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RESEARCH AND EDUCATION

Accuracy of artificial intelligence-designed single-molar dental prostheses: A feasibility study

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ABSTRACT

Statement of problem. Computer-aided design and computer-aided manufacturing (CAD-CAM) technology has greatly improved the efficiency of the fabrication of dental prostheses. However, the design process (CAD stage) is still time-consuming and labor intensive.

Purpose. The purpose of this feasibility study was to investigate the accuracy of a novel artificial intelligence (AI) system in designing biomimetic single-molar dental prostheses by comparing and matching them to the natural molar teeth.

Material and methods. A total of 169 maxillary casts were obtained from healthy dentate participants. The casts were digitized, duplicated, and processed with the removal of the maxillary right first molar. A total of 159 pairs of original and processed casts were input into the Generative Adversarial Networks (GANs) for training. In validation, 10 sets of processed casts were input into the AI system, and 10 AI-designed teeth were generated through backpropagation. Individual AI-designed teeth were then superimposed onto each of the 10 original teeth, and the morphological differences in mean Hausdorff distance were measured. True reconstruction was defined as correct matching between the AI-designed and original teeth with the smallest mean Hausdorff distance. The ratio of true reconstruction was calculated as the Intersection-over-Union. The reconstruction performance of the AI system was determined by the Hausdorff distance and Intersection-over-Union.

Results. Data of validation showed that the mean Hausdorff distance ranged from 0.441 to 0.752 mm and the Intersection-over-Union of the system was 0.600 (60%).

Conclusions. This study demonstrated the feasibility of AI in designing single-molar dental prostheses. With further training and optimization of algorithms, the accuracy of biomimetic AI-designed dental prostheses could be further enhanced. (J Prosthet Dent 2023;■:■-■)

Dental prostheses are a common treatment option for the replacement of one or more teeth and associated dental and alveolar structures. Dental prostheses should be customized according to individual patients' remaining dentition and oral environment. Appropriately designed dental prostheses restore esthetics, oral function, and occlusal integrity.[1-4] Occlusal discrepancies and oral dysfunctions might occur if dental prostheses do not mimic the occlusal morphology of the missing teeth.[1,2]

A major challenge in providing dental prostheses is the time required to design and fabricate the dental prosthesis by the dental laboratory

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Clinical Implications

This preliminary study supported the further development of and research into AI in restorative dentistry and prosthodontics.

technician, as well as the time for adjustments at the chairside during delivery.[5,6] With computer-aided manufacturing (CAM), the time needed for prosthesis fabrication can be significantly shortened. However, the challenges of the design process remain unsolved despite the advances in computer-aided design (CAD) software programs, as the built-in tooth libraries in the software programs may not be sufficiently advanced to customize the design for individual patients. Therefore, significant manual input is needed during the design stage. Moreover, even adopting the contemporary CAD-CAM approach, dental prostheses still require chairside time for adjustment during insertion and delivery.[7-10]

Artificial intelligence (AI) could be used to solve the problem. AI is capable of mimicking features of human intelligence such as reasoning, learning, and self-improvement.[11] AI has been recently utilized in prosthodontics to fabricate automated dental prostheses.[12] Such AI systems use biogeneric tooth libraries, statistical models, or computer-vision methods to reconstruct the tooth surfaces.[13] While the accuracy of current AI-designed teeth has been reported to provide an acceptable replica of the original tooth, human input is still required to finalize the design.[13]

Artificial neural networks (ANNs), a recent development in AI, are computing systems that mimic the biological neural networks and consist of layers of network.[14] Through learning of the training data, ANNs can modify the connections and weights of its layers to improve the outputs.[15] Three-dimensional (3D) Generative Adversarial Network (GAN) is a recent neural network development in which 2 neural networks, the generative network and the discriminative network contest with each other.[16] In prosthodontics, the generative network may be used to learn the features of teeth within a dental arch and to generate an AI-designed tooth. Its discriminative network then attempts to discriminate between the original and the AI-designed tooth, which itself is also being continuously modified (Fig. 1).[16,17] A 3D GAN AI system could automate the biomimetic designs of dental prostheses and emulate the anatomy of natural teeth by learning the morphology of remaining dentition which shares similar occlusal features such as the cuspal angles.[18-22]

This feasibility study aimed to determine the accuracy of single-molar dental prostheses designed by a novel AI system. The reconstruction performance of the AI system has often been determined by the Hausdorff distance and Intersection-over-Union.[23-25] Hausdorff distance is one of the common performance metrics for evaluating medical image segmentation and represents the error between the surface of an AI-designed tooth and the surface of its comparison tooth. The smaller the Hausdorff distance, the closer the AI-designed tooth is when compared with the original tooth in terms of morphology, with 0.000 representing a perfect reconstruction.[23] Intersection-over-Union has also been a widely adapted performance metric for segmentation models in the field of computer vision and neural networks and is presented as the ratio of true reconstruction to the ground truth.[24,25] The value of Intersection-over-Union ranges from 0.000 (0%) to 1.000 (100%), and 1.000 is considered a perfect reconstruction.[26] The common acceptable threshold is 0.500 (50%), and an AI system would be judged to have good prediction if the Intersection-over-Union is greater than 0.500.[26,27] The present study was performed by following the published protocol and reported by following the Consolidated Standards of Reporting Trials statement.[22,28,29] The research hypothesis was that a 3D GAN AI system could automate the biomimetic design of crowns with acceptable performance in terms of accuracy.

MATERIAL AND METHODS

Study participants, with at least 12 pairs of occluding units including an intact maxillary right first molar and a stable maximal intercuspal position (MIP) were assessed according to the inclusion and exclusion criteria (Table 1) by a calibrated assessor (W.Y.H.L.).[30,31] Participants fulfilling the criteria were recruited, and written consent was obtained. This study had been approved by the Institutional Review Board of the University of Hong Kong and Hospital Authority Hong Kong West Cluster (Reference Number: UW 20-848).

Impressions were made with an irreversible hydrocolloid impression material (Aroma Fine Plus, Normal set; GC Corp) and stock metal trays (Coe Impression Tray; GC Europe). The impressions were then poured with Type III gypsum (Denstone KD; Formula Saint-Gobain) using the recommended powder to water ratio. The dental casts were digitized with a high accuracy (±5 μm) laboratory scanner (Trios D2000; 3Shape A/S). The digitized data were then converted from standard tessellation language (STL) format into polygon (PYL) format using a 3D mesh processing software system (MeshLab v2021.07; Visual Computing Lab of the ISTI-CNR).[32] The occlusal surface of all incisors and second molars of all casts were then flagged. A self-developed aligning program was used to align all casts into the same orientation on the X-plane in an XYZ Cartesian coordinate system via a programming and numerical

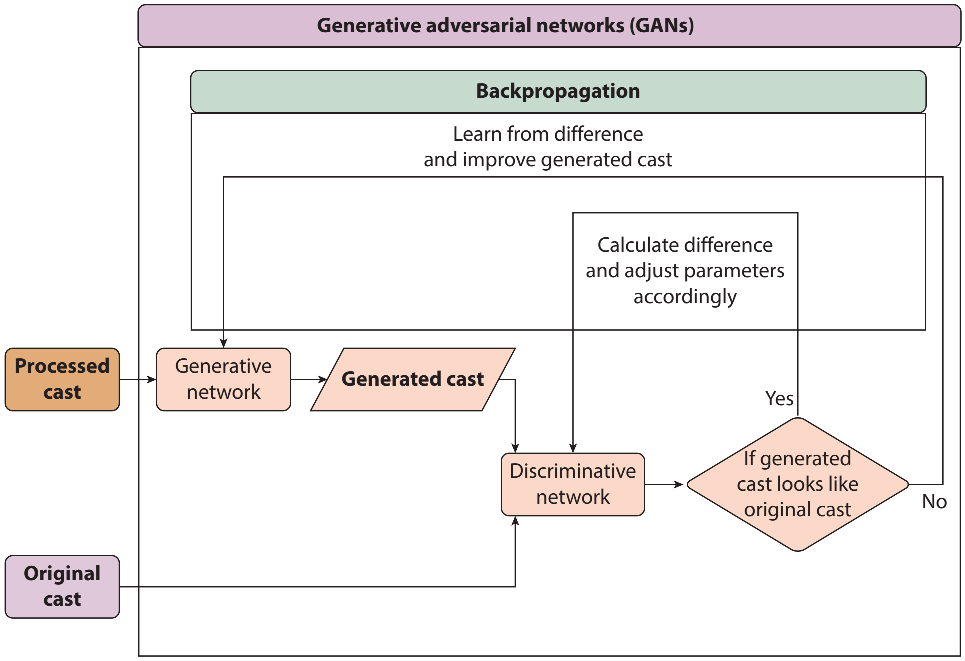

Figure 1. Architecture of Generative Adversarial Network (GAN).

Table 1. Inclusion and exclusion criteria

Inclusion criteria	Participant level	Participants with 12 or more functional occlusal units and stable maximal intercuspal position (MIP).
		Participants with maxillary right first molar tooth.
		Participants who score Grade 2 or less from Index of Treatment Need (IOTN) and have no ongoing or completed orthodontic treatment.
	Tooth level	Sound tooth or tooth with single surface restorations that still retain all natural occlusal landmarks.
Exclusion criteria	Participant level	Participants with periodontal disease (Basic Periodontal Examination BPE Score 3) whereby there may be pathological tooth migration and alteration of occlusal plane.
		Participants under the age of 18 and unable to give consent.
	Tooth level	Teeth with extensive (2 or more surfaces) restorations that affect morphology.
		Teeth with pathological tooth movements such as fremitus, drifting, and overeruption.

computing platform (MATLAB R2021b; The MathWorks, Inc), and the flagged occlusal surface was aligned with the plane of Y=0 and Z=0, as the 3D GAN networks training required all input casts to be in same orientation on a single consistent plane.

The digital casts were duplicated into 2 identical sets, with 1 set of files as the original maxillary arch and another set of files with the maxillary right first molar

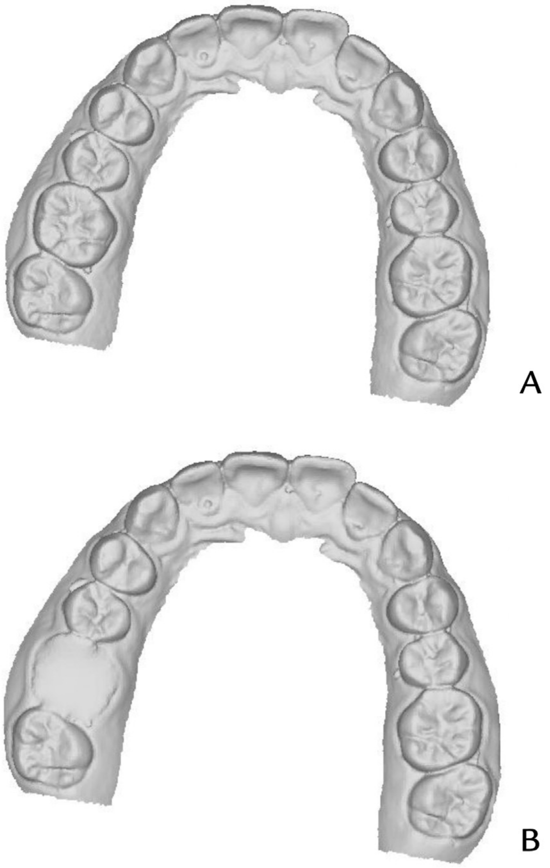

Figure 2. A, Original cast. B, Processed cast.

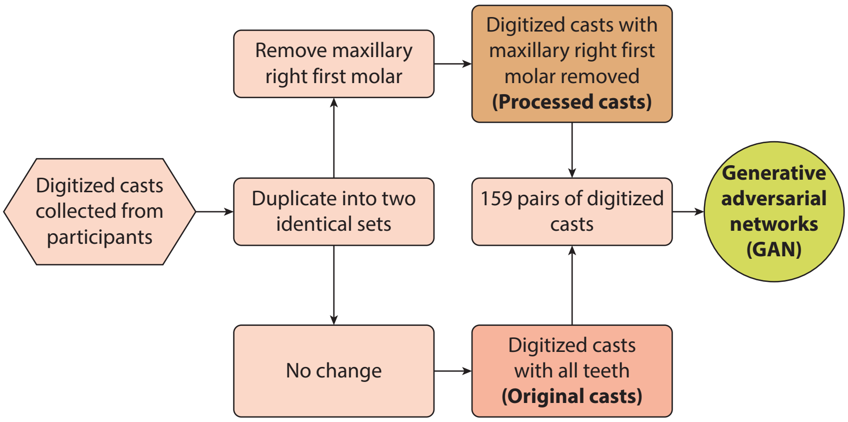

Figure 3. Simplified flow diagram of data collection and processing.

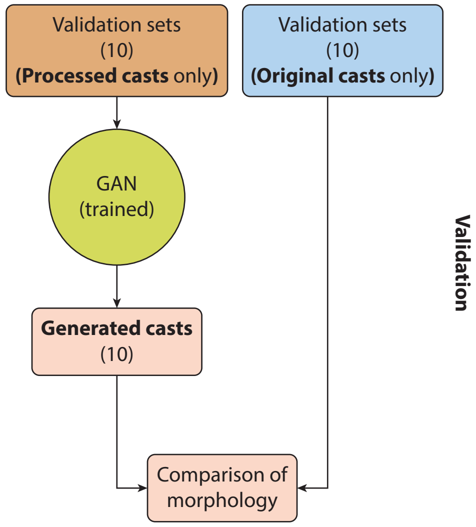

Figure 4. Brief illustration of validation process. GAN, Generative Adversarial Network.

removed to simulate a missing tooth. Casts with simulated missing teeth were designated as processed casts, while those with original arches were designated as original casts (Fig. 2). Ten pairs of original and processed casts were randomly assigned by a randomization table as validation sets, while the remaining casts were used as training sets.

The training sets were input into the 3D GAN networks to learn the relationship between individual maxillary teeth (maxillary right first molar) and the remaining dentition (Fig. 3). The 3D GAN networks were implemented based on a software library (Keras v2.12; Google LLC) with an interface for solving machine learning problems (TensorFlow 2 v2.9; Google LLC).[33-35] The training and validation of the network were performed on a high-performance computer (HPC2021; The University of Hong Kong) with a total of 149 computer nodes, 8544 physical CPU Cores, and 40 TB system

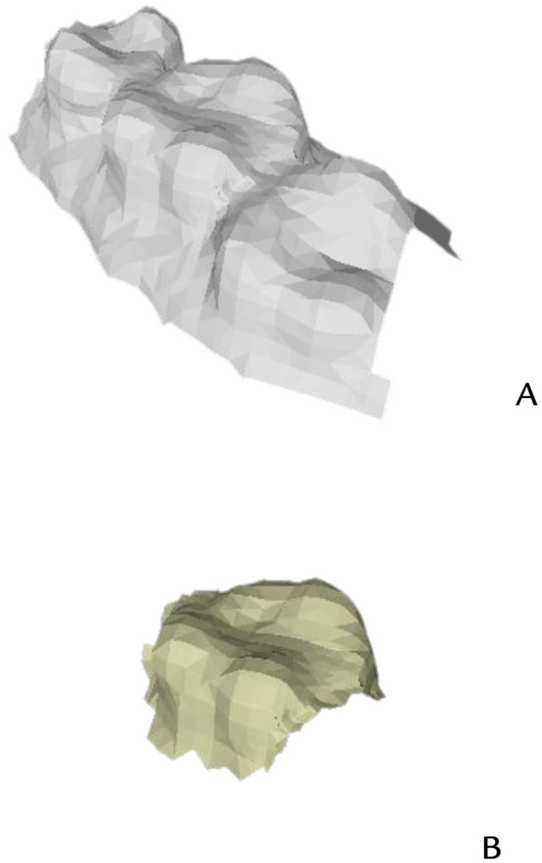

Figure 5. A, Part of generated cast. B, AI-designed tooth isolated from generated cast. AI, artificial intelligence.

memory provided by the Information Technology Services of the University of Hong Kong.[36]

After the completion of 3D GAN training, the 10 validation sets were input into the AI to generate the maxillary right first molar on the processed casts as the generated casts (Fig. 4). Then, 10 sets of AI-designed maxillary right first molars (Fig. 5) were isolated from the generated casts and were labeled as tooth 1′ to tooth 10′. Ten sets of original right maxillary first molars were also labeled as tooth 1 to tooth 10.

Every AI-designed tooth was compared with each of the 10 original teeth by a blinded assessor (R.C.W.C.) who did not know the correct labels of the teeth to reduce bias. Four occlusal landmarks, including the mesiobuccal cusp tip, mesiolingual cusp tip, distobuccal cusp tip, and distolingual cusp ridge, were marked as reference points for aligning the AI-designed teeth and the original teeth. Each pair of teeth was superimposed using the best-fit algorithms according to the occlusal landmarks, and the differences in the surface morphology were derived by calculating the mean Hausdorff distance of all data points on the AI-designed tooth against those on the original tooth using the 3D mesh processing software system (MeshLab) (Fig. 6). Intersection-Over-Union was applied to evaluate the overall performance of the AI system. If AI-designed tooth N′, where N was the label of a tooth, had the smallest mean Hausdorff distance with N among all 10 matches. When N was the corresponding original tooth among the 10 matches, it was considered a true reconstruction.

Although a sample size of 1000 has been suggested for full AI training of 3D images,[37] the accuracy of training often starts to reach a plateau in the receiver operating characteristic (ROC) curve at the sample size of 100 to 200.[37,38] Thus, such a range is an appropriate sample size for a feasibility study.

RESULTS

A total of 466 study participants were assessed, and 169 participants fulfilling the criteria were included in this study. After the AI training with 159 training data sets, 10 validations were performed with a total of 100 (10×10) comparisons assessed between an AI-designed tooth and its original counterpart. Differences between the morphology of each AI-designed tooth and each original tooth are presented as mean Hausdorff distance in Table 2. The mean Hausdorff distance between the morphology of each AI-designed tooth and that of the respective original is presented in Table 3. The status of true reconstruction is presented in Table 4. Of 10 reconstructions, 6 were considered true reconstructions, and thus the Intersection-over-Union was 0.600 (60%). Among the matching pairs of validations set, namely pairs of 1′ versus 1, 2′ versus 2, to 10′ versus 10, the mean ±standard deviation Hausdorff distance was 0.633 ±0.961 mm.

DISCUSSION

The result of this study supported the hypothesis that a 3D GAN AI system could automate the biomimetic design of crowns with acceptable accuracy. This preliminary study was one of the first few studies using a 3D GAN model to address a fundamental problem in restorative dentistry and prosthodontics, the fabrication of biomimetic dental prostheses.[13,39] The findings showed the feasibility of applying such a system in designing biomimetic single-molar dental prostheses with acceptable accuracy, as there were only small morphological differences as shown by a mean Hausdorff distance of 0.633 mm and 60% true reconstruction (0.600) as measured by the Intersection-over-Union between the original tooth. 3D GAN provided a novel approach to tooth reconstruction, as, once the AI system had been trained, it required minimal human input to initiate and complete the CAD stage. In a recent study of tooth reconstruction using AI, the mean Hausdorff distance between the AI-designed and the original tooth surfaces was reported to be 0.730 mm when tested in 10 models, similar to the result of the present study, 0.633 mm (Table 4).[40]

This was one of the first few studies that used natural tooth surfaces as the training and validation data.[13]

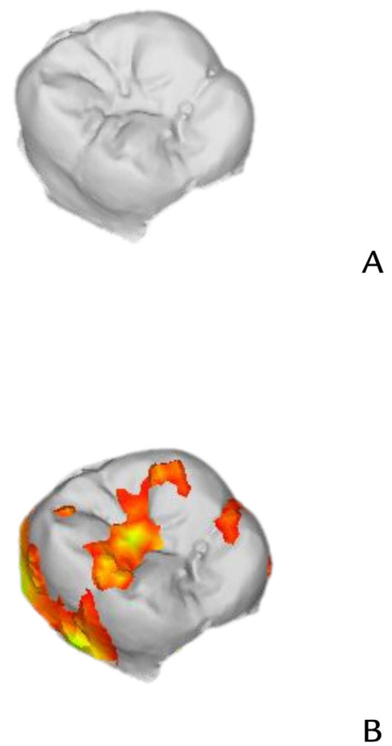

Figure 6. A, Original tooth. Demonstration of comparing AI-designed tooth to it. Hausdorff distance presented by color (relative measurement for each pair). B, Demonstration of comparing AI-designed tooth to it. Lowest Hausdorff distance in red (0.000 mm). Highest Hausdorff distance in blue (1.500 mm). AI, artificial intelligence.

Table 2. Measurements and comparison results of all 100 matches performed

	Mean Hausdorff Distance (mm)									
Comparison Against	1	2	3	4	5	6	7	8	9	10
1′	0.465	0.519	0.86	0.582	0.583	0.495	0.6	0.799	0.531	0.638
2′	0.757	0.458	0.722	0.779	0.782	0.714	1.033	0.653	0.74	0.631
3′	0.701	0.695	0.501	0.537	0.556	0.631	1.037	0.582	0.677	0.706
4′	0.827	0.988	0.837	0.979	0.913	0.852	0.958	0.991	0.83	1.019
5′	0.522	0.533	0.574	0.603	0.631	0.589	0.679	0.694	0.563	0.645
6′	0.792	0.808	0.898	0.681	0.657	0.504	0.929	0.729	0.648	0.743
7′	0.933	0.826	0.876	0.775	0.855	0.977	0.752	0.873	0.826	0.951
8′	0.63	0.542	0.809	0.791	0.66	0.619	0.741	0.441	0.833	0.705
9′	0.601	0.938	0.467	0.551	0.724	0.791	0.732	0.643	0.762	0.836
10′	0.665	0.761	0.695	0.78	0.717	0.728	0.812	0.768	0.678	0.844

Table 3. Measurements and comparison results of all 10 corresponding matches

Comparison	Mean Hausdorff Distance (mm)	Standard Deviation (mm)
1′ versus 1	0.465	0.664
2′ versus 2	0.458	0.642
3′ versus 3	0.501	0.719
4′ versus 4	0.979	1.560
5′ versus 5	0.631	0.978
6′ versus 6	0.504	0.858
7′ versus 7	0.752	1.140
8′ versus 8	0.441	0.665
9′ versus 9	0.762	0.959
10′ versus 10	0.844	1.421
Mean	0.633	0.961

Table 4. Color presentation of true predictions

Comparison	True Prediction?
1′ versus 1	Y
2′ versus 2	Y
3′ versus 3	Y
4′ versus 4	N
5′ versus 5	N
6′ versus 6	Y
7′ versus 7	Y
8′ versus 8	Y
9′ versus 9	N
10′ versus 10	N

Traditionally, dental prostheses fabricated by the dental laboratory technicians have been used for this purpose.[13] The authors considered that the natural tooth surfaces were in the functional equilibrium of the masticatory system and should result in reduced occlusal error.

Few-shot learning, which requires homogeneity of training materials to enable AI training using a small sample size, has been popular recently in the AI community.[41-44] This feasibility study adopted training samples of natural healthy teeth as it eliminated the impact of various dental diseases and treatments on tooth morphology, thus reducing the heterogeneity of the training materials and the sample size.

AI training usually requires the training data to be first labeled and annotated by an expert, a process that might introduce assessor variation and bias. In the present study, labeling was not required, as duplicate digital casts with both the presence and absence of the maxillary right first molar were used as the training material, thereby eliminating errors associated with labeling.

The findings of the present study should be interpreted with caution as the missing tooth scenario was made in a computer-simulated environment. Drifting, tilting, and supra-eruption of the teeth around the edentulous region, as occur clinically, were not considered. In addition, the present study was done on healthy dentition where 12 or more functional occlusal units were present for training the AI system. Hence, further enhancement of the AI algorithm is needed for patients with multiple missing teeth. Although the error of the present AI system seems small, it is still suboptimal, as some studies showed that the human occlusal tolerance level could be as small as 0.100 mm.[45] Furthermore, in vivo studies on how the AI-designed teeth affect the dynamic occlusion should be performed. In addition, with bigger and more diverse training data sets across different populations, the training outcome might produce further improvements and pave the way for more AI applications in prosthodontics.

CONCLUSIONS

Based on the findings of this feasibility study, the following conclusions were drawn:

1. A 3D GAN AI system was able to design a single-molar dental prosthesis that mimicked the morphology of a natural healthy tooth by learning the tooth features from the remaining dentition.
2. Additional development of AI algorithms and recruitments of participants with various clinical

conditions would be needed to further explore its applications in dentistry.

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CRediT authorship contribution statement

Reinhard Chun Wang Chau: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Richard Tai-Chiu Hsung:** Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Writing – review & editing, Supervision. **Colman McGrath:** Methodology, Writing – review & editing, Supervision. **Edmond Ho Nang Pow:** Methodology, Writing – review & editing, Supervision. **Walter Yu Hang Lam:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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