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Research Reports

Predicting the debonding of CAD/CAM composite resin crowns using AI

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ABSTRACT

INTRODUCTION: A preventive measure for debonding has not been established and is highly desirable to improve the survival rate of CAD/CAM CR crowns.

OBJECTIVES: The aim of this study was to assess the usefulness of deep learning with a convolution neural network (CNN) method to predict the debonding probability of computer-aided design/computer-aided manufacturing (CAD/CAM) composite resin (CR) crowns from two-dimensional images captured from three-dimensional (3D) stereolithography models of a die scanned by a 3D oral scanner.

METHODS: All cases of CAD/CAM CR crowns were manufactured from April 2014 to November 2015 at the Division of Prosthodontics, Osaka University Dental Hospital (Ethical Review Board at Osaka University Approval Number: H27–E11). The dataset consisted of a total of 24 cases of 12 trouble-free and 12 debonding as known labels. A total of 8,640 images were randomly divided into 6,480 training and validation images, and 2,160 test images. A deep learning with a CNN method was conducted to develop a learning model to predict the debonding probability. The prediction accuracy, precision, recall, F-measure, receiver operating characteristics (ROC), and area under the ROC (AUC) of the learning model were assessed for the test images. Also, the mean calculation time were measured during the prediction for the test images.

RESULTS: The prediction accuracy, precision, recall, and F-measure values of deep learning with a CNN method for the prediction of the debonding probability were 98.5%, 97.0%, 100%, and 0.985, respectively. The mean calculation time was 2 msec/step for 2,160 test images. The AUC value was 0.998.

CONCLUSION: Artificial intelligence technology, that is, the deep learning with a CNN method established in this study, demonstrated that considerably good performance in terms of predicting the debonding probability of a CAD/CAM CR crown using 3D stereolithography models of a die scanned from patients.

KEYWORDS Artificial intelligence, Composite materials, Restorative materials, Restorative dentistry, Resin(s), Prosthetic Dentistry/Prosthodontics

INTRODUCTION

Restorative materials, such as metals, ceramics, and composite resins (CRs), are applied for the routine restorative treatments. Particularly, CRs have been in widespread use because of the demand for esthetic treatment. With the rapid growth of computer-aided design/computer-aided manufacturing (CAD/CAM) technology (Ruse and Sadoun 2014), the restoration of the molar region using a CAD/CAM CR crown fabricated from a machinable block has consistently increased (Shembish et al. 2016). However, CAD/CAM CR crowns cemented on human dentin have a tendency to induce debonding in less than a year and the debonding of CAD/CAM CR crowns cemented on zirconia implant abutments has been reported to be 80% for a year (Schepke et al. 2016). The inappropriate preparation of the die shape has been indicated as one of reasons for debonding (Rosentritt et al. 2019). When patients visit clinics/hospitals after debonding, dentists possibly modify the preparation design (height and taper angle) (Rosentritt et al. 2019) based on their clinical experience/knowledge and set the crown again. A preventive measure for debonding has not been established and is highly desirable to improve the survival rate of CAD/CAM CR crowns.

Artificial intelligence (AI) technologies are widely accepted into society against a background of an exponential improvement of computer power. Deep learning using convolution neural networks (CNNs) (LeCun et al. 2015) is well known as an AI technology that mimics neural networks in the human brain and is applied to medical fields to support tumors (lung, brain, breast, and prostate) detection (Bi et al. 2019), colorectal cancer detection (Bychkov et al. 2018; Takiyama et al. 2018), and retinal detachment classification (Ohsugi et al. 2017). In the dental field, applications to the diagnosis of caries (Lee et al. 2018a), periodontally compromised teeth (Lee et al. 2018b), and cervical lymph nodes with oral cancer (Ariji et al. 2018) have been reported. These AI-assisted diagnosis technologies could result in faster recovery for patients, decrease medical expenditure, and reduce the burden of dentists.

For greater prediction accuracy for those applications, huge number of known images are required to develop an excellent learning model. Image augmentation techniques, such as rotation, width and height shifting, scaling, and horizontal flip of original images, have been commonly used to increase the number of two-dimensional (2D) images and improve the prediction accuracy (Shin et al. 2016). In the case of CAD/CAM CR restoration, the die, adjacent teeth, and antagonist of study models fabricated from a patient's impression are scanned by a three-dimensional (3D) oral scanner and saved as 3D stereolithography (STL) models (Guth et al. 2017). The 3D STL models are freely observable from various view directions in CAD software and can be exported as 2D images in each view direction; that is, image augmentation techniques are possibly better matched to 3D STL models compared with 2D images.

The aim of this study was to assess the validity of deep learning with a CNN method to predict the debonding probability of CAD/CAM CR crowns from 2D images captured from 3D STL models of a die scanned by a 3D oral scanner.

2. MATERIALS AND METHODS

2.1. Image datasets

All cases of CAD/CAM CR crowns manufactured from April 2014 to November 2015 at the Division of Prosthodontics, Osaka University Dental Hospital were obtained from the dental technician record, and their clinical courses from the hospital chart were reviewed (Ethical Review Board at Osaka University Approval Number: H27–E11). Crowns involving the following were excluded: (1) the data showed any inconsistency between the technician record and hospital chart; (2) a crown was not inserted; (3) special treatment (e.g., filling for a perforation of root canal) was conducted on the abutment teeth; (4) the progress after crown insertion was not monitored; and (5) digital data were not available for any reason. After the exclusion of these crowns, 30 crowns remained. The investigation duration was from the date of insertion to April 30, 2017. Debonded crowns in the investigation duration were treated as trouble cases.

Anonymized STL models consisting of a die, adjacent teeth, and antagonist were acquired. The datasets consisted of 24 cases of 12 trouble-free (50.0%) and 12 debonding (50.0%) as known labels. Detailed information about the patients and the commercially available CAD/CAM CR block used are summarized in Table 1. The restoration was conducted by 18 dentists.

2.2. Preprocessing and image augmentation

All adjacent teeth and antagonists were removed from the original STL models, and each remaining die were saved as a single STL model using CAD software (Leios, Ver.2009, Datadesign, Nagoya, Japan). These STL models were exported as Joint Photographic Expert Group (JPEG) images cropped and resized to 100 × 100 pixels for every degree rotation (from 0 to 360 degrees) in the *y*/*z*-axis. The image size of 100×100 pixels was applied in this study and was relatively lower than the original image size of 700×700 pixels captured in CAD software to save computational costs. The 8,640 images obtained were randomly divided into 6,480 training and validation images and 2,160 test images. The training and validation images consisted of 3,240 trouble-free and 3,240 debonding, and the test images consisted of 1,080 trouble-free and 1,080 debonding in the same ratio.

2.3. Structure of deep learning with a convolution neural network and the running environment

A schematic illustration of the structure of deep learning with a CNN used in this study is shown in Figure 1. The training images were randomly separated into 32 batches for every epoch, and 100 epochs were run at a learning rate of 0.0001. A CNN was implemented using the Keras library (Ver. 2.2.4) on top of TensorFlow (GPU version, Ver. 1.12.2) in Python (Ver. 3.7.2) and run on a laptop computer (Thinkpad X280: Core i7-8650U CPU and 16GB RAM, Japan) connected to a graphic processing unit box (AKiTiO Node, CA, USA) with the high-performance graphics card (GeForce RTX2080: 8GB RAM, MSI, Japan) via Thunderbolt 3 cables.

2.4. Assessment

True positives (the number of correctly predicted case as debonding), true negatives (the number of correctly predicted case as trouble-free), false positives (the number of incorrectly predicted case as debonding), and false negatives (the number of incorrectly predicted case as trouble-free) were obtained for the test images. The prediction accuracy (= (true positives + true negatives) / total cases), precision (= true positives / (false positives + true positives)), recall (= true positives / (false negatives + true positives)), F-measure (harmonic mean value that results from combining precision and recall), receiver operating characteristics (ROC) (the relationship between true positive rate (= recall) and false positive rate (= false positives / (false positives + true negatives)) for various thresholds to predict classes (debonding or trouble-free)), and area under the ROC (AUC) of the learning model were assessed for the test images (Lee et al. 2018a). The shape of the ROC curve should be convex to the upper left and an ideal AUC value should be close to 1.0. Also, the mean calculation time were measured during the prediction for the test images.

3. RESULTS

The learning curve of the validation images is shown in Figure 3. After 20 epoch repetitions, the learning curve had mostly converged.

The prediction accuracy, precision, recall, and F-measure values of deep learning with a CNN method for the prediction of the debonding probability were 98.5%, 97.0%, 100%, and 0.985, respectively.. The mean calculation time was 2 msec/step for 2,160 test images.

The results of ROC analysis are shown in Figure 4, and the AUC value was 0.998.

3. DISCUSSION

AI technology using deep learning with CNN methods established in this study could be predict the debonding or trouble-free for CAD/CAM composite crown with high prediction accuracy by using images of three-dimensional preparation scan.

The current prediction accuracy of 2,160 test images obtained in this study was 98.5%, whereas those of other applications in the dental field have been reported to be 78.2% (Lee et al. 2018a). Even given the use of a different type and number of input data, the prediction accuracy was higher than that of a conventional study. In 2015, the prediction accuracy of deep learning with a CNN proposed by Google (GoogLeNet (Szegedy et al. 2015)) and Microsoft (ResNet (He et al. 2016)) exceeded that of humans (error rate = 5.1% (Russakovsky et al. 2015)). GoogLeNet has achieved 8 million classifications by learning a 200 million image dataset with 95.1% prediction accuracy.

Regarding the CNN method implemented in this study, the source code for the classification of 10 classes referred to examples in the Keras library and were modified for the classification of two classes. Well-established structures of deep learning with a CNN, such as GoogLeNet and ResNet, are available and could generate a relearning model using our images. Those structures may result in greater prediction accuracy. A higher throughput graphics board with a large number of compute unified device architecture cores had to be used to achieve a reasonable computational cost.

An image augmentation technique was used to increase the number of images to develop the learning model. Rotation, width and height shifting, zooming, shearing, and horizontal flip were applied to the training/validation images (Shin et al. 2016). In the case of the 3D STL model used in this study, the view direction of the models could be easily changed and automatically saved as different JPEG images using batch processing code. Whereas quasi-generated images are obtained by shearing and horizontal flip techniques, images in which the view direction is changed could reflect actual scenes, that is, the views of dentists/dental technicians. This suggests that great prediction accuracy is obtained even for fewer images as a result of developing a learning model, and the obtained learning model will be useful for an application to medical/dental fields because of the difficulty in collecting a huge number of clinical cases.

In the case of the classification of the trouble-free/debonding of CAD/CAM CR crowns, the recall value is a more important criterion than the precision value. If the learning model predicts debonding despite the crown actually being trouble-free, dentists must apply an ineffective preparation such as no retention for crown (Rosentritt et al. 2017; Rosentritt et al. 2019) before the debonding of CAD/CAM CR crowns. In this regard, the ideal recall value is 1.0.

Fifteen cases of both trouble-free and debonding were used to develop the learning model in this study. When a huge number of trouble-free cases were compared with the debonding cases, the prediction accuracy increased despite the use of few cases of debonding. A high F-measure value close to 1.0 is better for avoiding false predictions.

The ROC curve obtained in this study showed greater true positive rate at the lower false positive rate, suggesting that the debonding cases are correctly predicted with low false prediction.

Within the limitations of this study, the deep learning with a CNN method demonstrated considerable good performance in terms of predicting the debonding probability of CAD/CAM CR crowns. However, it is difficult to explain what the main factor to induce debonding was. Calculation process in deep learning with CNN can be visualized by using Grad-CAM method (Selvaraju et al. 2017). Visualized map overlaid to images may be helpful to understand the interest of AI and the relation to clinical conditions. An AI-assisted system for navigating die preparation is now in development. If the debonding of CAD/CAM CR crowns is detected with a high probability during/after treatment, then the system will be able to display a candidate die shape that corresponds to the same type of tooth to improve the longevity of CAD/CAM CR crowns. The debonding probability and candidate die shape will be shown in front of the dentist's eye through a head-mounted display (picoLinker, Westunitis, Japan) during treatment. Clinicians and technicians can modify the die shape by following suggestion from the system. The head-mounted display will be a useful option to show supporting information in the medical/dental field (Joda et al. 2019; Kwon et al. 2018; Yamaguchi et al. 2011), and not only industry (Regenbrecht et al. 2005).

In conclusion, AI technology, that is, the deep learning with a CNN method established in this study, demonstrated that considerably good performance in terms of predicting the debonding probability of CAD/CAM CR crowns using 3D STL models of a die scanned from patients. This technology may be useful to assist dentists during/after restorative treatments, and possibly be applied to other trouble cases, such as root fracture/ die fracture.

AUTHOR CONTRIBUTIONS

S. Yamaguchi contributed to conception, design, data acquisition, analysis, and interpretation, and drafted and critically revised the manuscript. C. Lee and O. Karaer contributed to data acquisition, analysis, and interpretation, and critically revised the manuscript. S. Ban and A. Mine contributed to data acquisition and critically revised the manuscript. S. Imazato contributed to conception, design, data analysis, and interpretation, and drafted and critically revised the manuscript. All authors gave final approval and agree to be accountable for all aspects of the work.

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Table legends

Table 1. Detailed information about the patients and the commercially available CAD/CAM CR block used. HC: Shofu Block HC (Shofu, Kyoto, Japan), CS: Cerasmart (GC, Tokyo, Japan). Cement: 1. ResiCem (Shofu, Kyoto, Japan), 2. Panavia SA Cement Plus (Kuraray Noritake Dental, Tokyo, Japan), 3. Panavia V5 (Kuraray Noritake Dental, Tokyo, Japan), 4. G-CEM (GC, Tokyo, Japan).

State	No.	Sex	Age	Tooth	Products	Term (days)	Cement	Taper (°)	Thickness (mm)
Trouble-free	1	F	51	14	HC	1000	1	6	1.22
	2	M	74	44	CS	916	1	15.1	1.12
	3	F	56	14	HC	871	1	12.8	0.99
	4	F	59	14	HC	1005	2	37.2	1.15
	5	M	45	24	CS	835	1	13.2	1.38
	6	F	45	35	CS	835	1	29.5	0.51
	7	M	66	25	CS	788	2	16.8	1.45
	8	F	71	25	HC	1180	2	23.3	2.26
	9	F	56	14	HC	871	1	20	1.2
	10	F	39	35	HC	830	1	28.8	1.09
	11	F	71	24	HC	836	1	25.3	1.82
	12	F	59	14	HC	858	1	15.1	0.98
Debonding	1	F	25	35	HC	747	1	24	1.25
	2	F	60	35	HC	40	1	24.8	0.52
	3	F	47	35	HC	70	3	27	0.53
	4	F	75	24	HC	742	2	17	0.9
	5	M	71	45	HC	6	2	27.2	1.41
	6	F	82	45	HC	434	1	35	0.52
	7	F	56	25	CS	393	2	32.5	0.17
	8	F	55	25	CS	222	1	32	0.82
	9	F	44	15	HC	7	2	33.3	0.51
	10	F	66	45	HC	119	2	20	0.71
	11	F	64	44	CS	58	4	17.8	0.61
	12	M	63	14	HC	52	1	48.2	1.8

Figure Legends

Fig. 1. Schematic illustration of the structure of deep learning with a CNN used in this study. The feature extraction layer consists of four convolution layers and two max pooling layers. The classifier conducts binary classification between trouble-free and debonding.

Fig. 2. Example image captured from one of the 3D die models for the development of the learning model. Trouble-free (No.5 described in Table 1)(left) and debonding (No. 6 described in Table 1)(right).

Fig. 3. Learning curve of the validation images. Blue line indicates the accuracy over the course of training. Red line indicates the loss on the training data set.

Fig. 4. ROC curve with AUC obtained after training for the test images.

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