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Original Article

Applying machine learning to assess the morphology of sculpted teeth

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Abstract *Background/purpose:* Producing tooth crowns through dental technology is a basic function of dentistry. The morphology of tooth crowns is the most important parameter for evaluating its acceptability. The procedures were divided into four steps: tooth collection, scanning skills, use of mathematical methods and software, and machine learning calculation.
Materials and methods: Dental plaster rods were prepared. The effective data collected were to classify 121 teeth (15th tooth position), 342 teeth (16th tooth position), 69 teeth (21st tooth position), and 89 teeth (43rd tooth position), for a total of 621 teeth. The procedures are divided into four steps: tooth collection, scanning skills, use of mathematical methods and software, and machine learning calculation.
Results: The area under the curve (AUC) value was 0, 0.5, and 0.72 in this study. The precision rate and recall rate of micro-averaging/macro-averaging were 0.75/0.73 and 0.75/0.72. If we took a newly carved tooth picture into the program, the current effectiveness of machine learning was about 70%—75% to evaluate the quality of tooth morphology. Through the calculation and analysis of the two different concepts of micro-average/macro-average and AUC, similar values could be obtained.
Conclusion: This study established a set of procedures that can judge the quality of hand-

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carved plaster sticks and teeth, and the accuracy rate is about 70%—75%. It is expected that this process can be used to assist dental technicians in judging the pros and cons of hand-carved plaster sticks and teeth, so as to help dental technicians to learn the tooth morphology more effectively.

Introduction

Human teeth are susceptible to damage and loss due to accidents, tooth decay, old age, and oral diseases. As a result, dental restoration is one of the most prevalent dental tasks. Repairing or removing tooth damage requires making a tooth, which was traditionally carried out by dental technicians by hand. This requires repeated practice to accumulate experience, but various people might have different opinions as to the quality of the tooth. The first step in making a tooth is that the tooth morphology must be correct and aesthetically pleasing. Therefore, in this study, we used machine learning (ML) of artificial intelligence (AI) to evaluate tooth morphology. The aim of this study was to facilitate the process of digital dental technology, as AI may help improve digital dental technologies. The current software development of digital dental technology still needs personnel to modify and correct the tooth morphology, and computers can possibly do this more quickly than human technicians. There are two kinds of engineering processes worldwide: forward engineering and reverse engineering. Forward engineering includes computer-aided design, computer-aided engineering, and computer-aided manufacturing. Reverse engineering uses a scanner to scan a model. The user gets digital imaging and communications in medicine file from scanner and transfers it to a standard template library (STL) file. Finally, the user employs computer numerical control or 3D printing machine to fabricate an actual product (Fig. 1).

Current scanning technology includes a scan model, energy, and format. In the 1980s, because computer-aided design and drawing required one to learn the process to make it easy to use, reverse engineering technology emerged. Oral scanning is common in dental clinics.[1—3] The invention of computed tomography and nuclear magnetic resonance imaging was used to scan patients with electron injection, and then integrate this into a 3D image output.[4,5] Positron emission tomography imaging applied protons as an energy source to scan patients.[6,7] Dental computed tomography scans for the oral cavity have also begun to be marketed, so mastering scanning technology is still very important.[4,5] Artificial intelligence includes calculation, methodology, and analysis. McCarthy defined AI as "the science and engineering of making smart machines".[8] There are currently a large number of tools using AI, including search and mathematical optimization, and logical deduction. AI is also used in robotics, economic and political decision-making, control systems, and simulation systems.[9—16]

Machine learning is a type of AI that focuses on building systems that can learn or improve their performance based on the data they use. To evaluate a model, the researcher usually divides the available data into three groups: training set, validation set, and testing set. The researcher trains the model with the training dataset and evaluates the model with the validation dataset. Once the model is trained and validated, the data can be tested for final testing. Convolutional neural networks are deep learning models commonly used in computer vision, especially when there are insufficient training data samples. This helps the model learn more oriented data and get better generality.[2,3,5,9—16] There are also many applications of AI in dentistry, from semi-supervised blurring to tooth segmentation by x-ray images, and applications in orthognathic surgery. As to current concepts and glimpses into the future of big data and ML applications, there is the assessment of periapical lesions calculated by cone beams, and applications of machine learning in dental, oral, and craniofacial imaging. This is a modern, digital transformation of oral care, and there have been several reviews of the current status and future of AI in dentistry.[17—30]

The main goal of this study was to enhance the process of digital dental technology. However, current developments in the software of digital dental technology still require personnel to modify the correct tooth morphology, but computers can perhaps do this more quickly. Designing tooth morphology that meets functionality and aesthetic requirements by a technician, coupled with manufacturing by computer-aided design/computer-aided manufacturing or 3D printing, is bound to greatly increase the production efficiency of the entire denture production process, and determining how to allow a computer to automatically generate the correct tooth morphology and machine learning of AI to reduce the case return rate were our aims.

Materials and methods

Oral science is divided into three specialties: dentistry, dental technology, and oral hygiene. Dental technology has strikingly evolved from the past to the present and future. Fig. 2 shows the past, present, and future dental technology eras.

The procedures are divided into four steps: (1) tooth collection, (2) scanning skills, (3) use of mathematical methods and software, and (4) calculation of machine learning (Fig. 3). The topic of this study was tooth morphology transferred from the man-made process to the help and judgment of ML.

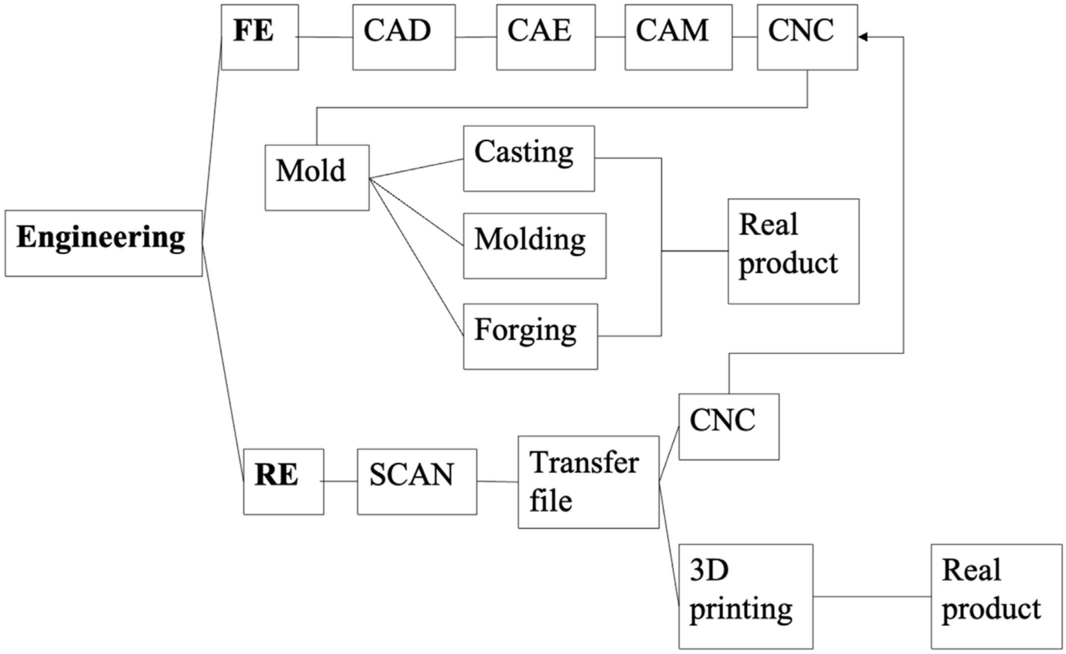

Figure 1 The engineering use direction classification. Abbreviations: FE: forward engineering; CAD: computer-aided design; CAE: computer-aided engineering; CAM: computer-aided manufacturing; CNC: computer numerical control; RE: reverse engineering; 3D: three dimension.

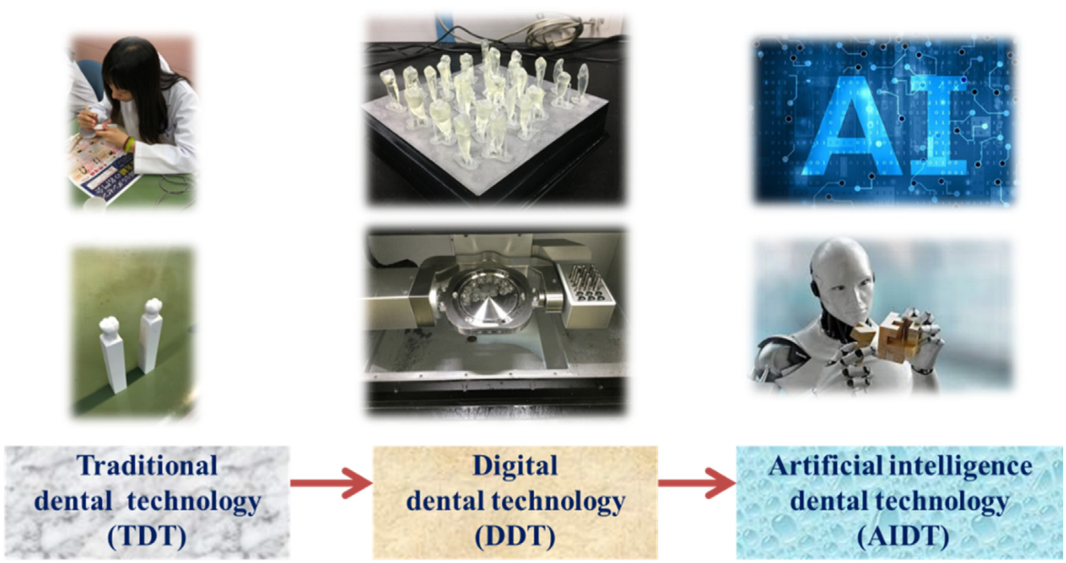

Figure 2 The era of the past, present, and future dental technology.

In response to improvements in dental technology, this study used AI to improve the identification of tooth morphology. Dental plaster rods were prepared by collecting work saved in an internal and external dental contour sculpture competition at our university. The effective data collected were in accordance with Fédération Dentaire Internationale (FDI; World Dental Federation) tooth position (ISO-3950) notation to classify 121 teeth of the 15th tooth position, 342 teeth of the 16th tooth position, 69 teeth of the 21st tooth position, and 89 teeth of the 43rd tooth position, for a total of 621 teeth (Fig. 4a).

After the selection of plaster sticks, each tooth was scanned with a desktop scanner to obtain tooth shape data. In order to reduce human error, the scanning program was changed from an intraoral scanner to a desktop scanner (Identica T500, Medit, Seoul, South Korea). We used a desktop scanner to scan the collected dental plaster sticks and store them in STL file (Fig. 4b).

After obtaining the STL files of tooth type, the data obtained had to be converted for use in ML theory and software. Then, we used the two steps for file processing.

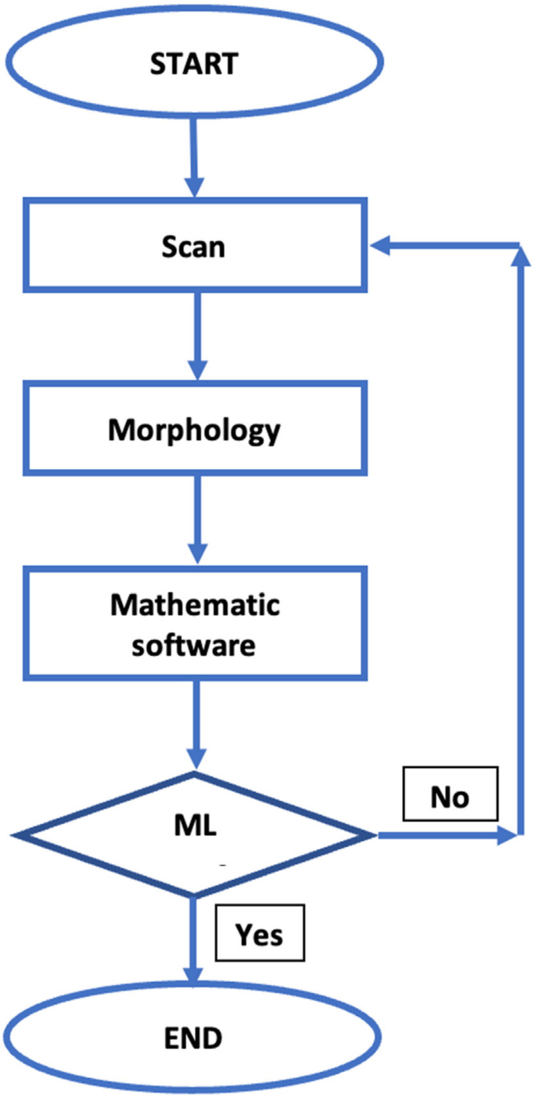

Figure 3 The flow chart of teeth morphology making by machine learning (ML) of artificial intelligence.

Step 1: We adjusted the angle, axis, and orientation of the scanned STL file to be consistent with Meshmixer software (AUTODESK, San Francisco, CA, USA) (Fig. 4c).

Step 2: We used FastStone capture software (FastStone, Alberta, Canada) to arrange the neatly arranged tooth model to a fixed size (width and height of 330 pixels, horizontal and vertical resolution of 96 dots per inch, and a bit depth of 24), and turn individual screenshots into JPEG file to capture the face with the largest feature point of tooth type. For example, the labial side (front view) of the front teeth was captured (Fig. 5a), while the occlusal surface (top view) was captured for the posterior teeth (Fig. 5b).

When a suitable model is obtained through machine learning, this model can provide dental technicians with the ability to judge the pros and cons of engraved teeth. After dental technicians have carved their teeth, the scanned data can be placed in the model to judge the good or worse of these engraved teeth, which can improve the dental technician's ability. A model (No. is C7-26T.4 (14S), Fig. 5cd) acted as the reference group (epically at FDI-16). This is used as a machine learning exercise for sculpting the morphology of teeth. The authors expect to pass machine learning, then artificial intelligence can have the ability to personalize recognition and serve customization.

A typical convolutional neural network architecture comprises repetitions of a stack of several convolution layers and a pooling layer, followed by one or more fully connected layers. The following plan was used to reduce the problems caused by insufficient materials. Step (1): Pictures were taken of teeth in the same FDI tooth position, scoring results of the judges of the competition were referenced, and they were classified into three ranks (A, B, and C) according to the scores, from high to low. Step (2): One picture of each category was saved as a test set. Step (3): Since the number of data sets was insufficiently large, the remaining original images of each category were removed. After the image files of the same size were adjusted, data augmentation technology was used (Fig. 6). After the data were augmented, they were divided into a training set and a validation set. Step (4): The convolutional neural network model was used for machine learning.

Results

Supervised learning is currently the most common method of machine learning. The main method is to have all training data with corresponding labels, and then the machine learns to map each data point in the data set to the corresponding label. In order to evaluate the classification performance of a classifier, it is necessary to introduce some evaluation indicators. The confusion matrix, precision, recall, F1 value, micro-averaging, and macro-averaging have been used to understand the performance of learning algorithm.[10,14] Achieving very high accuracy is very easy by carefully selecting the sample size but if we use accuracy as a measure for testing the system's performance, the system can be biased and can attain very high accuracy. However, precision, recall, and F1 Value are not dependent on the training's size and the test samples. If there is only one two-class confusion matrix, then the indicators (such as precision (P), recall (R), and false positive rate (FPR) can be used for evaluation, there is no controversy, but when we want to comprehensively examine the evaluation indicators on n two-class confusion matrices, we will use macro-averaging and micro-averaging. When P (Micro) $>$ P (Macro), it means that the classification accuracy of model for the main class is good, but the results for the small class are poor for engraved teeth. The authors use micro-averaging and macro-averaging to predict the morphology of engraved teeth.

The following plan tries to reduce the problems caused by insufficient data in this way. Confusion matrix (It is shown in Fig. 7): It is also called an error matrix and is a special, two-dimensional (actual and predicted) contingency table. TP, FP, FN, and TN are the number of true positives, false positives, false negatives, and true negatives that correspond to the relative importance of precision versus recall and are usually set to 1.

Precision: It is also called the precision rate, which is for the prediction result.

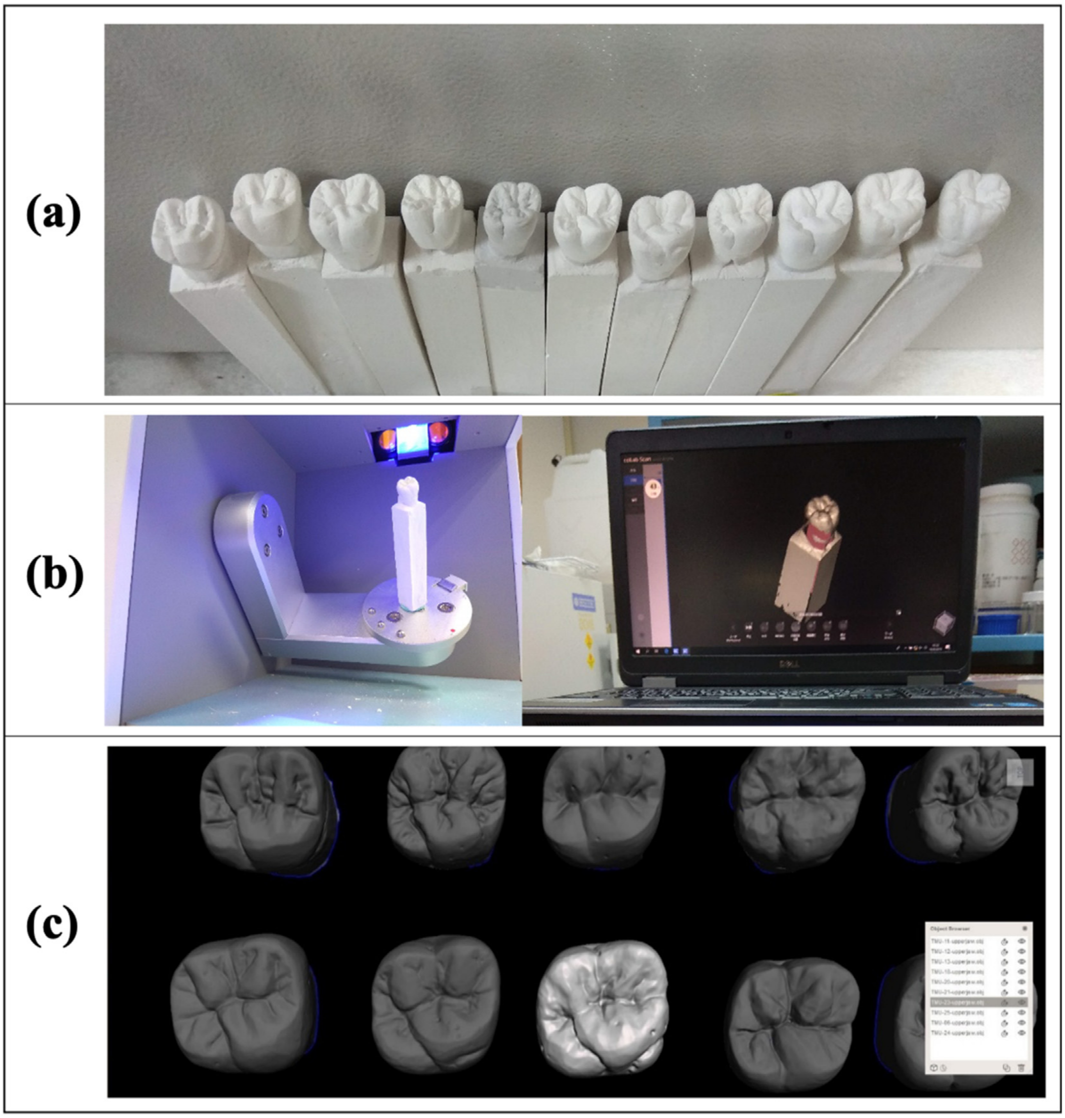

Figure 4 Collection and Scanning of teeth. (a) Part of dental plaster sticks (Fédération Dentaire Internationale (FDI)-16) collected. (b) Scanning and file creation by desktop scanner. (c) Plaster rods after scanning and scanning are arranged by Meshmixer software.

$$\textit{Precision} = \frac{TP}{TP + FP} \tag{1}$$

Recall: The recall is for the original sample, and its meaning is the probability of being predicted as a positive sample in an actual positive sample. It is also called the true positive rate (TPR).

$$\textit{Recall} = \frac{TP}{TP + FN} \tag{2}$$

False positive rate: Number of negative sample results predicted to be positive/actual number of negative samples.

$$FPR = FP/(FP + TN) \tag{3}$$

F1 value: Find a balance between precision and recall.

$$\begin{aligned} F_1 &= \frac{2 \times \textit{Precision} \times \textit{Recall}}{\textit{Precision} + \textit{Recall}} \\ &= \frac{2 \times TP}{2 \times TP + FP + FN} \end{aligned} \tag{4}$$

Micro-averaging: It is to establish a global confusion matrix for each instance in the data set regardless of category, and then calculate the corresponding indicators.

$$\begin{aligned} P_{micro} &= \frac{TP}{TP + FP} = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} TP_i + \sum_{i=1}^{n} FP_i} \\ R_{micro} &= \frac{TP}{TP + FN} = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n} TP_i + \sum_{i=1}^{n} FN_i} \\ F_{micro} &= \frac{2 \times P_{micro} \times R_{micro}}{P_{micro} + R_{micro}} \end{aligned} \tag{5}$$

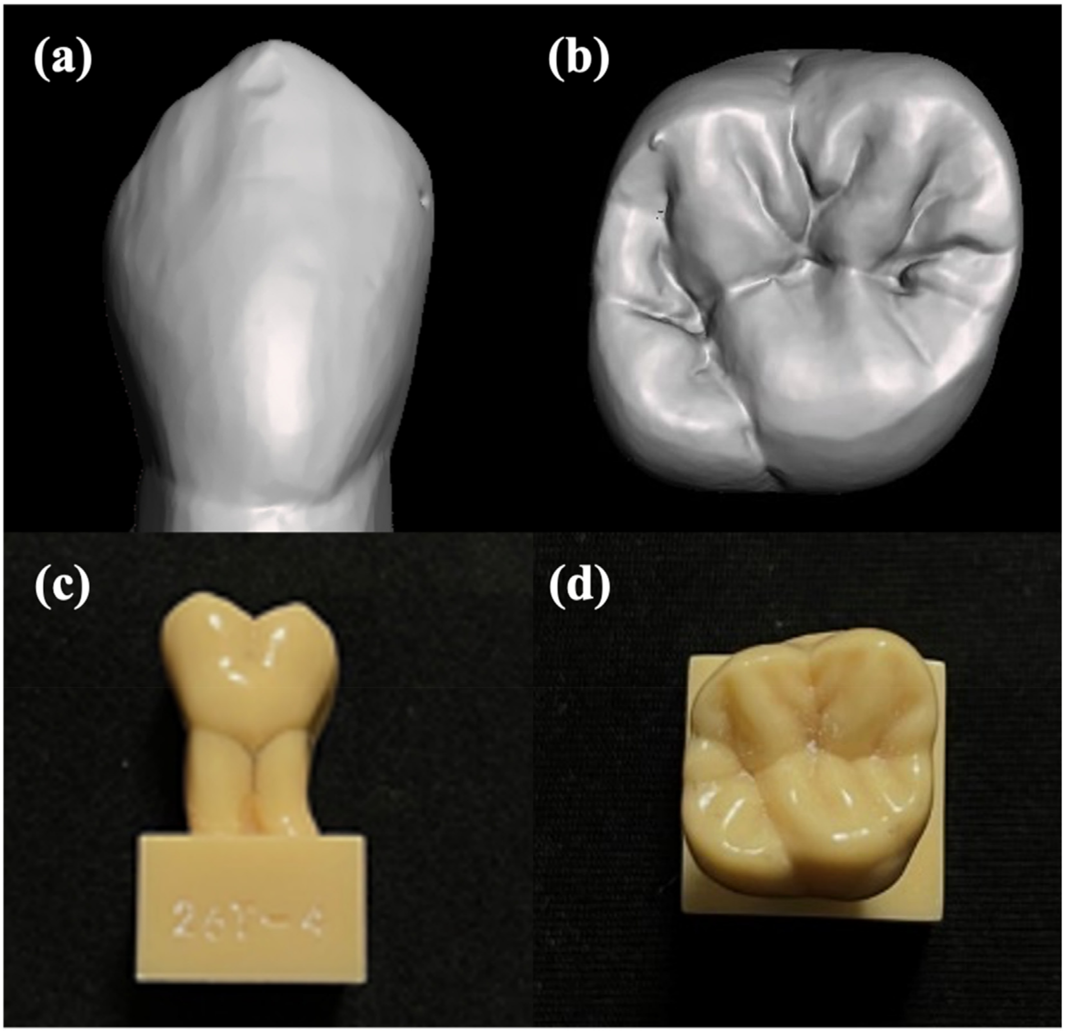

Figure 5 Fast Stone capture software captures fixed size of different teeth. (a) anterior teeth (Fédération Dentaire Internationale (FDI)-43 front view). (b) posteriorteeth (Fédération Dentaire Internationale (FDI)-16 top view). (c) Front view (Model No. is C7-26T.4 14S). (d) Top view (Model No. is C7-26T.4 14S).

Macro-averaging: It is to first calculate the statistical index value of each class, and then calculate the arithmetic mean of all classes.

$$P_{macro} = \frac{1}{n}\sum_{i=1}^{n} P_i$$
$$R_{macro} = \frac{1}{n}\sum_{i=1}^{n} R_i \tag{6}$$
$$F_{macro} = \frac{2 \times P_{macro} \times R_{macro}}{P_{macro} + R_{macro}}$$

Among all of the tooth profile data sets, the largest number of teeth of FDI tooth position 16 was collected (342 teeth in total), and so this tooth was selected to train the prediction model. When we input a new FDI tooth position 16, the picture was transferred to the convolutional neural network prediction model (Fig. 8).

Discussion

The judgment results were obtained in Table 1. The tooth pictures of the same FDI tooth position will be classified into three grades, A, B, and C, from high to low, according to the scoring results of the judges of the current competition. The precision rate of micro-averaging was 0.75 and the recall rate was 0.75; the precision rate of macro-averaging was 0.73 and the recall rate was 0.72. Therefore, it is estimated that if we take a newly carved tooth picture into the program, the current effectiveness of machine learning is about 70%—75% to correctly assess the pros and cons of tooth morphology.[14]

The authors also used another method to evaluate the estimated accuracy of the tooth morphology. First, calculate the TPR and FPR. Then draw the receive operating characteristic (ROC) curve with the aforementioned two values (Fig. 9). Finally, calculate the aforementioned area under the curve graph is obtained as the area under the

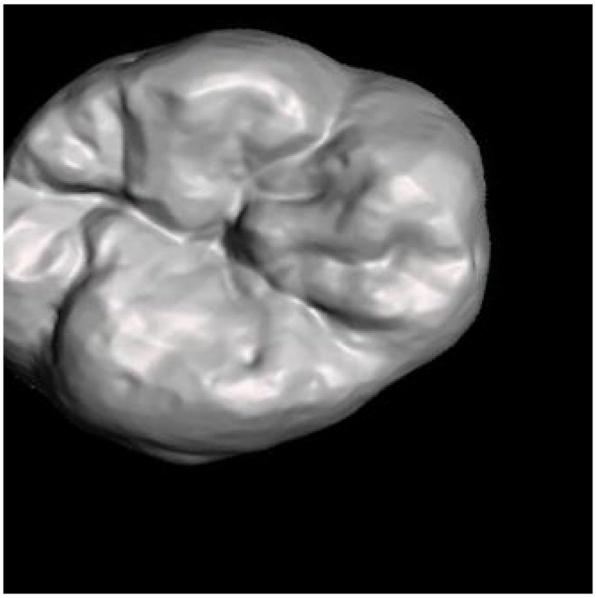

Figure 6 Tooth shape legend with data augmentation.

Figure 8 Newly imported tooth legend (Fédération Dentaire Internationale (FDI)-16).

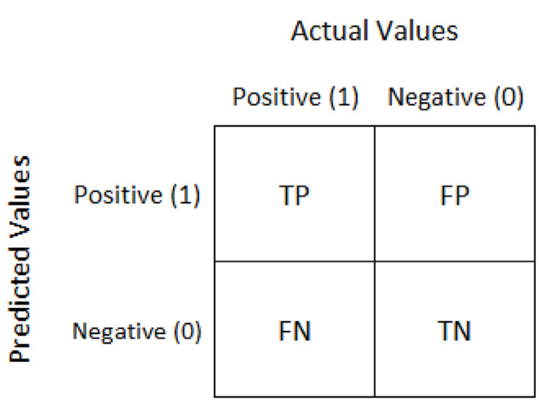

Figure 7 Confusion matrix. Abbreviations: TP: true positives; FP: false positives; FN: false negatives; TN: true negatives.

Table 1 Prediction for micro average, macro average, and weighted average.

	precision	recall	F1-score
A[a]	0.00	0.00	0.00
B[a]	1.00	1.00	1.00
C[a]	0.78	1.00	0.68
Micro average	0.75	0.75	0.75
Macro average	0.73	0.72	0.72
Weighted average	0.73	0.74	0.70

[a] The tooth pictures of the same FDI tooth position will be classified into three grades, A, B, and C, from high to low, according to the scoring results of the judges of the current competition.

curve (AUC) (Table 2). If we start from the various results of actual performance, the problem of sample imbalance can be avoided, which is why the authors choose TPR and FPR as the indicators of ROC/AUC.[10,14,20]

The ROC curve, also known as the receive operating characteristic curve, was originally used in the field of radar signal detection to distinguish between signal and noise. Later, it was used to evaluate the prediction ability of the model. To calculate points on the ROC curve, we can evaluate the logistic regression model multiple times with different classification thresholds, but this is very inefficient. There is an efficient ranking-based algorithm that provides this information, this algorithm is AUC.

The judgment results obtained are shown in Fig. 9 and Table 2. The AUC was 0, 0.5, and 0.72. The larger the AUC value, the better the model. Therefore, it is expected that if the authors bring a new photo of engraved teeth into the program, the efficiency will be around 70%–75% after machine learning calculations, and the quality of tooth morphology can be correctly assessed.[14,20]

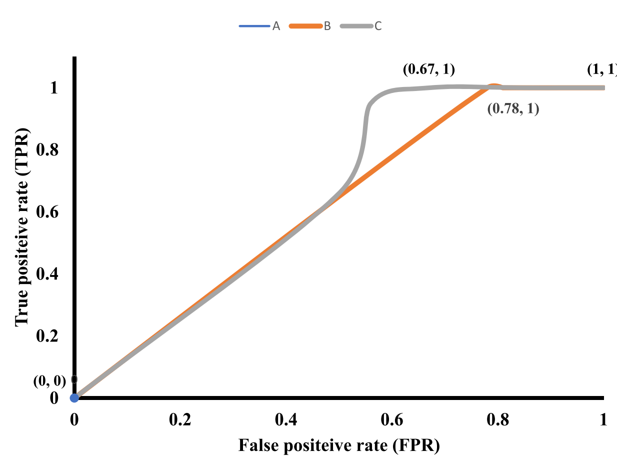

Figure 9 Receive operating characteristic curve (False positive rate (FPR)-True positive rate (TPR) curve).

To sum up, similar values can be obtained through the calculation and analysis of two different concepts of micro-averaging/macro-averaging and AUC. Finally, it is

Table 2 Prediction for area under curve (AUC).

	False positive rate	True positive rate	Area under curve
A[a]	0.00	0.00	0.00
B[a]	0.78	1.00	0.5
C[a]	0.56	1.00	0.72

[a] The tooth pictures of the same FDI tooth position will be classified into three grades, A, B, and C, from high to low, according to the scoring results of the judges of the current competition.

estimated that if we bring a new carved tooth photo into the program, the current effectiveness of machine learning is about 70%—75% to correctly assess the pros and cons of the tooth morphology.

In the experiment of this study, the lack of a data set was one of the factors that affected the final results. This study established a set of procedures that can judge the quality of hand-carved plaster sticks and teeth, and the accuracy rate is about 70%—75%. It is expected that this process can be used to assist dental technicians in judging the pros and cons of hand-carved plaster sticks and teeth, so as to help dental technicians to learn the tooth morphology more effectively.

Declaration of competing interest

The authors have no conflicts of interest relevant to this article.

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References

1. Keeling A, Wu J, Ferrari M. Confounding factors affecting the marginal quality of an intra-oral scan. *J Dent* 2017;59:33—40.
2. Cai HX, Zhao BC, Tian Y, et al. Design of a single-tooth model and its application in oral scan system assessment. *Scanning* 2021;2021:8891396.
3. Stanley M, Paz AG, Miguel I, Coachman C. Fully digital workflow, integrating dental scan, smile design and CAD-CAM: case report. *BMC Oral Health* 2018;18:134.
4. Handschel J, Naujoks C, Depprich RA, et al. CT-scan is a valuable tool to detect mandibular involvement in oral cancer patients. *Oral Oncol* 2012;48:361—6.
5. Vercruyssen M, Jacobs R, Assche NV, Steenberghe DV. The use of CT scan based planning for oral rehabilitation by means of implants and its transfer to the surgical field: a critical review on accuracy. *J Oral Rehabil* 2008;35:454—74.
6. Civantos FJ, Gomez G, Duque C, et al. Sentinel node biopsy in oral cavity cancer: correlation with PET scan and immunohistochemistry. *Head Neck* 2003;25:1—9.
7. Liao CT, Fan KH, Lin CY, et al. Impact of a second FDG PET scan before adjuvant therapy for the early detection of residual/relapsing tumors in high-risk patients with oral cavity cancer and pathological extracapsular spread. *Eur J Nucl Med Mol Imag* 2012;39:944—55.
8. McCarthy J, Minsky ML, Rochester N, Shannon CE. A proposal for the dartmouth summer research project on artificial intelligence. *AI Mag* 2006;27:12—4.
9. Jiao P, Alavi AH. Artificial intelligence in seismology: advent, performance and future trends. *Geosci Front* 2020;11:739—44.
10. Vasudevan RK, Choudhary K, Mehta A, et al. Materials science in the ai age: high-throughput library generation, machine learning and a pathway from correlations to the underpinning physics. *MRS Commun* 2019;9:1557.
11. Ly HB, Le LM, Duong HT, et al. Hybrid artificial intelligence approaches for predicting critical buckling load of structural members under compression considering the influence of initial geometric imperfections. *Appl Sci* 2019;9:2258.
12. Jiao P, Alavi AH. Artificial intelligence-enabled smart mechanical metamaterials: advent and future trends. *Int Mater Rev* 2021;66:365—93.
13. Duan J, Asteris PG, Nguyen H, Bui XN, Moayedi H. A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model. *Eng Comput* 2021;37:3329—46.
14. Kong Q, Trugman DT, Ross ZE, Bianco MJ, Meade BJ, Gerstoft P. Machine learning in seismology: turning data into insights. *Seismol Res Lett* 2019;90:3—14.
15. Rajan K. Materials informatics: the materials "gene" and big data. *Annu Rev Mater Sci* 2015;45:153—69.
16. Le LM, Ly HB, Pham BT, et al. Hybrid artificial intelligence approaches for predicting buckling damage of steel columns under axial compression. *Materials* 2019;12:1670.
17. Son LH, Tuan TM. Dental segmentation from X-ray images using semi-supervised fuzzy clustering with spatial constraints. *Eng Appl Artif Intell* 2017;59:186—95.
18. Bouletreau P, Makaremi M, Ibrahim B, Louvrier A, Sigaux N. Artificial intelligence: applications in orthognathic surgery. *J Stomatol Oral Maxillofac Surg* 2019;120:347—54.
19. Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. *Int Endod J* 2020;53:680—9.
20. Ren R, Luo H, Su C, Yao Y, Liao W. Machine learning in dental, oral and craniofacial imaging: a review of recent progress. *PeerJ* 2021;9:11451.
21. Alauddin MS, Baharuddin AS, Ghazali MIM. The modern and digital transformation of oral health care: a mini review. *Healthc Amst* 2021;9:118.
22. Sharma S. Artificial intelligence in dentistry: the current concepts and a peek into the future. *Int J Contemp Med Res* 2019;6:5—9.
23. Chen YW, Stanley K, Att W. Artificial intelligence in dentistry: current applications and future perspectives. *Quintessence Int* 2020;51:248—57.
24. Tandon D, Rajawat J. Present and future of artificial intelligence in dentistry. *J Oral Biol Craniofac Res* 2020;10:391—6.
25. Khanagar SB, Ehaideb AA, Maganur PC, et al. Developments, application, and performance of artificial intelligence in dentistry-A systematic review. *J Dent Sci* 2020;10:391—6.
26. Perez CF, Pecho OE, Morales JC, et al. Applications of artificial intelligence in dentistry: a comprehensive review. *J Esthetic Restor Dent* 2022;34:259—80.
27. Babu A, Onesimu JA, Sagayam KM. Artificial intelligence in dentistry: concepts, applications and research challenges. *E3S Web of Conferences* 2021;297:01074.
28. Shan T, Tay FR, Gu L. Application of artificial intelligence in dentistry. *J Dent Res* 2021;100:232—44.
29. Pethani F. Promises and perils of artificial intelligence in dentistry. *Aust Dent J* 2021;66:124—35.
30. Ossowska A, Kusiak A, Świetlik D. Artificial intelligence in dentistry-narrative review. *Int J Environ Res Publ Health* 2022;19:3449.