is shown in Fig. 3.

3. Results and Discussion

Radiographic examinations contribute greatly to the improvement of disease diagnosis and treatment. Dental radiography equipment are increasingly being used due to the increase in the demand for dental treatment and the expansion of the implant market with the increase in the national income [28].

For radiography, the most important diagnostic tool in modern dentistry, panoramic radiography is generally utilized because of its usefulness in patient care. It is a basic method for the overall evaluation of the upper and lower jaws. Due to the development of digital technology and the rapid spread of digital equipment, access to and use of panoramic radiography has become simple. The demand for panoramic radiography in dentistry, particularly in diagnosis and treatment, is expected to further increase with increased demand for dental services.

Moreover, as interest in AI increases, research is continuing to expand the field of its application [2]. In recent years, this trend has also been grafted into the field of dentistry. However, there are no reports of research showing the possibility of diagnosis with deep learning models using panoramic radiographic images. Therefore, this study evaluated the applicability and reliability of panoramic radiographic images in deep learning analysis.

In the preliminary study with a low number of radiographic images, the diagnostic accuracy was 85.71 %. Using a high-performance graphics processing unit or GPU (RTX 2080 12GB vRAM), the elapsed time could be reduced by 100 seconds with 117 radiographic images.

To understand neural network training, the training progress demonstrates useful information. Especially, monitoring the accuracy and loss plots shows how training works during the tanning. The accuracy and loss plots in the preliminary study are shown in Fig. 4. According to the results of the tanning progress, the accuracy and the loss value were sharply optimized to 100 % and 0, respectively. However, the validation of the accuracy line did not reach 100 % continuously. In addition, the validation of loss showed a higher value during the training.

Figures 5 and 6 show different CAM patterns. In fact, "deep learning technology" is already known to have a high potential for use in analyzing radiographic dental

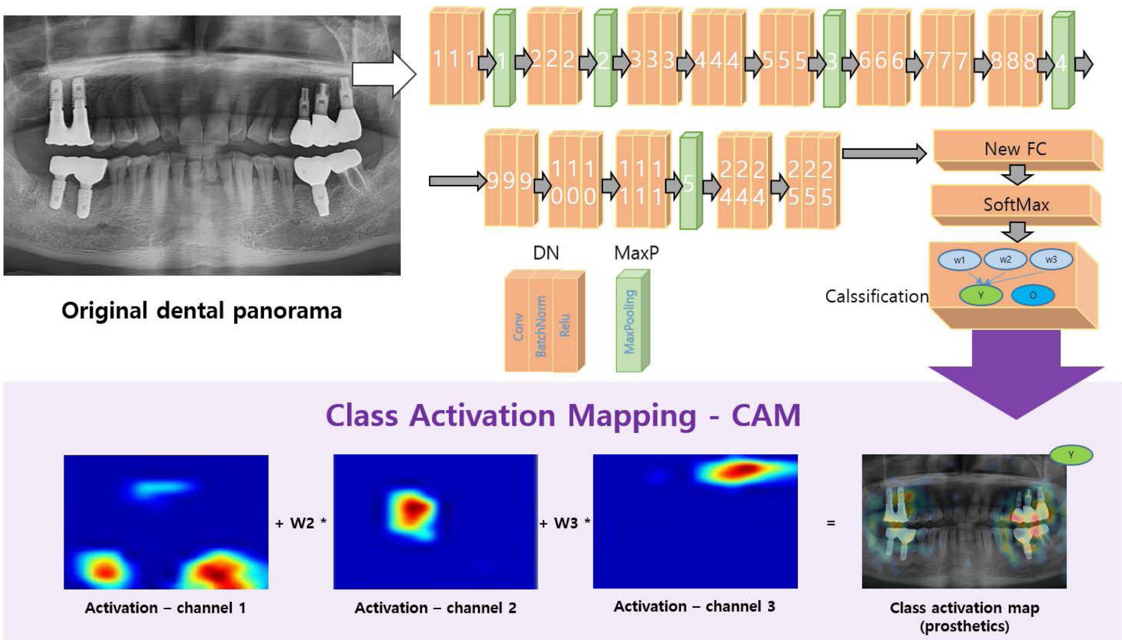

Fig. 3. (Color online) The class activation mapping (CAM) technique.

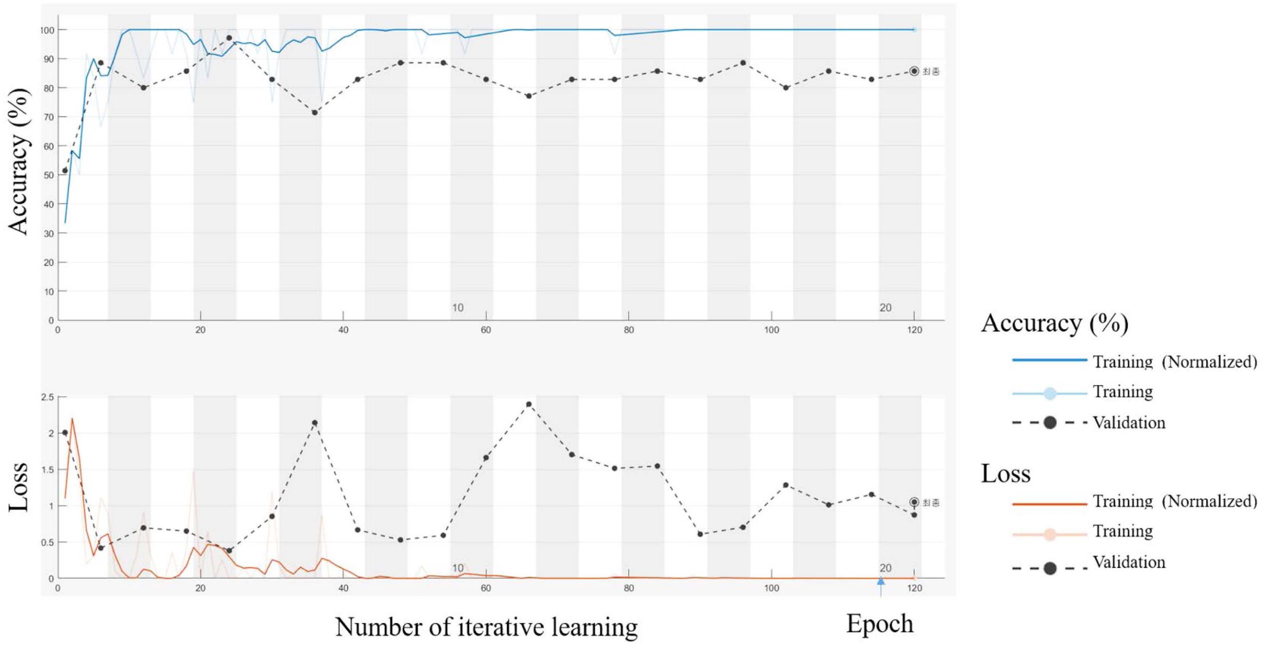

Fig. 4. (Color online) The training progress.

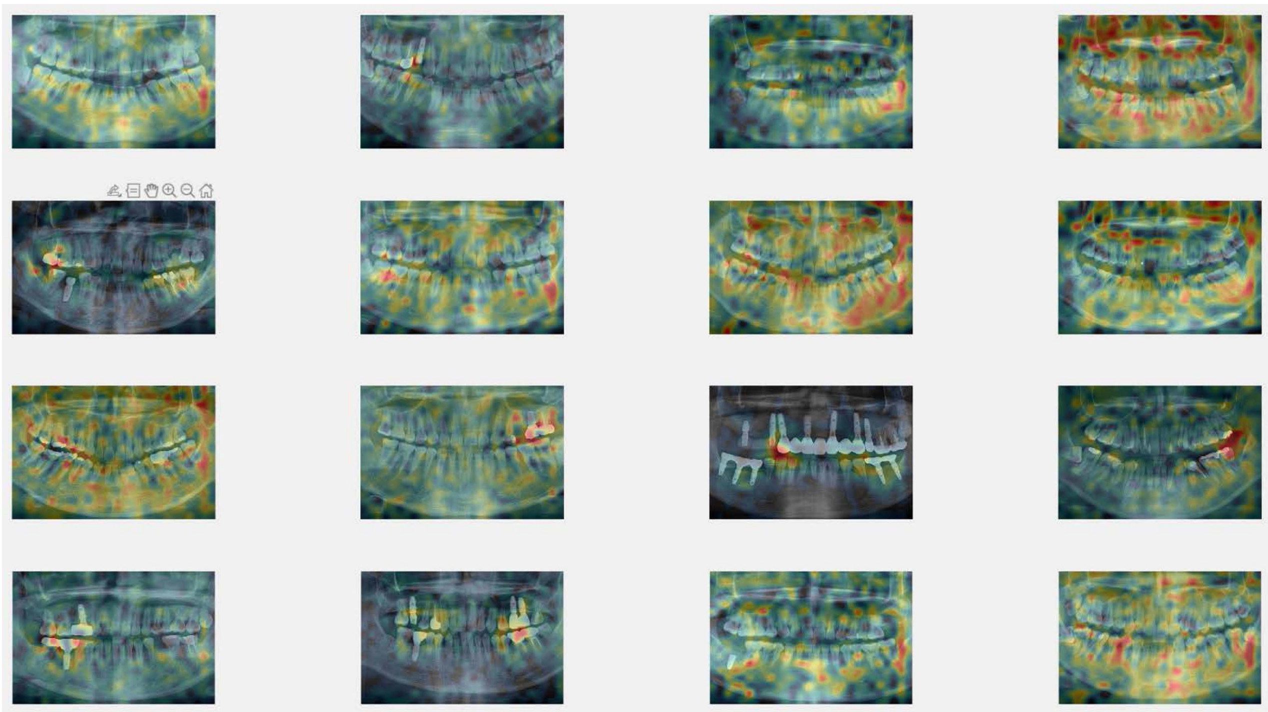

Fig. 5. (Color online) The 16 randomly selected radiographic images from the young group.

images. However, it requires thousands of radiographic images [9]. In this study, only 117 radiographic images were used, and they showed higher accuracy with unique CAM features. This study demonstrated the various potentials of the deep learning technique for application in dentistry. Figure 5 shows the CAM results for the young group. The randomly selected image shows a spread CAM pattern. Only a few images showed a focused CAM pattern on a tooth or gum. Figure 6 shows different results estimated from the old group, and 16 radiographic images selected from the same group. All the CAM patterns showed more focal patterns in this group than in the

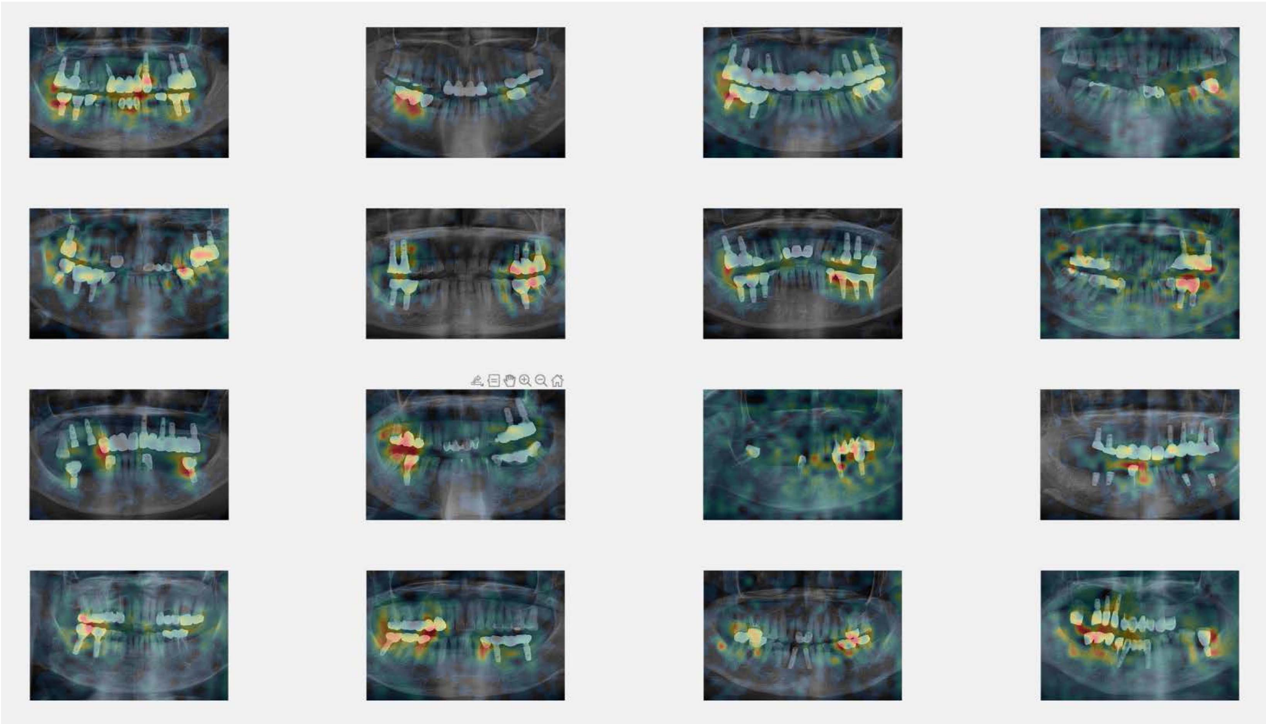

Fig. 6. (Color online) The 16 randomly selected radiographic images from the old group.

young group. Especially, the CAM of the old group was commonly localized on the low alveolar bone height and the implant placement. Table 1 shows the quantitative results. The final accuracy of 85.71 % was reached in 100 seconds using only one GPU. A total of 120 random repetitive learnings were performed at six training times per epoch for a total of 20 epochs. For the weight update, the learning rate was set at 0.0003 during the learning process.

Studies have long confirmed that tooth loss among the elderly causes the resorption of the residual alveolar bone [29]. It has been reported that the posterior teeth are lost before the anterior teeth [30], and the fewer the remaining teeth are, the more severe alveolar bone resorption is [31]. In this study, the reading of dental panoramic images using AI showed that the old group had a lower alveolar bone height than the young group due to alveolar bone resorption. This is because AI recognized the alveolar bone height as a reading standard, and therefore distinguished the old group from the young group.

Due to rapid aging, there is continued interest in a policy that will reinforce dental coverage of the elderly. Since July 2014, dental implants for the elderly have been included in health insurance benefits. They were introduced for the elderly aged 75 years or older, but after 2016, the age was expanded to 65 years or older. Perhaps due to this, the number of dental implant placements (Step 2, UB121-UB129) increased 13-fold from 36,703 cases in 2014 to 491,082 cases in 2016 [32]. The results of this study also confirmed that the images of the old group were read based on the traces of implants that would replace the function of teeth due to multiple tooth loss. The study results confirmed that the reading criterion for distinguished the old group from the young group was the presence or absence of multiple implants in the dental panorama radiographic images.

In this study, the potential of the quantitative evaluation was estimated based on dental panoramic images, with only around 50 radiographic images for each group (young and old). The health of the alveolar bone could be an

Table 1. Classification results with the computational environment.

Accuracy (%)	Tanning				Validation	Hardware		
	Elapsed Time (sec)	Epoch	Iteration per Epoch	Maximum Iteration	Frequency	Resource	Learning Rate Schedule	Learning Rate
85.71	100	20	6	120	12	Single GPU	Constant	0.0003

important quantitative indicator of dental conditions. The results confirmed the possibility of estimating the alveolar bone age based on AI, as shown in Figs. 5 and 6. In particular, Figure 6 shows the estimation of the focal CAM (the height of the alveolar bone and the major places where other treatment actions took place) area to identify the old group. In fact, the features that AI used in the evaluation are included in the domain that general people can understand. On the other hand, in the case of the young group, a wide CAM area over the entire area was estimated as a feature. Although there were insufficient datasets for learning and testing using deep learning, significant results and features were derived to show the potential for use of quantitative indicators for dental care. In other words, although there were only 50 data, which was set as a criterion that AI can determine, AI showed significant characteristics that can be fully understood and inferred.

The limitation of this study is that it used insufficient data. Since training data should represent the population of the data to solve the problem, more data than the 117 data used in this study are needed. This should be evaluated after learning, so if the number of fundamental training data is increased, not only can the evaluation data be processed, but a model with improved performance can also be trained. It will be possible to more accurately and quickly predict the oral disease shown in the panorama.

The researchers hope that this study will be helpful for future researchers who want to start to develop or research on AI for dental application.

4. Conclusion

If age groups are divided only by panorama, oral care methods suitable for life cycle are recommended, and oral care products can be prescribed according to the condition of the prosthesis and alveolar bone recognized in the panorama. Therefore, if an algorithm using panorama is developed, the oral management of patients can be used more efficiently. Using dental panorama radiographic images, AI-attempted reading was confirmed to be useful in providing fundamental data in dentistry. This is expected to contribute to the convergence of information and communication, and of biology and AI, by diagnosing oral conditions and diseases through the establishment of an AI database.

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