Transfer Learning via Artificial Intelligence for Guiding Implant Placement in the Posterior Mandible: an *in vitro* Study

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Abstract

Background: To explore the capacity of a single shot multibox detector (SSD) and Voxel-to-voxel prediction network for pose estimation (V2V-PoseNet) based artificial intelligence (AI) system in automatically designing implant plan.

Methods: 2500 and 67 cases were used to develop and pre-train the AI system. After that, 12 patients who missed the mandibular left first molars were selected to test the capacity of the AI in automatically designing implant plan. There were three algorithms-based implant positions. They are Group A, B and C (8, 9 and 10 points dependent implant position, respectively). The AI system was then used to detect the characteristic annotators and determine the implant position. For every group, the actual implant position was compared with the algorithm-determined ideal position. And global, angular, depth and lateral deviation were calculate. One-way ANOVA followed by Tukey's test was performed for statistical comparisons. The significance value was set at $P < 0.05$.

Results: Group C represented the least coronal (0.6638 ± 0.2651 , range: 0.2060 to 1.109 mm) and apical (1.157 ± 0.3350 , range: 0.5840 to 1.654 mm) deviation, the same trend was observed in the angular deviation ($5.307 \pm 2.891^\circ$, range: 2.049 to 10.90°), and the results are similar with the traditional statistic guide.

Conclusion: It can be concluded that the AI system has the capacity of deep learning. And as more characteristic annotators be involved in the algorithm, the AI system can figure out the anatomy of the object region better, then generate the ideal implant plan via deep learning algorithm.

Background

Optimal three-dimensional (3D) position of dental implants is the key for functional and aesthetic outcomes^{1,2}. Virtual implantation improves the accuracy of implant placement. Subsequently, guided surgery opens up possibilities to transfer the 3D pre-surgical planning to implant surgery, to achieve ideal 3D implant placement¹⁻⁴.

As surgical templates can reduce human error, guided surgery has come to play an important role in precise bone drilling and implant placement⁴⁻⁶. However, traditional surgical templates still have several disadvantages, including extensive manual work for preoperative planning and increased cost of template fabrication for each case. Besides that, the accuracy of guided implant surgery depends on the dentist and technician, while there are learning curves and expenses related to training⁷. Our approach to improve the traditional surgical template is the use of artificial intelligence (AI).

AI refers to a serious of technologies that allow computers and machines to imitate human intelligence⁸. It has come to play an important role in healthcare, including analyzing a diverse array of patient data and simulating human logic to perform some tasks⁹⁻¹². AI iteratively learn the intrinsic statistics underlying the pairing data and algorithm, to make plan on unseen data^{8,10}. Recently, there has been a significantly increasing tendency in the number of AI studies in medicine, mostly for disease detection and classification purposes^{8,10,13-15}. And the use of AI for radiological images reading has been widely explored^{12,13,16}.

AI system would enable all clinicians to design and practice the complicate cases at the same level of practical expertise as the very best clinicians. Since database could be shared between physicians without the privacy risks of leaking patient data, there is almost limitless potential to renew the system learned from the diverse physicians and diverse patients^{11,17}.

Recently, AI technique has also been used in dentistry for various purposes^{8, 18, 19}. For instance, Shintaro et al.²⁰ used AI to accurately classify dental implant brands from various panoramic X-ray images, Joel et al.²¹ presented a deep learning system for mandibular canal segmentation, Jin-Ju et al.²² used AI for automatic 3D analysis of bone alteration after maxillary sinus augmentation. Jun et al.¹⁶ developed a deep neural network to determine the peri-implant marginal bone loss. The accuracies for most of the tasks are promising.

The usage of AI for dental diagnostics has been developed quickly in the recent years^{8, 18, 23}. It worth further focusing on the possibilities of automatically generated implant surgery plans. To our knowledge, there were rare studies in this field. This study explored a deep learning model, named SSD²⁴, with V2V-PoseNet²⁵ as its backbone architecture, to automatically recognize the target region, detect the bone contour and capture the characteristic annotators, then generate the implant plan. Then we assessed the accuracy of the automatically designed templates, which satisfies the well-established algorithm.

The purpose of this *in vitro* study was to explore the capacity of the AI system in automatically designing implant plan, through deep learning. And compare the accuracy of 8, 9 and 10 characteristic annotators based algorithm guided surgery in posterior mandible.

Methods

All patients consented to the use of their data for research purposes and signed informed consent forms accordingly. This study protocol was approved by the ethical committees of the Guanghua School of Stomatology, Hospital of Stomatology, Sun Yat-sen University (KQEC-2020-063-01).

1.1 Sample

The datasets were divided into pre-training, training and test sets. The pre-training set, including 2500 various edentulous sites undergoing CBCT image (2018.10-2020.10), were used to train and develop the model parameters. After that, the model hyper parameters and architecture selected using the training set, which includes 67 cases who undergo CBCT and intraoral scanning. The selected 67 patients should meet the following conditions: 1) just miss the mandibular left first molar; 2) with the normal occlusion; 3) without any metallic prosthesis; 4) ≥ 18 years old. Finally, 12 patients undergoing CBCT (NewTom VGi CBCT imaging unit, Verona, Italy) and intraoral scanning (SWEDEN & MARTINA, Veneto, Italy) who met the above criteria were collected for the following automatically designed implant surgery guide generation. To avoid over-optimistic results because of over-fitting, that is, memorizing specific features of edentulous sites, each of the three sets had an independent set of patients.

1.2 Software workflow

The AI software workflow is presented in Fig. 1. A model named SSD²⁴ has been proposed for edentulous site and related key points detection.

2.2.1 Evaluation of edentulous area condition

The image flow chart of automatically implant position design is shown in Figure 2. SSD model, a convolutional neural network (CNN), was used to construct the AI system. All files were uploaded to SSD for evaluation of edentulous area condition. First, the software automatically generated a panoramic image and detect the missing tooth position through CBCT (DICOM data) reading. Second, the region of interest (ROI) was constructed. All slices were extracted from ROI of the panoramic image ribbon and a small box area was cut out from the DICOM data for

processing. Third, detect the bone contour and capture the designed characteristic annotators based on V2V-PoseNet. Then the implant axis was generated. Finally, the implant position was created automatically.

2.2.2 haracteristic annotators capture

The characteristic annotators were recorded based on the condition of the alveolar bone 3D features, the neighboring teeth and the opposite teeth (Fig. 3). They are: Point 1 (P1): The buccal junction point between the alveolar ridge of the missing tooth and the adjacent anterior tooth; Point 2 (P2): The buccal middle point between the alveolar ridge of the adjacent anterior and posterior teeth; Point 3 (P3): The buccal junction point between the alveolar ridge of the missing tooth and the adjacent posterior tooth; Point 4 (P4): The lingual junction point between the alveolar ridge of the missing tooth and the adjacent anterior tooth; Point 5 (P5): The lingual middle point between the alveolar ridge of the adjacent anterior and posterior teeth; Point 6 (P6): The lingual junction point between the alveolar ridge of the missing tooth and the adjacent posterior tooth; Point 7 (P7): The height of the contour of the adjacent anterior tooth approaching to the target site; Point 8 (P8): The height of the contour of the adjacent posterior tooth approaching to the target site; Point 9 (P9): The function cusp of its opposite teeth; Point 10 (P10): The central fossa of its opposite teeth.

2.2.3 Implantation plan generation

All of the characteristic points were detected using V2V-PoseNet method. The characteristic points provided information about the implant position. In brief, there are three measurements. The first measurement showed the central spot of the implant neck (P_a), the second measurement showed the axial feature spot (P_b), and the third measurement showed the implant axis (Fig. 4). The linkage between P_a and P_b represented the implant axis. Besides that, the inferior alveolar nerve were marked by the operator. All the planed implants were bone level implants (NobelReplace CC; Nobelbiocare) of 4.3 mm × 10 mm or 4.3 mm × 11.5 mm. The implant length was determined by the operator, to keep a safe distance (≥ 2 mm) from the inferior alveolar nerve.

There are three kinds of calculation methods for the three measurements (P_a , P_b and implant axis). Accordingly, for every case, there are three groups of implantation plans. They are (1) Group A: 8 points (P1-P8) dependent implant position; (2) Group B: 9 points (P1-P9) dependent implant position; (3) Group C: 10 points (P1-P10) dependent implant position. In each group, P_a and P_b follow specific algorithm (Table 1).

Table 1. The specific algorithm for P_a and P_b

Group	P_a	P_b
A	$\frac{\sum_{i=0}^6 P_i}{6}$	$\frac{\sum_{i=7}^8 P_i}{2}$
B	$\frac{\sum_{i=0}^6 P_i}{6}$	$\frac{\sum_{i=7}^9 P_i}{3}$
C	$\frac{\sum_{i=0}^6 P_i}{6}$	$\frac{\sum_{i=7}^{10} P_i}{4}$

2.2.4 Surgical guides fabrication

Based on the plan, implant surgical templates were fabricated from ultraviolet sensitive liquid resin E-Dent (EnvisionTEC). Each surgical guide was 3mm thick. All the templates were teeth-supported and full guided. And all the templates were equipped with metal sleeves to serve as the guidance for drill key. According to the 12 partially edentulous cases, physical surgical resin models (B9R-1-RED; B9Creations) were 3D printed. For each guide and surgical model, one implant was inserted on the basis of the fully guided surgical protocol.

The implant site preparation and implant placement were performed using commercial surgical guide kits (Nobel Surgical Kit). Once the templates were properly fitted on the *in vitro* models, all the drilling steps and implant placement took place without removing the guide. The manufacturer's recommendations were followed through the process of implant site preparation and implant placement, to avoid unpredictable deviation. After the osteotomy, a planned NobelReplace CC implant was placed with the guided portable adaptor. And all the surgeries were accomplished by the same clinician, to estimate the intra-observer variability.

2.2.5 Accuracy evaluation

Following implant placement, specific implant scan body was used for accuracy evaluation. In brief, the scan body was attached on the implant, and intraoral scanning was performed to obtain STL data. Then the reverse engineering software (Geomagic Studio; Raindrop Geomagic) was used to analyze the deviation between the implant position and the algorithm bases ideal implant position.

For every group, the virtual implant position according to the various algorithm was marked for reference. Through aligning the data sets, the actual implant position was compared with the algorithm-determined position, and the deviations were performed in 3D²⁶ (Fig. 5). Besides, perforations of the apical buccal/lingual bone were assessed.

The angular deviation was defined as the angle between the centerline of the actual and virtual algorithm-determined implant (α). The global deviation was calculated as the 3D distance of apical/coronal center between the placed and algorithm-determined implant. The global deviation was subdivided into the lateral deviation (perpendicular to it) and the depth deviation (along the implant axis). Moreover, the lateral deviation was split into the bucco-lingual deviation (along the bucco-lingual axis) and the mesio-distal deviation (perpendicular to the bucco-lingual axis). Furthermore, to illustrate the deviations in exact directions, a positive value was used when the placed implant was mesial/buccal/apical to the virtual algorithm-determined implant, while a negative value corresponded to distal/lingual/coronal placement compared with the algorithm-determined position. For this study, all the measurements were accomplished by one observer.

2.2.6 Statistics

All quantitative data are presented as means $\pm$ SD. One-way analysis of variance (ANOVA) followed by Tukey's test was performed for statistical comparisons. The significance value was set at $P < 0.05$. All data were analyzed with SPSS statistics v25.0. (IBM Corporation, Armonk, NY, USA).

Results

The parameters for the three different groups are shown in Tables 2 and 3. The tables illustrating the differences among the groups are presented in Figure 6A–F. In Table 2, the global (apical and coronal), depth and angular deviations are shown. According to the statistical tests, Group C represented the best in accuracy. Group C

represented significantly lower apical global deviation (1.157 ± 0.3350) than Group A (1.717 ± 0.3355) ($P=0.0045$). The same trends were observed in coronal global deviation and depth deviation, with no significant difference. And for angle deviation, Group B (4.424 ± 1.505) represented the best, however, no significant difference was shown.

The lateral, bucco-lingual (apical and coronal), and mesio-distal (apical and coronal) deviations were shown in Table 3. Group C represented the best in accuracy. The apical bucco-lingual deviations were significantly smaller in Group C in both buccal direction (0.6377 ± 0.5287 , $P=0.0103$) and absolute value (0.7149 ± 0.4069 , $P=0.0011$) when compared with Group A. Group C represent the same trend in the lateral, coronal bucco-lingual, coronal mesio-distal, and apical mesio-distal (mesial direction) deviations, with no significant difference. And for the mesio-distal (absolute value) deviation, Group B (4.424 ± 1.505) represented the best, with no significant difference.

In regard to the exact direction, for all the groups the placed implants were buccal to the algorithm calculated position. Group C represented the least buccal shift both at the apical (0.6377 ± 0.5287 mm) and coronal level (0.2088 ± 0.2523 mm). And the difference was significant between Group C and Group A at the apical level ($P=0.0103$). Moreover, in this study no buccal or lingual bone perforation was found. For mesio-distal deviation, Group C showed the least shift. And for Group C, no obvious tendency was found either towards mesial or distal, at coronal or apical level. Moreover, there was neither buccal nor lingual perforation in all the groups.

Table 2
Global (coronal and apical), angular, and depth deviations of various group

Deviation type		Global deviation		Angular deviation	Depth deviation	
		Coronal	Apical		Considering direction	Absolute value
Group A	Mean	0.9077	1.717	5.073	-0.2085	0.4548
	Min	0.2590	0.8220	2.076	-1.376	0.1130
	Max	1.478	2.240	9.460	0.5740	1.376
	SD	0.3220	0.3555	2.270	0.5605	0.3686
Group B	Mean	0.8238	1.551	4.424	-0.2742	0.4295
	Min	0.2800	0.6570	1.681	-1.247	0.01440
	Max	1.332	2.354	6.860	0.5870	1.247
	SD	0.3140	0.4905	1.505	0.5060	0.3700
Group C	Mean	0.6638	1.157	5.307	-0.1886	0.3599
	Min	0.2060	0.5840	2.049	-1.106	0.04900
	Max	1.109	1.654	10.90	0.2930	1.106
	SD	0.2651	0.3350	2.891	0.4639	0.3358
Max: maximum; Min: minimum; SD: standard deviation; negative value: the deviation towards coronal direction.						

Table 3

Lateral, bucco-lingual (coronal and apical), and mesio-distal (coronal and apical) deviations of various group

Deviation type		Lateral deviation	Bucco-lingual deviation				Mesio-distal deviation			
			Coronal		Apical		Coronal		Apical	
			Con	Abs	Con	Abs	Con	Abs	Con	Abs
Group A	M	0.7033	0.2013	0.5210	0.4530	1.302	0.3225	0.3285	0.3578	0.6560
	Min	0.2240	-0.7480	0.2160	-1.4570	0.8110	-0.3672	0.0002	-0.7830	0.0770
	Max	0.9700	0.7890	0.7890	1.5830	1.583	0.7090	0.7090	1.292	1.292
	SD	0.2007	0.5375	0.1926	1.2960	0.2325	0.2465	0.2265	0.6836	0.3708
Group B	M	0.5660	0.1613	0.3677	0.8626	1.076	0.2008	0.2738	0.2655	0.6843
	Min	0.2780	-0.8138	0.0950	-0.9240	0.3540	-0.2341	0.0170	-0.9283	0.2576
	Max	1.009	0.6800	0.8138	1.8130	1.813	0.8080	0.8080	1.848	1.848
	SD	0.2128	0.4134	0.2275	0.7919	0.4204	0.2151	0.2142	0.8336	0.5107
Group C	M	0.4737	0.2088	0.2602	0.6377	0.7149	0.03465	0.1963	-0.04674	0.4441
	Min	0.0800	-0.2347	0.0740	-0.4633	0.1640	-0.3950	0.0120	-0.8630	0.0210
	Max	1.454	0.6446	0.6446	1.408	1.408	0.4235	0.4235	0.7950	0.8630
	SD	0.3647	0.2523	0.1932	0.5287	0.4069	0.0042	0.1423	0.5237	0.2479
M, Mean; Max: maximum; Min: minimum; SD: standard deviation; Con, Considering direction; Abs, Absolute value; negative value: the deviation towards lingual or distal direction;										

Discussion

The technology underlying AI applications was machine learning, which iteratively learned the inherent statistical patterns from specific datasets and algorithms⁵. However, as the most effective number of characteristic annotators was unclear, the data used to train the machine was small, and the result generation process was invisible, there were doubts about the accuracy and replicability^{8, 27}.

This study developed a SSD and V2V-PoseNet based system for image recognition and characteristic points capture, then implant position design. Based on the deep learning frame, the datasets were trained using the designed SSD algorithm to generate image identification and location models. Besides that, V2V-PoseNet method was used to detect the feature of the ROI. After training the image set, 12 independent test images were used to evaluate the trained model. Our AI system showed good performance for the implant position design and the accuracy is similar with the recently reported statistic guide²⁸.

Moreover, we found that the number of characteristic annotators influenced the performance of our AI system. A trend of more characteristic annotators induced more accuracy was observed. In brief, Group C performed better than Group A and B, for global (apical and coronal), angular, depth, lateral, bucco-lingual and mesia-distal deviations. In another word, Group C was the most accurate, and it was used to further improve the AI system. This phenomenon reminded us that our AI system was full of learning ability, and more information contributed to the accuracy.

In Group C, the average deviations were 0.6638 ± 0.2651 (range: 0.2060 to 1.109 mm) for the coronal deviation, 1.157 ± 0.3350 (range: 0.5840 to 1.654 mm) for the apical deviation, and $5.307 \pm 2.891^\circ$ (range: 2.049 to 10.90°) for the angular deviation (Table 2, Fig. 6A-B), and the results are similar with the traditional statistic guide²⁸. For instance, Zhaozhao et al.²⁶ recently reported 0.85mm (range:0.42 to 1.51 mm) global deviation at the coronal level, 0.93 mm (range: 0.64 to 1.72 mm) global deviation at the apical level, and 3.11° (range:0.66 to 4.95°)for the angular deviation. Vinci et al.⁶ reported 0.43 mm (range: 0.30–1.77 mm) global deviation at the apical level and 0.28 mm (range: 0.08–1.18 mm) at the coronal level.

For the depth deviation, the average deviation was -0.1886 ± 0.4639 for Group C, smaller than Group A (-0.2085 ± 0.5605) and Group B (-0.2742 ± 0.5060) (Table 2, Fig. 6C). And for all the three groups, the implants were in a more coronal direction compared to the virtual position. This phenomenon also has been reported by Vercruyssen et al.²⁹ and Zhaozhao et al.²⁶. However, as more characteristic annotators been calculated, the deviation decreased.

Regarding the bucco-lingual deviation, the implants tended to move buccally both at coronal and apical level, and a greater deviation was found at the apical level. The coronal/apical deviation may occur during the processes of either drilling or implant placement²⁶. However, the bucco-lingual deviation was small in Group C (Table 3, Fig. 6E). As to the mesia-distal deviation, for Group C, there were nearly no tendency neither toward mesial nor distal, both at the coronal and apical level (Table 3, Fig. 6F). For Group C, tiny bucco-lingual and mesia-distal deviations would bring mechanical equilibrium, which be beneficial to the long-term success of dental implant.

The high accuracy of our AI system mostly depended on SSD, a deep learning technology based superior convolutional neural network (CNN) algorithm³⁰. SSD is one of the best AI models in image identification and location, which consist of at least 16 layers^{31,32}. It is an effective object detector for multiple targets recognition within just one stage¹⁰. Yao-Kuang et al.³¹ used a SSD system for diagnosing esophageal cancer, which showed good diagnostic performance and the accuracy can achieve 90%. Orhan et al.³³ also reported that the volume calculation with CNN algorithm were compatible with the clinicians.

The high accuracy of our AI system also attributes to the V2V-PoseNet algorithm. It's a 3D CNN put forward by Gyeongsik Moon et al.³⁴, which provided accurate estimates. V2V-PoseNet took voxelized grids as inputs and estimated the per-voxel likelihood for the key parameters. This 3D CNN can detect the actual contour of the objects without perspective distortion and estimate the per-voxel likelihood of each parameter, so it can learn the designed task easily³⁴.

To sum up, SSD and V2V-PoseNet were used to train the datasets^{32, 35}, and the deep learning neural network, especially the 10 characteristic annotators based algorithm group, was fairly accurate and clinically reliable. The core of SSD model is to explore objects and corresponding locations in given bounding boxes, realizing object location prediction³⁶. It relatively simplified the processing, while increasing the identification.

However, due to the limited test size, the results in this study should be interpreted with caution, and more training images were needed to improve the performance of our system. Besides that, there are some real clinical elements, such as limited view and inter-occlusal distance³⁷ that the present *in vitro* study cannot reflect. Moreover, based on the pronounced learning abilities of the AI system, in the future more key parameters would be incorporated into the algorithm to figure out the best implant plan.

Conclusion

It can be concluded that the SSD and V2V-PoseNet based AI system has the capacity of deep learning from the data and specific algorithms. And as more characteristic annotators be involved in the algorithm, the AI system can figure out the anatomy of the object region better, then generate the ideal implant plan via specific algorithm.

Abbreviations

SSD: single shot multibox detector; V2V-PoseNet: Voxel-to-voxel prediction network for pose estimation; AI: artificial intelligence; 3D: three-dimensional; CNN: convolutional neural network; ROI: region of interest.

Declarations

Ethics approval and consent to participate

This study was approved by the ethical committees of the Guanghua School of Stomatology, Hospital of Stomatology, Sun Yat-sen University (KQEC-2020-063-01).

Consent for publication

All patients consented to the use of their data for research purposes and signed informed consent forms accordingly.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no conflict of interests.

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Authors' contributions

Yun Liu: Conceptualization, methodology & data curation, and figures 5-6 preparing

Zhi-cong Chen: Writing the main manuscript

Chun-ho Chu: Formal analysis and figures 1-4 preparing

Fei-Long Deng: Funding acquisition, tables 1-3 preparing and manuscript review & editing

All authors read and approved the final manuscript.

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Figures

Figure 1

AI software workflow.

Figure 2

Image flow chart of automatically implant position design. (A) The panoramic image was created from the CBCT data. (B) The mandibular left first molar was detected based on SSD algorithm. (C) Construct a region of interest (ROI) from the CBCT data. (D) Detect the bone contour from the CBCT data based on V2V-PoseNet. (E) Capture and study the designed characteristic annotators through V2V-PoseNet. (F) Generate the implant axis based on the characteristic annotators. (F) Implant position automatically generated.

Figure 3

Diagram of the characteristic points.

Figure 4

Diagram of three measurements (P_a , P_b and Implant axis).

Figure 5

Measurement of deviations between AI designed and ideal implant. (A) Depth, angular & global deviation: h : depth deviation; α : angular deviation; global deviation (c : coronal deviation; a : apical deviation); (B) L: lateral deviation ($x1$: coronal bucco-lingual deviation; $z1$: coronal mesio-distal deviation); (C) Apical deviation ($x2$: apical bucco-lingual deviation; $z2$: apical mesio-distal deviation).