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Dental Cavity Analysis in Restorative Dentistry Using Deep Learning and Explainable Artificial Intelligence

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Highlights:
- Explainable artificial intelligence used in dentistry education,
- Width of dental cavities detected with artificial intelligence
- Different deep learning models found successful in dentistry education

Keywords:

- Explainable Artificial Intelligence
- Class I Cavity
- Computer-Aided Assessment
- Convolutional Neural Networks
- Deep Learning

ABSTRACT:

In dental education, it is important for instructors to objectively evaluate the cavities prepared by students on mannequin teeth. However, this evaluation process is difficult due to factors such as physical fatigue and eye strain, which can compromise the quality of feedback. Therefore, interest in computer-aided systems that provide objective evaluations is increasing. The rapid advancements in artificial intelligence, particularly deep learning, have shown promise in various fields, including medicine and dentistry. Convolutional neural networks (CNNs), inspired by the mammalian visual system, perform in tasks such as classification and object detection within computer vision. Despite its potential, there is no research on the use of CNN to evaluate cavities. This study aimed to explore the feasibility of using CNNs to classify cavities into narrow, normal width, or wide categories based on photographs. Ten different CNN models were used to classify them. Additionally, the decision-making processes of these models were visualized through heat maps, offering insights into their predictions. According to the test results, the highest accuracy, precision and recall values were found for DenseNet-169 (98.85%, 98.61%, 99.10%). This study can be conceivable for future research in automating cavity evaluations in dental education, enhancing objectivity, and enabling self-assessment for students.

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INTRODUCTION

In addition to theoretical lessons, teaching practical applications to students has an important place in dentistry education. For this purpose, during the training of restorative dental treatment applications, students are made to prepare cavities on mannequin teeth. Objective evaluation of the prepared cavities by the instructor is also an important part of the practical training. During this evaluation, parameters such as the form, depth and width of the cavities that the students are asked to prepare according to certain rules are evaluated (Zou, Jin, Sun, & Dai, 2016).

During the evaluation of the cavity, it is also important for the instructor to give objective feedback to the student. However, this evaluation is not an easy process. Moreover, in crowded classroom environments, factors such as physical fatigue, eye strain and inattention may pose problems in the objectiveness of the evaluation. Non-objective evaluation has a negative impact on the student's learning process. Moreover, it is desirable for the students to reach a level where they can evaluate themselves. For this purpose, consistent and objective feedback to the student is very important (El-Kishawi, Khalaf, Al-Najjar, Seraj, & Al Kawas, 2020; Skinner et al., 2015). In this context, computer-aided systems that can objectively evaluate the cavities prepared by students may be beneficial.

Nowadays, artificial intelligence technology is developing quite rapidly. In particular, deep learning, which is a sub-branch of artificial intelligence, appears to solve many problems, from computer vision to natural language processing better than human performance. There are many studies reporting the successful use of deep learning algorithms for diagnostic purposes, especially in the field of medicine and dentistry (Bayraktar & Ayan, 2022; Carrillo-Perez et al., 2022; Çelik, İnik, & Technology, 2023; Kaul, Enslin, & Gross, 2020). In addition, there are studies showing that deep learning can be used in medical and dental education (Ayan, Bayraktar, Celik, & Ayhan, 2024; Sapci & Sapci, 2020).

Convolutional neural networks, one of the deep learning algorithms, were developed by taking inspiration from the mammalian visual system. These networks have successfully solved important problems such as classification, object detection and segmentation in computer vision (Chai, Zeng, Li, & Ngai, 2021; Voulodimos, Doulamis, Doulamis, & Protopapadakis, 2018).

In this field, a software in which cavities are evaluated and scored by CNNs will be a major development in the field of dentistry education. Moreover, possible errors that may arise from the instructor will be minimized. In addition, the dentistry student will be able to evaluate himself/herself when an instructor is not present. However, to the best of our knowledge, there are no studies investigating the evaluation of cavities with CNNs. This study was considered as a pilot study for possible future studies. In the study, 10 different CNN models were used to classify cavities as narrow, normal or wide based on photographs of previously prepared cavities. Cavities up to 1/3 of the tooth in the vestibulo-lingual direction were labelled as narrow, between 1/3 and 2/3 were labelled as normal, and cavities larger than 2/3 were labelled as wide. Also, the decision-making processes of CNN models were analyzed by visualizing the predictions provided by the models through heat maps

MATERIALS AND METHODS

In this study, it was aimed to evaluate the classification performance of CNN models as wide, narrow and normal cavities. The prepared specimens were obtained from the archives of the Department of Restorative Dentistry. In this context, ten different CNN models were trained with the transfer learning method. At the end of the study, the predictions of the most successful model were visualized by heat maps. A visual summary of the study is shown in Figure 1.

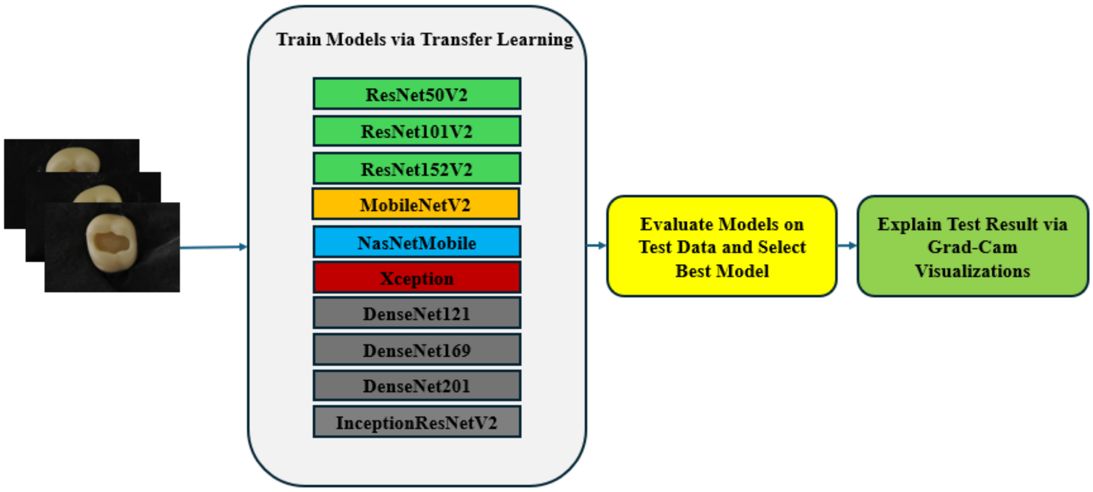

Figure 1. The summary of the study

Dataset

All images were taken with the same camera (Nikon D3000, Tokyo, Japan) using 105 mm lens (AF-S VR Micro Nikkor 105mm f/2.8G IF ED, Tokyo, Japan). All images were also taken with the same settings, from the same height, under the same lighting conditions. The dataset includes images in three classes according to cavity dimensions: 128 wide, 180 narrow and 108 normal. Some examples from the dataset are shared in Figure 2. The data is first split into 70:10:20 for training, testing and validation. After the splitting process, the training data was augmented by applying data augmentation methods to the training data. No data augmentation was performed for validation and test data. The distribution of data after data augmentation is shown in Table 1.

Table 1. Training, validation and test class distributions of the dataset

Cavity Class	Training	Validation	Test
Narrow	500	18	37
Wide	500	12	27
Normal	500	10	23
Total	1500	40	87

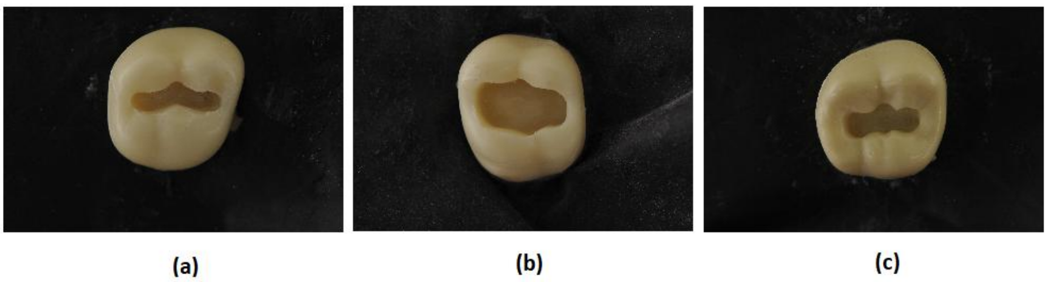

Figure 2. Examples from the dataset are narrow (a), wide (b) and normal (c)

Convolutional Neural Networks

The basis of convolutional neural networks is based on cat experiments conducted in a previous study (Hubel & Wiesel, 1965). Through these experiments, the visual perception systems of mammalian organisms have been explored, leading to the development of convolutional neural networks (CNNs). Since the introduction of the first convolutional neural network, Neurocognition researchers have developed various CNN architectures for use in computer vision problems (Fukushima & Miyake, 1982). A basic CNN architecture consists of convolutional layers, pooling layers, and fully connected layers (Krizhevsky, Sutskever, & Hinton, 2012). In convolutional layers, images are processed with the help of filters. Each filter is used to extract specific features from the input image. Filters move across the image like a sliding window and are used to detect certain features. In pooling layers, the spatial dimensions of images are reduced, thereby alleviating the computational load on the network. The most commonly used types of pooling are Max Pooling and Average Pooling. Fully connected layers take the features extracted by the convolutional layers, convert them into a vector, and perform classification (Krizhevsky et al., 2012). CNNs play a significant role in the world of machine learning and artificial intelligence due to their strong performance on visual data and broad range of applications. The CNN models used in the study are as follows:

DenseNet

DenseNet (Dense Convolutional Network) is a deep learning architecture developed by Huang Gao et al. in 2016 (Huang, Liu, Van Der Maaten, & Weinberger, 2017). The most distinctive feature of DenseNet is that each layer uses the feature maps from all previous layers as input. These dense connections allow each layer to receive gradients directly from all preceding layers, which helps prevent the vanishing gradient problem and facilitates the training of deeper networks. These connections enhance information sharing, enabling better performance with fewer parameters. There are different DenseNet architectures based on the number of layers they contain. In this study, DenseNet-121, DenseNet-169, and DenseNet-201 models have been used.

InceptionResNetV2

InceptionResNetv2 is a deep learning architecture developed by Google and introduced in 2016 (Szegedy, Ioffe, Vanhoucke, & Alemi, 2017). This model combines the strengths of the Inception architecture and Residual (Residual) network structures. The Inception architecture enhances the model’s width by using convolution filters of different sizes simultaneously, while residual connections reduce the gradient vanishing problem often encountered in deep networks and accelerate training. By integrating these two approaches, InceptionResNetv2 offers both a deeper and wider network structure, achieving high performance in image recognition tasks.

MobileNetv2

MobileNetV2 is a deep learning architecture proposed by Google in 2018 (Sandler, Howard, Zhu, Zhmoginov, & Chen, 2018). This model is designed to deliver high performance in environments with limited computational resources, such as mobile and embedded devices. MobileNetV2 introduces two main innovations: depthwise separable convolutions and inverted residual structures. Depthwise separable convolutions significantly reduce computational cost and model size, while inverted residual structures improve gradient flow and enhance the model's learning capacity. With these features, MobileNetV2 provides low latency and high accuracy, making it effective for various computer vision tasks such as image recognition, object detection, and segmentation.

NasNet

NASNet is a deep learning architecture developed by the Google Brain team and introduced in 2017 (Zoph, Vasudevan, Shlens, & Le, 2018). This model is optimized using the Neural Architecture Search (NAS) algorithm, which is used to automatically design the architecture of deep learning networks. NASNet discovers the network structure that provides the best performance within a specific search space, creating more efficient and effective deep learning architectures compared to human-designed models. In this process, architectural blocks (normal and reduction cells) are optimized and reused to build larger networks. This model demonstrates the potential of automation in the design of deep learning architectures and has gained widespread acceptance in both research and application domains. NASNetMobile architecture has been used in this study.

ResNetV2

ResNet V2 is an improved version of the original ResNet (Residual Network) architecture and was introduced by Kaiming He and his colleagues in 2016 (He, Zhang, Ren, & Sun, 2016). This model further enhances the "residual" connections designed to address the gradient vanishing problem encountered during the training of deep neural networks. ResNet V2 uses batch normalization layers and ReLU activation functions in the residual connections, which increases the depth of the network while stabilizing the learning process and improving performance. Additionally, in this version, batch normalization and ReLU are applied at the beginning rather than at the end of each residual block, which facilitates more effective gradient flow (Szegedy et al., 2017). In this study, the ResNet50V2, ResNet101V2, and ResNet152V2 models have been used.

Xception

Xception (Extreme Inception) is a deep learning architecture developed and introduced by François Chollet in 2016 (Chollet, 2017). Xception is an extended version of the Inception architecture and aims to improve parameter efficiency and performance by using depthwise separable convolutions. Instead of traditional convolutional layers, Xception processes each channel separately and then combines these channels using pointwise convolutions. This structure reduces computational cost while enhancing the model’s learning capacity and accuracy.

Transfer Learning

Transfer learning is a commonly used technique in the field of deep learning. With CNNs, transfer learning allows a model to leverage knowledge learned from one task to more quickly and efficiently learn a new task (Shin et al., 2016). This approach is particularly prevalent in the training of large and complex models like CNNs. Transfer learning is based on the principle of reusing a model that has been previously trained on a large dataset rather than training a model from scratch for a specific task. This technique shortens training time and provides better performance, especially in computer vision problems with limited data (Shin et al., 2016). In the study, all models were trained using weights pre-trained on ImageNet. Global Average pooling was used at the end of all convolutional layers, and each model was concluded with an output layer consisting of three neurons.

Experimental Setup and Hyperparameters

The experiments in this study were conducted on a computer running the Ubuntu operating system, equipped with 32 GB of RAM and an NVIDIA GeForce GTX 1080 Ti graphics card. The training of the CNN models was performed using the Keras deep learning library. This setup provided the necessary computational resources to efficiently train and evaluate the models. Table 2 shows the hyperparameters used during the training of the models. These parameters were selected to optimize the training process and ensure effective learning.

Table 2. Hyperparameters of CNN models

Hyperparameter	Value
Learning Rate	0.001
Optimizer	Adam
Loss Function	Categorical Cross Entropy
Batch Size	32
Epochs	30
Output Activation	Softmax
Input Size	224x224x3-299x299x3

Evaluation Criteria

In this study, the classification performance of the models was evaluated using accuracy, precision, recall, and F1 score metrics. To calculate these metrics, the confusion matrix shown in Figure 3 was utilized.

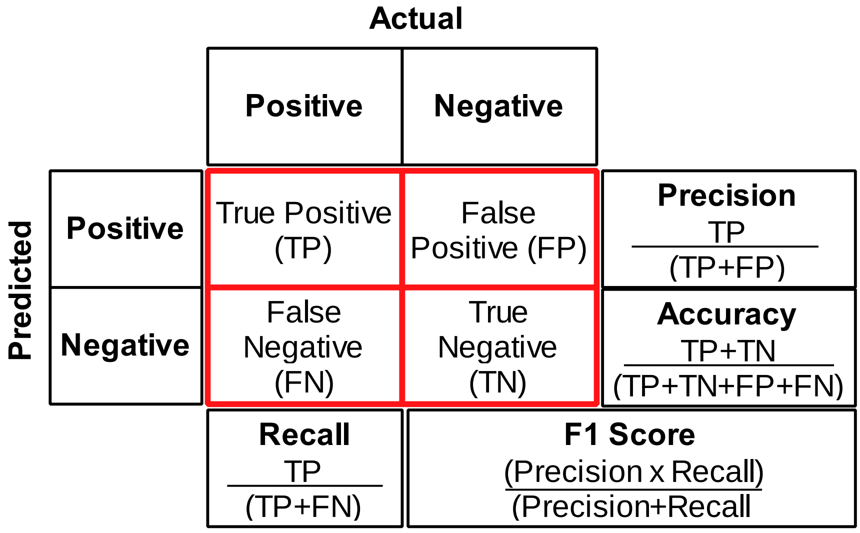

Figure 3. Confusion Matrix

RESULTS AND DISCUSSION

In this study, eleven different CNN models were trained using transfer learning techniques. The test results are provided in Table 3. According to the results obtained from the study, the highest classification performance was obtained with DenseNet-169. The accuracy value obtained with DenseNet 169 was 98.85%, precision value was 98.61%, recall value was 99.10% and F1 score was 98.83. The lowest classification performance was obtained with the Xception model with an accuracy value of 89.66, a precision value of 89.67, a recall value of 88.82 and an F1 score of 89.20. DenseNet 121, InceptionResNetV2, NasNetMobile and Resnet 101V2 achieved the same classification performances in all metrics. Additionally, the complexity matrix of the best model is given in Figure 4.

Table 3. Average classification performances of the models (in %)

Model	Accuracy	Precision	Recall	F1
DenseNet-121	97.70	97.65	97.65	97.65
DenseNet-169	98.85	98.61	99.10	98.83
DenseNet-201	96.55	96.73	96.20	96.44
InceptionResNetV2	97.70	97.65	97.65	97.65
MobileNetV2	96.55	97.50	95.65	96.38
NasNetMobile	97.70	97.65	97.65	97.65
ResNet50V2	96.55	96.30	96.75	96.50
ResNet101V2	97.70	97.65	97.65	97.65
ResNet152V2	96.55	97.50	95.65	96.38
Xception	89.66	89.67	88.82	89.20

Table 4. Performance Scores of the DenseNet-169 Model (in %)

	Precision	Recall	F1
Narrow	100	97.3	98.6
Normal	95.8	100	97.9
Large	100	100	100

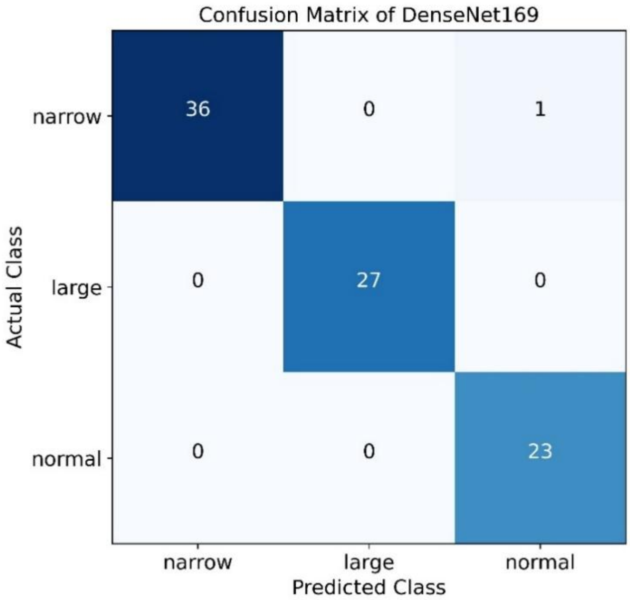

Figure 4. Confusion matrix of DenseNet169

Grad-CAM (Gradient-weighted Class Activation Mapping) is a technique used to visualize the decision-making processes of deep learning models, particularly for image classification models such as Convolutional Neural Networks (CNNs) (Selvaraju et al., 2017). This method shows which areas of an image the model focuses on when predicting a particular class. To understand how the model detects the width of the cavity, the attention maps of the best-performing model (DenseNet169) were used to visualize the regions of the image that the model focuses on. Figure 5 presents examples of narrow, wide, and medium-width prepared cavities along with the heatmaps of the regions where the model has focused. An examination of Figure 5 clearly shows that the model is indeed focusing on the area where the cavity is prepared.

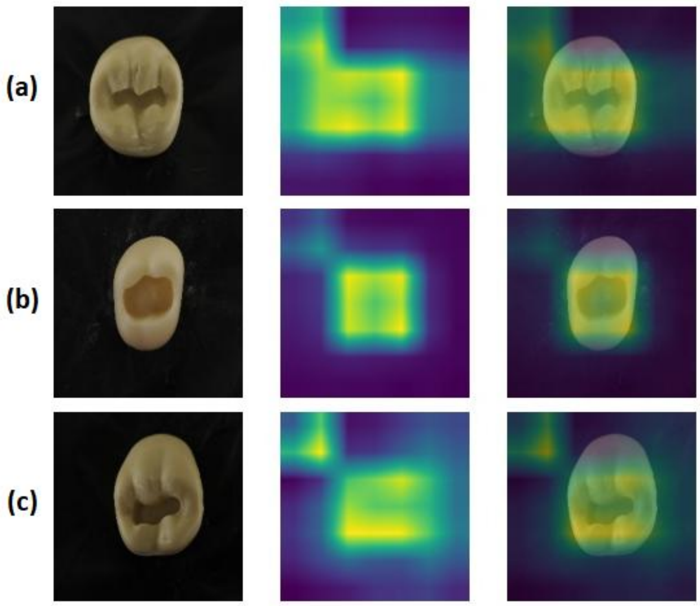

Figure 5. Heatmaps showing the areas of focus for the model on (a) narrow, (b) wide, and (c) normal examples

Among the models trained in this study, the most successful model, DenseNet169, made an error on only one instance in the test set. An examination of Figure 6 reveals that the model classified the one image that is actually narrow as normal. Upon inspection, it is clear that the image is very close to a normal cavity.

(a) (b)

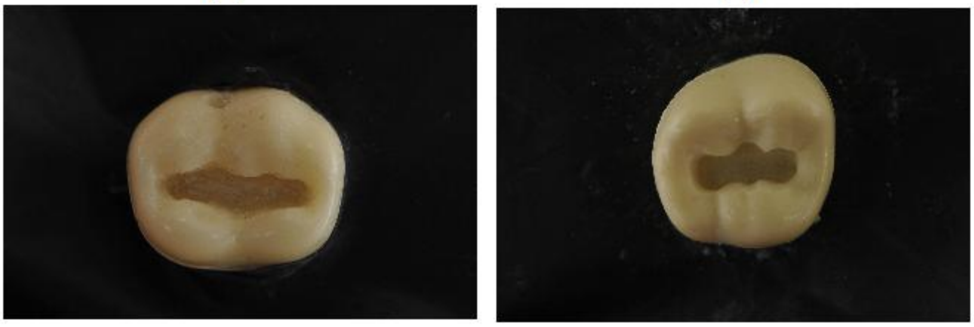

Figure 6. (a) An image that is actually narrow but classified as normal by the model, (b) an image from the dataset of the normal class

Upon reviewing the literature, no studies were found that dental cavities evaluated with 3D volumetric imaging except for one study (Zou et al., 2016). However, with the mentioned study (Zou et al., 2016) no deep learning model was used. Considering the high cost and limited availability of 3D imaging devices, the proposed 2D method has yielded promising results for cavity classification in this study. However, the results of our study need to be discussed.

In this context, this study is the first to perform cavity assessment using 2D images. The size of the dataset used in this study can be seen as a limitation, as increasing the amount of data would likely improve classification performance. Another limitation of the study is that criteria such as depth and length have not yet been evaluated. This is a pilot study, and future work will consider the criteria of length and depth.

The deep learning method has been successfully used in the field of dentistry such as diagnosis of tooth decay (Bayraktar & Ayan, 2022), the numbering of teeth (Bilgir et al., 2021), the diagnosis of soft tissue lesions in the mouth (Keser, Bayrakdar, Pekiner, Celik, & Orhan, 2023), training of students in caries diagnosis (Ayan et al., 2024), and many other areas (Corbella, Srinivas, Cabitza, & Radiology, 2021; Shan, Tay, & Gu, 2021). However, there is a need for studies in which the cavities prepared by students on their teeth are evaluated with deep learning. Evaluating dental students' practical assignments using deep learning could be a major innovation in the field of dentistry education.

CONCLUSION

This pilot study demonstrates the potential of using explainable artificial intelligence, specifically convolutional neural networks (CNNs), for the objective evaluation of cavities in restorative dentistry education. By classifying cavities into narrow, normal, and wide categories based on photographs, the study provides a novel approach to enhance the assessment process, reducing the subjectivity often encountered in traditional evaluations.

The findings suggest that CNNs can effectively analyze cavity characteristics, offering consistent feedback that is crucial for student learning. Moreover, the incorporation of heat map visualizations enhances transparency, allowing both instructors and students to understand the decision-making processes of the models. This advancement not only minimizes possible evaluator errors but also empowers students to self-assess their work in the absence of an instructor.

As this study is exploratory, further research is needed to refine the models and expand their applicability in dental education. The integration of explainable AI into dental training could significantly improve educational outcomes, ultimately contributing to the development of more competent dental professionals. As a conclusion, the CNN models used in this study showed successful rates in determining the widths of cavities. Using CNN models is found promising in terms of objectively evaluating the students' cavity preparation practices.

Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

Yusuf BAYRAKTAR: Designed the study and wrote the manuscript. Enes AYAN: Conducted experiments on deep learning models. Baturalp AYHAN: Prepared the cavities and took the photographs.

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