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EFFICACY OF ARTIFICIAL INTELLIGENCE MODEL IN DENTAL IMPLANT RECOGNITION USING X RAY IMAGES

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Abstract
Purpose: To develop and evaluate the accuracy of a computer-assisted system based on artificial intelligence for detecting and identifying dental implant brands using digital periapical radiographs.
Materials and Methods: A total of 1,800 digital periapical radiographs of dental implants from distinct manufacturers acquired from regional implantologists were split into training dataset (n = 1,440 [80%]) and testing dataset (n = 360 [20%]) groups. The images were evaluated by software developed by means of convolutional neural networks (CNN), with the aim of identifying the manufacturer of the dental implants contained in them. Accuracy, sensitivity, specificity, positive and negative predictive values, and the receiver operating characteristic (ROC) curve were calculated for detection and diagnostic performance of the CNN algorithm. **Results**: At the final epoch (25), system accuracy values of 98.78% were obtained for group training data, 98.36% for group testing data, and 87.29% for validation data. The latter value corresponded to the actual accuracy of carrying out the system learning process.
Conclusion: This study demonstrated the effectiveness of CNN for identifying dental implant manufacturers, which was proven to be a precise method of great clinical significance
Keywords: artificial intelligence, deep learning, dental implants, radiology, supervised machine learning
Keyword : Dental Implant , Artificial Intelligence , Machine Learning, Radiograph , Data Science

Introduction

The lack of traceability of implantable medical devices (IMDs) is a major concern of modern medicine in terms of public health. The number and diversity of IMDs has only increased in recent years in all surgical disciplines, and it is sometimes impossible to identify them.[1] In implant dentistry, this concern translates into many dental implant manufacturers, with many similar or even identical implants developed by each brand.[2] In clinical practice, this makes it very difficult to identify the brand and model of a dental implant placed by a colleague in a new patient. However, it is essential to know the implant's characteristics, in the event of an oral rehabilitation request, a fracture of prosthetic parts, or a product recall by the manufacturer, for example.

To another extent, being able to identify a dental implant can be useful in forensic identification. This failure may be due to a lack of information from surgeons who do not provide traceability documents to patients, as well as a loss of these documents by patients themselves. The impossibility to contact the implant dentist or the lack of traceability provided by the manufacturer are other excuses that can be invoked. Very few authors have attempted to solve this problem, and the field of forensic dentistry has been particularly concerned about it on several occasions.[3–6]

These teams theorized on the interest of knowing how to recognize the brand and model of a dental implant as an aid for the post-mortem identification of an individual, especially during major disasters or for incinerated individuals. This problem of implant identification from a clinical point of view was raised rather late in the history of the discipline,[7,8]

with the same questions as today. In 2003, it was already estimated that more than 2,000 different dental implants were available on the market.[9]Teams then proposed databases that listed the morphologic characteristics of the largest possible number of implant systems to assist clinicians.[10]

A computational method has been proposed,[11] based on a dental implant radiographic database, in which the desired implant is isolated from nine questions concerning its characteristics, using a logistic regression principle. The same principle is used by the website http://whatimplantisthat.com, an online platform for recognizing a dental implant from a radiograph; the website has the advantage of having a considerable database. Furthermore, a research group tested computer programs for automatic recognition via a machine learning method to identify and classify implants, although this was not the focus of their study.[12]

It is in this field of computational methods, with the recent increase of interest in artificial intelligence techniques for image recognition, that some teams have succeeded in increasing the accuracy with which these techniques can identify lesions from clinical photographs and anatomopathologic, radiographic, or scanographic examinations.[12–16] The technology that is most often used in these types of studies is deep learning using convolutional neural networks (CNNs).

The general principle of a CNN in image recognition is to present to a computer model many previously sorted images and then training it to automatically identify them using computer calculations. Thus, once the model is trained, it will be able to establish a prediction on the identity of an image presented to it.[17,18] The objective of this study was to develop a CNN that would identify the brand and model of a dental implant from a radiograph.

MATERIALS AND METHODS

Sample Acquisition :1,800 digital periapical radiographs of dental implants were acquired from regional implantologists based on predetermined eligibility criteria and complied with the EQUATOR guideline STARD 2015: An Updated List of Essential Items for Reporting Diagnostic Accuracy Studies .

Eligibility Criteria

The inclusion criteria for the purposes of this study were the existence of digital periapical radiographs showing a complete view of the dental implants (associated, or not, with healers and prosthetics) and adjacent structures; radiographs obtained with the incident x-ray beam perpendicular to the axis of the dental implants and sensor, and parallel to the implant threads; and the image of the dental implants contained in the radiographs had to be close to the length indicated in the patient files. The exclusion criteria were as follows: patient records that did not show previous identification of implant brands and models; images with positioning errors, distortions, and/or artifacts that could affect analysis; implants not belonging to the Neodent, Straumann, or SIN brands; and superposition of implant threads.

Preprocessing and Data Augmentation

All images were cropped and resized to be 70 pixels wide × 125 pixels high, in order to retain only the implant and adjacent areas in the image. Each image was converted into a grayscale palette (Figs 1a to 1c). The neural network was trained with information relative to input data (images) and expected outputs (manufacturers) transmitted to the computer. By modifications of parameters, this information made it possible to obtain characteristics that the computer considered important in order to differentiate one brand from the other by analyzing patterns in data. The dataset was split into two groups: training dataset (n = 1,440 [80%]), which was used to fit the parameters (eg, weights of connections between neurons) and testing dataset (n = 360 [20%]), which was used to assess the performance after the parameters were fitted. To minimize overfitting issues that may arise when a dataset that is not large is used for deep learning, and increase the model reliability, the training dataset was artificially augmented by using an “imgaug” library totaling 402,000 images.

The augmented dataset (artificially generated images) included horizontally rotated, angulated, partial images and alteration in sharpness, blur, contrast, and brightness in order to provide the system with diverse and realistic situations during the training. In the learning process, the machine starts by recognizing primal features, such as edges, lines, and shadows, processing them in the shallower neuron layers; the deeper the layer, the more complex the features learned. Then, it recognizes relevant features in a hierarchical way (more or less relevant), learning and mapping them.

Statistical Analysis The accuracy obtained by using the software after training and testing was reported in percentage by the neural network itself. Diagnostic accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), receiver operating characteristic curve (ROC), and area under the ROC curve (AUC) for the testing dataset were assessed. Values of $P < .05$ were considered statistically significant, and 95% confidence intervals (CIs) were calculated.

Architecture of CNN

This study made use of deep CNNs, deployed by using “Keras” and “Tensorflow” frameworks (Google), which are software packages that implement neural network methods, helping to simplify the overall programming for building a specific type of application. The CNN architecture was composed of five convolutional layers (enforcing a local connectivity pattern between neurons of adjacent layers), with each one followed by a pooling layer (pooling the main values of the activation map, retaining the higher values, and generating a more compact map) and five dense layers (implementing the activation function). Input data (images) were supplied to the neuron. Then, the neuron carried out mathematical operations with the data supplied and delivered the output (manufacturers). The “Categorical Crossentropy” loss function, which is embedded in the Keras framework, was used. This loss function improves the network performance on generalizing its application beyond the training process. The "Stochastic Gradient Descent" optimization algorithm (an iterative method for optimizing an objective function with suitable smoothness properties, with the aim of reducing the error level) was used. It was set with the following hyperparameters:

• Learning Rate: 0.005
• Decay: 1e–6 (one times 10 to the power minus six)
• Momentum: 0.8
• Nesterov: enabled

The neural network was trained for 25 epochs (the number of epochs refers to the number of times that the learning algorithm worked through the entire training dataset) totaling 321,600 training images and 80,400 test images. Test images were previously used during the training process to estimate the partial performance of the neural network. Later, the model performance was estimated in the images initially selected for this purpose (validation), resulting in an accuracy of 85.29%. The validation accuracy refers to the ability of the system to generalize its training in order to identify dental implant brands of unknown dental implants found in radiographs, including diverse variations, such as different positioning, distortion, color variation, and presence of artifacts, among others, meaning its clinical application.

RESULTS

After analysis and data processing by the software based on CNN, an accuracy of 87.29% (78.4% to 90.5%) was obtained for dental implant manufacturer identification. The sensitivity was 89.9% (81.1% to 95.6%), specificity was 82.4% (73.7% to 87.3%), PPV was 82.6% (74.1% to 86.6%), and NPV was 88.5% (79.8% to 93.9%;).

The accuracy in training data reached 98.78% at the 25th epoch, while the testing data accuracy stabilized at a slightly lower value (98.36%). Both the training and testing data groups were used only during the artificial neural network training period. Later, the network performance was tested with data that were previously unknown by it, the so-called validation data. At this time, the network had an accuracy of 87.29%.

DISCUSSION

Fast and precise identification of dental implants placed in patients are major factors for agility and safety in clinical practice for both dentists and forensic professionals since knowledge about the dental implant model placed is essential before beginning with any type of prosthetic clinical intervention, and these data provide major support in the forensic field. Currently, there are several brands and models of dental implants for oral rehabilitation, which have different abutment systems, frequently making it impossible for a professional to identify the implant merely by analyzing a radiograph or with clinical examination alone.[7,10,25,26]

Studies have shown that it is possible to identify dental implants by means of periapical radiographs. However, in the latter method, implants were identified by dentists, and not by machines, which makes the expertise of each professional a major variable for successful identification by the observer.

These studies have standardized each type of implant they analyzed, in charts, and have shown that the incident angle of the radiographic beam has a direct effect on dental implant identification since it may cause structural distortions in radiographic images.[7,10,25,26] Artificial intelligence is capable of overcoming this restriction by neural network training and learning, as shown in the present study.

Michelinakis et al[11] developed software for dental implant identification based on a database collected from implant manufacturer websites. This software worked, based on nine questions answered by the dentist relative to the dental implant features noted in the radiographs.
Later, Berketa et al [4] showed that in many instances, the use of this software was unable to provide correct information about which dental implant was placed and shown in the radiographic image under study.[4] This may be justified by the variations in interobserver perceptions; thus, the software was dependent on individual aptitude. In contrast, artificial intelligence outperforms this variability, because it is independent.
Berketa et al described the amount of correct identification of implants ranging from 40% to 65% when two examiners were compared[6] The present CNN model showed higher accuracy in identifying dental implants compared with human identification aided by software. Up to now, there have been no methods or resources that enable the precise identification of dental implants.

The present study introduces a pioneer experiment in which artificial intelligence was used for this purpose, showing a very satisfactory hit rate with an accuracy of 85.29%. Recently, several studies have evaluated the applicability of artificial intelligence in medical image interpretation, showing promising results. Many of these studies have shown accuracy rates ranging from 72% to 97% for this technology as an aid to diagnosis involving images and pathologic lesions. In analysis of teeth with periodontal impairment, the neural network could correctly show extraction in 82.8% of the cases in premolar teeth and 73.4% in molar teeth compared with the diagnostic concordance of three periodontists. In the identification of carious lesions, 88% and 89% accuracy was obtained in premolars and molars, respectively.[10,21–27]

Corroborating the findings of studies in the dental field, the present study showed a high degree of accuracy and great effectiveness in the identification of dental implant manufacturers. These findings reinforce the concept that CNNs can be useful to dental clinical practice. It is important to highlight that this neural network will be extended to other implant manufacturers and different prosthetic platforms. A superficial conventional architecture is sensitive to small changes, such as morphology, positioning, and geometry of dental implants, therefore increasing the chances of errors.
However, deep CNNs have better performance for computational viewing and are able to automatically learn hierarchical representations of resources and identify patterns in radiographs, showing efficient border detection throughout their multiple hidden and convolutional layers.28 Therefore, the results of using a CNN in this study showed that it provided improved and reliable detection of the desired data.
The main limitations of this study were the challenge of acquiring a more complete dataset, including more dental implant brands and models, and the sample size (compensated by using data augmentation techniques). Furthermore, there was variability in thread design, diameter, and length of implants from the same brands, as the companies provide different implant designs with the same connection.
Consequently, it was not a simple task to identify and classify the dental implants, although there were only three brands. Thus, in the present study, the accuracy of artificial intelligence

for identifying the manufacturer of dental implants with three distinctive dental implant brands was analyzed, with the aim of proving the effectiveness of this automated identification system that was not dependent on the dentist's expertise for this purpose.

It showed that the method was efficient and outperformed other aforementioned methods with the same objectives. Based on this evidence, it is suggested that new studies should be conducted including a larger number of manufacturers in the database.

CONCLUSIONS

The results obtained in this study showed that the deep CNN algorithm provided a high degree of accuracy for identifying dental implants by means of digital periapical radiographs and is a useful tool in dental practice. With a more comprehensive database, this system could be widely used and help dentists to work with more predictability, by eliminating the challenge of having to discover the implant model placed in patients when there is no previous treatment information available.

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