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RESEARCH ARTICLE

Tooth Development Prediction Using a Generative Machine Learning Approach

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ABSTRACT This study pioneers the use of generative deep learning in pediatric dentistry to predict dental growth using panoramic radiography, going beyond numerical analysis and providing dynamic representations of tooth development. We employed StyleGAN-XL, a state-of-the-art generative adversarial network (GAN), to generate realistic images of dental development stages in children. Our dataset consisted of 8,092 anonymized panoramic radiographs from Osaka University Dental Hospital containing various dentition stages and conditions. By interpolating latent vectors from primary or mixed dentition images with those from permanent dentition, we generated continuous transitioning images that visually represented the progression of dental development. The performance of the StyleGAN-XL model was evaluated using Fréchet inception distance scores. Pivotal tuning inversion was used to project real images onto the model's latent space, allowing us to effectively interpolate between current and future dental states. The resulting images showed a smooth transition from primary to permanent dentition, closely resembling the actual stages of dental development. This method represents a significant advancement in dental imaging and predictive analytics, offering a novel approach for clinicians and patients to visualize and understand dental growth. Our findings suggest broader applications for generative models in medical imaging, extending beyond traditional enhancement and modeling tasks. Our study highlights the transformative potential of GANs in medical imaging and provides a foundation for future advancements in predictive dentistry.

INDEX TERMS Artificial intelligence, machine learning, medical informatics applications, pediatric dentistry, orthodontics, dental informatics.

I. INTRODUCTION

In pediatric dentistry, assessment of growth and development in children is essential for making appropriate diagnoses and treatment decisions [1]. Traditionally, a child's development is monitored through physical attributes such as height, weight, posture, skull development, and facial structure, as well as oral aspects such as soft tissues, periodontal tissues, and occlusion of teeth [2]. Although dental age estimation using panoramic radiography provides a snapshot of the current developmental stage [3], it does not address a key challenge in dentistry: accurately predicting future dental growth, even if machine learning approaches were applied [4]. One possible area in dentistry that is focused on predicting future outcomes is dental space analysis [5], [6], [7]. Predicting dental caries in children is also promising research [8], [9], [10]. However, these methods merely yield numerical estimates. Moreover, this numerical approach cannot predict complex and dynamic dental changes, thereby indicating a significant gap between treatment forecasting and patient-specific outcome planning.

To fill this gap, it is important to develop an approach that goes beyond static and numerical data and provides dynamic and visual representations of tooth development. In this

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context, the use of deep learning is critical because it can analyze complex patterns in images and has the potential to generate predictive visualizations of dental development [11], [12]. This innovation not only improves predictive accuracy in pediatric dentistry but also represents a radical shift in how dental professionals approach treatment planning and patient education, moving towards more personalized and visually informed clinical practice.

Deep learning in computer vision has developed rapidly in recent years. A generative adversarial network (GAN) is an unsupervised deep-learning method that can generate images [13]. A GAN consists of two neural networks: a generator and a discriminator. In GANs, a latent vector that represents certain data in a latent space is used to generate new images; it is a compressed representation of the data that captures the most important features. The latent space is a high-dimensional space that contains the latent vectors of all the data in a training dataset. The generator uses a latent vector as input and produces a new image similar to the training dataset. The discriminator attempts to distinguish between real and generated images, whereas the generator is trained to fool the discriminator network. Consequently, the latent vector and latent space allow the generator to learn the underlying distribution of the training data, and the generator can output realistic and diverse images.

In previous studies using GANs in dentistry, modality changes [14], artifact reduction [15], image denoising [16], and prosthesis modeling [17] have been reported. Intraoral image generation [12] and periapical image generation [18] have been performed with reasonable visual quality and a resolution of 512 × 512 pixels. In this study, building on these advancements, we aim to leverage GANs to pioneer the field of dental growth prediction using panoramic radiography in children, generating continuous transitioning images that visually represented the progression of dental development.

Our proposed system was built by first training a GAN using panoramic radiographs as the training data. We then determined the latent vectors from actual images of primary or mixed dentition. By linearly interpolating these latent vectors with those derived from permanent dentition images, we generated continuously transitioning images, which is completely different from landmark-based morphing algorithms [19], [20]. Our results may contribute to the feasibility of creating panoramic radiographs that represent the progression of dental development in children, highlighting the potential of GANs as tools not only for image generation but also for biological process modeling.

II. MATERIALS AND METHODS

This study was retrospective and observational in nature and is summarized in Figure 1. We performed our experiments on a computer running the Ubuntu 20.04.6 LTS operating system with four NVIDIA RTX A6000 GPUs and 48 GB of VRAM. The NGC Docker container was used to create the development environment, specifically nvcr.io/nvidia/pytorch:21.06-py3 [21].

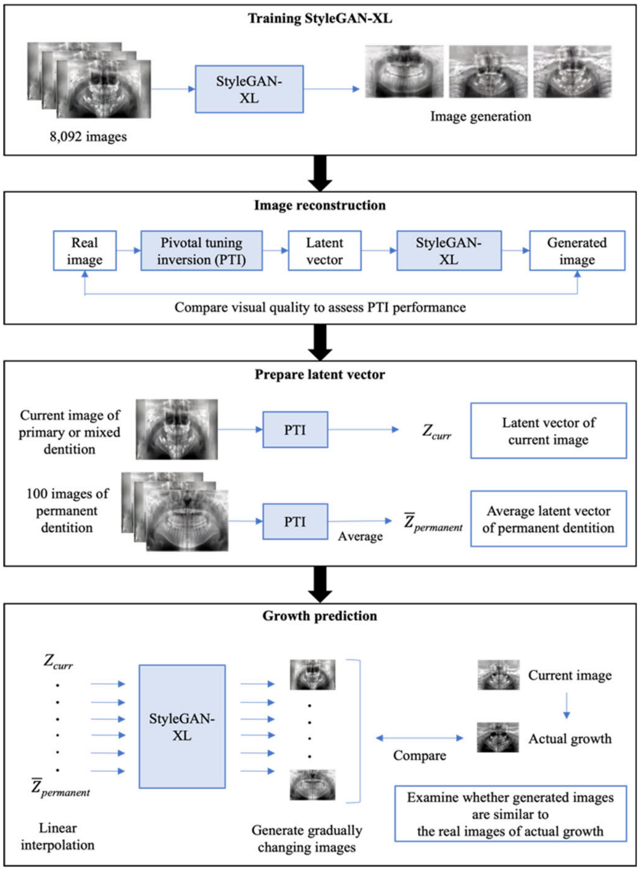

FIGURE 1. Our comprehensive pipeline for predicting dental growth in children using StyleGAN-XL.

A. DATASET

A total of 8,092 panoramic radiographs were used in this study. All images were obtained from patients who underwent dental treatment at the Department of Pediatric Dentistry, Osaka University Dental Hospital, Osaka, Japan.

For ethical reasons, all images were anonymized and had no metadata such as patient name, chronological age, sex, dentition, or disease. Therefore, the exact number for each condition was unknown; however, roughly speaking, the datasets contained a relatively high number of images that showed healthy dentition. These images included primary, mixed, and permanent dentitions. Various tooth conditions were represented, such as healthy teeth, caries, stains, composite resin restorations, metal inlays, stainless steel crowns, space maintainers, orthodontic appliances, and hypomineralization.

B. NETWORK ARCHITECTURE

In the field of image generation research, the StyleGAN family is a popular GAN choice. For our image-generation model, we utilized StyleGAN-XL [22], an enhanced version of StyleGAN3 [23] that has demonstrated state-of-the-art performance in image synthesis task. StyleGAN-XL employs progressively growing training to facilitate fast and stable training [24]. In our study, we increased the resolution of the model from 16 × 16 to 512 × 512 pixels, doubling the resolution at each training stage. As the resolution increases, the StyleGAN-XL network needs to learn more complex features and represent finer details. To achieve high-resolution image generation, some layers containing information from the previous resolution are discarded, and new layers are added to enhance the network's capability. In this study, with each increase in resolution, two layers were discarded, and four new layers were added to reduce the model parameters. Additionally, we halved the following parameters of the generator network: number of image synthesis layers, capacity multiplier, and maximum number of feature maps. These modifications are based on the recommendation settings of StyleGAN-XL to reduce parameters when working with smaller and well-curated datasets.

For the batch size, we performed two types of training. The first was based on the StyleGAN-XL settings. The batch sizes were set to 2048 for 16 × 16 and 32 × 32 resolutions; 256 for 64 × 64, 128 × 128, and 256 × 256 resolutions; and 128 for 512 × 512 resolutions. The second method was based on the previous StyleGAN families. The batch size was set to 32 for all resolutions. To quantitatively evaluate our model performance, we measured the Fréchet inception distance (FID) [25]. FID measures the similarity between the distribution of real and generated images. A smaller FID value indicates a better ability of the model to generate images. Therefore, the FID was continuously monitored during the training process, and the model weights that produced the lowest FID values were used in this study. There may be some limitations in applying FID to medical images. When calculating the FID, an Inception V3 network was used for image feature extraction, which was trained with ImageNet but not with medical images [26]. An alternative encoder network such as RadImageNet is potentially more appropriate [27]. However, the use of an alternative is considered to affect consistency and comparability with previous or future studies, and there are suggestions that a pre-trained model is preferable to a randomly initialized model for calculating the FID of medical images [28]. Therefore, we retained the original FID implementation in this study.

C. DENTAL GROWTH PREDICTION

Recently, image editing techniques based on latent space have been proposed [29], [30]. Therefore, we must first invert the image into the latent space of the generator to determine the latent vector of the real images. In this study, pivotal tuning inversion (PTI) was used to obtain the latent vector of a given image from the latent space of our model [31]. To assess the feasibility of reconstructing real images using PTI, we projected real images into the latent space, generated images

TABLE 1. Fréchet inception distance (FID) values at each resolution with varying batch sizes. A lower FID value indicates superior image generation performance. We conduct two types of training: the one shown in the left three columns follows the StyleGAN-XL settings, and the one shown in the right three columns adheres to the settings of previous StyleGAN families. Our findings suggest that a constant batch size of 32 yields optimal results.

Resolution	Batch size	FID	Resolution	Batch size	FID
16	2048	3.55	16	32	1.87
32	2048	3.42	32	32	2.69
64	256	4.39	64	32	3.50
128	256	6.92	128	32	4.99
256	256	6.83	256	32	5.32
512	128	9.71	512	32	6.59

from the resulting latent vectors, and visually compared the real and reconstructed images.

By interpolating two latent vectors, the generated images gradually change between vectors [12], [29], [30]; this capability suggests the possibility of synthesizing growth images from primary to permanent dentition by interpolating the latent vectors of the current images with those of the permanent dentition images. We derived latent vectors of current images by inverting real images of primary or mixed dentition, denoted as Z_{curr}. To obtain the latent vectors of future images, we used 100 latent vectors from 100 real images of healthy permanent dentition and calculated their mean, denoted as $\overline{Z}_{permanent}$. To generate a series of future predictions, we linearly interpolated multiple latent vectors Z_i (where $i = 0, 1, 2, \ldots 50$). This process produced a sequence of 50 latent vectors, smoothly transitioning between the current-state latent vector Z_{curr} and the permanent-dentition-state latent vector $\overline{Z}_{permanent}$. The interpolation was calculated as follows:

$$Z_i = \frac{i}{50} \times \overline{Z}_{permanent} + \frac{50 - i}{50} \times Z_{curr} \tag{1}$$

where $i = 0, 1, 2, \ldots 50$. These latent vectors Z_i were then input into StyleGAN-XL to output future predictions as a series of 50 images. Because the generated images were expected to gradually change from the current image to the average permanent dentition image, we examined whether the generated images could include images similar to the real image of actual growth.

III. RESULTS

The FID values are listed in Table 1. A lower FID value indicates better image generation quality. Our results indicate that a constant batch size of 32 is optimal for achieving superior image-generation performance compared to larger batch size. We used the best weight of the 512 × 512 model trained with a batch size of 32 for the subsequent experiments.

Examples of the generated images are presented in Figure 2A. These images are considered visually realistic. We observed a smooth transition when creating a video from images generated by continuously changing various latent

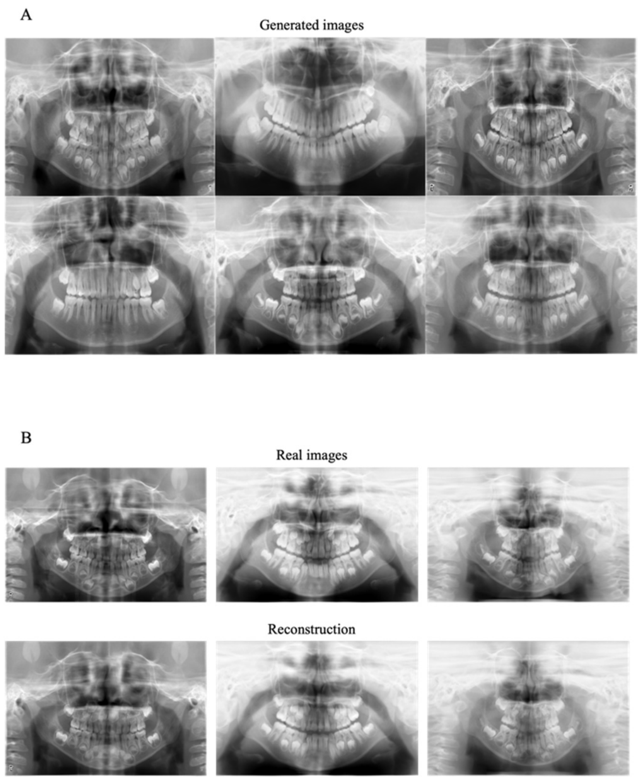

FIGURE 2. **A: Examples of both real and generated images. Supplemental image generation movie is available in the online version. B: Example of image reconstruction. The top row shows the original images, and the bottom row shows the reconstructed images generated using the inverted latent vector.**

variables. Supplemental image-generation videos are available online.

The reconstruction of real images using StyleGAN-XL is shown in Figure 2B. Although minor variations were observed in the tooth shape or arrangement, a high degree of congruence was evident between the original and reconstructed images, which is as same phenomenon as StyleGAN-XL [22]. This observation demonstrates the effectiveness of deriving appropriate latent vectors, denoted as Z_{curr}, through the inversion of real images into the latent space of StyleGAN-XL.

An example of growth prediction for children's panoramic radiographs is shown in Figure 3. Starting from the top-left image of the primary dentition period, the images gradually show growth and tooth exchange as we move to the ends of the right and bottom rows. The starting image was generated by Z_{curr}, and the final image by $\overline{Z}_{permanent}$. The intermediate images were generated by Z_i, which were derived from Equation (1).

Visual comparisons between the real image of growth and the generated image illustrating predicted growth are illustrated in Figure 4. These comparisons reveal a general similarity in the absorption of primary tooth roots, eruption of permanent teeth, and formation of tooth germs.

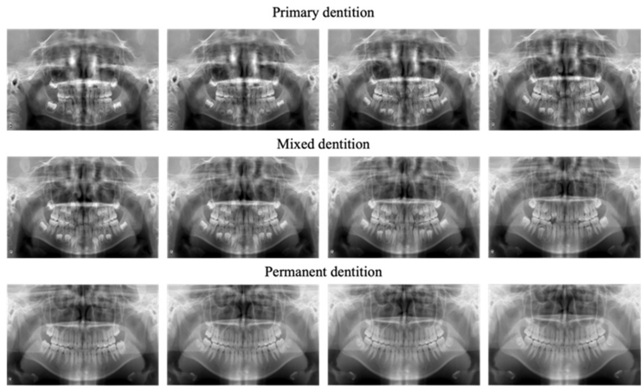

FIGURE 3. **Examples of generated dental development images. Starting from the top left image of the primary dentition period, the images gradually show growth and tooth replacement as we move to the right and bottom rows. The images are generated using specific latent vectors: Z4, Z8, Z12 and Z16 for the top row, Z20, Z24, Z28, and Z32 for the middle row, and Z36, Z40, Z44, and Z48 for the bottom row. This visual representation effectively illustrates the stages of dental development.**

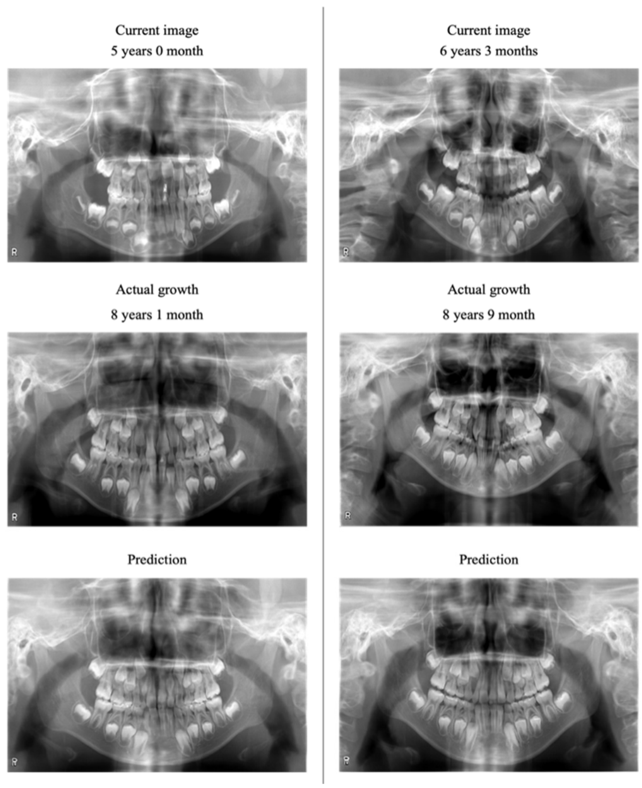

FIGURE 4. **Two examples of growth prediction, with comparisons between the real image of actual growth and the prediction images generated by our model. The prediction images are generated using latent vector Z12 for the left column and Z18 for the right column. This side-by-side display highlights the model's ability to accurately simulate the progression of dental development.**

IV. DISCUSSION

In this study, we developed a method to predict dental growth using StyleGAN-XL, a generative machine-learning model. Our method involved training the model with panoramic radiographs of children and subsequently generating images that visually represented the progression from primary to permanent dentition. The results showed that our model could generate images that closely resembled real images, indicating its potential for predicting dental growth. This study offers an overview of the future of dental imaging and growth prediction for clinicians, potentially supporting treatment planning and patient education. Patients may benefit from more informed discussions regarding dental development and treatment options.

Our StyleGAN-XL has been trained with many kinds of images of diverse patients from a university hospital, so the average latent vector $\overline{Z}_{permanent}$ could reflect general growth patterns. This high generalization performance is necessary for the application of this study to a variety of children. Since one of the goals of pediatric dentistry is to perform dental treatment on children's teeth in order to grow healthy permanent teeth, the use of the average latent vector is considered to be reasonable. As shown in Figure 4, the use of the average latent vector can predict the dental growth reasonably, indicating that our method might be suitable for use in pediatric dentistry.

This study is unique in its pioneering approach to dental growth prediction using a GAN. Previous dental applications of GANs focused on tasks such as image enhancement and prosthesis modeling [14], [15], [16], [17], [18]. Our study extends this application to the dynamic process of dental development, offering a novel tool for visualizing and understanding dental growth. The successful generation of realistic images of the dental growth phase suggests that StyleGAN-XL effectively captures and replicates the complex process of dental development. This capability highlights the potential of GANs as a tool not only for image generation but also for modeling biological processes, indicating that the methodology of this study holds the potential for broad application in medical images. For example, in elderly patients, tooth loss might be predicted using panoramic radiographs; in the case of carpal bone X-ray images, bone age development could be predicted. Its utility can be explored in oncology for tracking tumor progression or regression in response to treatment. The flexibility and adaptability of this method render it a promising tool for a wide array of medical imaging scenarios with gradually and continuously changing characteristics.

The predictive capabilities demonstrated by our generative machine learning approach can be extended beyond visualizing dental development to several other applications in predictive dentistry. One significant potential application is in the early prediction and monitoring of orthodontic treatment outcomes. By simulating the progression of dental growth, clinicians can forecast the future alignment of teeth and make more informed decisions about the timing and type of orthodontic interventions needed. Additionally, our approach can be leveraged to predict the development of dental pathologies, such as caries or periodontal disease, by integrating it with other diagnostic data like microbiome analysis or patient health records. This can lead to early interventions and personalized treatment plans, thereby improving patient outcomes. Furthermore, the dynamic and visual nature of the predictions can enhance patient education and compliance by providing clear and comprehensible visualizations of potential dental changes, making complex dental growth processes more understandable for patients and their families.

The image generator's latent vector sampling method in the latent space, utilizing PTI adopted in this study, has shown potential as an effective feature extraction method to indicate the transition state from primary to permanent teeth from a total of 8,092 panoramic radiographs. In the section on Dental Growth Prediction, the presence of a distance space was confirmed from the two extracted latent vectors (permanent tooth image group and primary tooth image group). As a result, mapping to the latent space using PTI is considered a universal method that can likely be applied not only to the panoramic radiographs targeted in this study but also to facial and intraoral photographs. Furthermore, the prediction of rare diseases, which are events with undetermined variance due to their occurrence frequency distribution, is challenging to model mathematically and statistically. Therefore, a prediction method that does not predefine the probability density function, like this method, is anticipated. It is highly probable that latent vectors fitting rare diseases can be found, making it easier to generate similar cases. This approach could potentially solve the significant issue of dataset imbalance when constructing AI for distinguishing rare diseases. These broader applications underline the transformative potential of generative models in enhancing predictive analytics in dentistry and paving the way for more personalized and proactive dental care strategies.

We discovered that a batch size of 32 optimizes the FID values for our study, as summarized in Table 1. Original StyleGAN-XL gives better results using large batch size to train with ImageNet, which is different from our medical images. Our results suggest that batch size could be one of the hyperparameters to be tuned based on the training dataset. On the other hand, we must consider that the generative models that yield the best FID scores may not always generate high-quality images, suggesting the importance of visual inspection. To advance our research, a visual Turing test could be a beneficial evaluation in the future to validate the quality of the generated images [12], [18].

In addition to visual assessments, quantitative metrics are necessary for further research to compare actual and predicted growth. Some simple comparison metrics, such as the root-mean-square error, do not fully capture the two-dimensional nature of the images. A promising approach involves contrastive representation learning to develop domain-specific models [32], [33]. These models can extract image features after training, and we can calculate the cosine similarity of the embedding vectors to evaluate the image similarity. In particular, self-supervised learning approaches such as SimCLR [34] or Barlow Twins [35], which do not require extensive labeling, could be particularly useful in medical image training, where annotation is often costly.

Those approaches are promising methods to evaluate medical image similarity. However, due to their high computational requirements, these methods should be investigated as separate research from our study.

Another limitation is the small size of the training dataset used. The original StyleGAN-XL model was extensively trained on ImageNet, which is a large dataset. In contrast, our study used a training dataset of only approximately 8,000 images. This may have limited our ability to take full advantage of the capabilities of StyleGAN-XL. Furthermore, our dataset was biased towards healthy dentition. Consequently, the quality of the generated images was diminished for certain dental materials, such as composite fillings, metal inlays, stainless-steel crowns, space maintainers, and orthodontic appliances. For a more comprehensive understanding and visual details, please refer to the online supplementary video; this resource provides an in-depth visual representation of the findings of the study and offers a clearer perspective on the limitations and capabilities of our generative models. To overcome the small and imbalanced datasets, one solution could be to add public datasets, such as Tufts Dental Database [36]. Federated learning across multiple medical institutions may also be another solution to be consider [37].

This tendency to generate images of healthy dentition is similar to that observed in our growth prediction models. Our method involves linear interpolation with the latent vector $\overline{Z}_{permanent}$, which is based on the average latent vector of permanent dentition. By replacing the latent vector $\overline{Z}_{permanent}$ with alternative vectors, we can generate various growth patterns that differ from those observed in this study. This flexibility allows our model to simulate challenging conditions, including congenitally missing teeth, supernumerary teeth, tumors, malalignments, and various syndromes. In addition, beyond linear interpolation, other interpolation methods like polynomial interpolation or spline interpolation can be applied to enhance the predictive capabilities of the model. If a large amount of paired data of primary and permanent teeth becomes available, it may be possible to create a neural network that predicts the latent vector of permanent teeth from the latent vector of primary teeth, leading to personalized predictive healthcare using our method. Advanced techniques of latent space analysis, such as StyleSpace [38] and StyleMC [39] may also be useful for improving predictive performance. Future research in these areas has considerable value and could be the key to advancing personalized predictive dental care.

V. CONCLUSION

Our study demonstrates the groundbreaking application of StyleGAN-XL in pediatric dentistry and offers a new method for predicting dental growth using panoramic radiography beyond numerical approaches. Our findings have the potential to revolutionize predictive diagnostics, extending their impact beyond dentistry to various fields of medical imaging. The application of our method may improve the ability to predict and plan for medical conditions, thereby providing a transformative approach in healthcare diagnostics.

SUPPLEMENTARY DATA

One supplementary data "supplemental.mp4", which shows image generation movie associated with this article can be found in the online version. This resource provides an in-depth visual representation of our findings and offers a clearer perspective on the limitations and capabilities of our generative models.

ETHICS

The Ethics Committee of Osaka University Graduate School of Dentistry approved this study (approval number: R3-E27) and the requirement for informed consent was waived because of the retrospective nature of the study. All the methods used in this study were performed in accordance with the Act on the Protection of Personal Information and Ethical Guidelines for Medical and Health Research Involving Human Subjects. All methods were performed in accordance with relevant guidelines and regulations.

COMPETING INTERESTS

The authors have no conflicts of interest to declare.

AUTHOR CONTRIBUTIONS

Kazuma Kokomoto wrote the main manuscript and contributed to the study design, data acquisition, analysis, and interpretation; Kazuma Kokomoto, Rena Okawa, and Kazuhiko Nakano contributed to data acquisition, clinical analysis, and interpretation; and Kazuma Kokomoto and Kazunori Nozaki contributed to the network analysis and interpretation. All authors gave their final approval and agree to be accountable for all aspects of the work.

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