Original Article

Machine learning for identification of dental implant systems based on shape – A descriptive study

Veena Basappa Benakatti, Ramesh P Nayakar, Mallikarjun Anandhalli[1]

Department of Prosthodontics and Crown and Bridge, KAHER'S KLE VK Institute of Dental Sciences, [1]Department of Electronics and Communication Engineering, KLS Gogte Institute of Technology, Belagavi, Karnataka, India

Abstract

Aim: To evaluate the efficacy of machine learning in identification of dental implant systems from panoramic radiographs based on the shape.

Settings and Design: *In vitro*–Descriptive study

Materials and Methods: A Dataset of digital panoramic radiographs of three dental implant systems were obtained. The images were divided into two datasets: one for training and another for testing of the machine learning models. Machine learning algorithms namely, support vector machine, logistic regression, K Nearest neighbor and X boost classifiers were trained to classify implant systems from radiographs, based on the shape using Hu and Eigen values. Performance of algorithms was evaluated by its classification accuracy using the test dataset.

Statistical Analysis Used: Accuracy and recover operating characteristic (ROC) curve were calculated to analyze the performance of the model.

Results: The classifiers tested in the study were able to identify the implant systems with an average accuracy of 0.67. Of the classifiers trained, logistic regression showed best overall performance followed by SVM, KNN and X boost classifiers.

Conclusions: Machine learning models tested in the study are proficient enough to identify dental implant systems; hence we are proposing machine learning as a method for implant identification and can be generalized with a larger dataset and more cross sectional studies.

Keywords: Artificial intelligence, classification, dental implants, dental radiography, machine learning

Address for correspondence: Dr. Veena Basappa Benakatti, Department of Prosthodontics and Crown and Bridge, KAHER'S KLE VK Institute of Dental Sciences, Neharu Nagar, Belagavi - 590 010, Karnataka, India. E-mail: kenganalveena@gmail.com

INTRODUCTION

Implants have become the most promising and accepted prosthetic alternative for missing teeth. Continuing innovation and advanced technologies have improved the performance and long-term prognosis of dental implants. Owing to the rising demand for dental implants, many manufacturers have entered the industry and produce over 220 implant brands and the diversity continues to grow. Each of these implants varies in structure, morphology, connections, and surface characteristics.[1]

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These dental implants will need follow-ups and aftercare in due course of time due to biologic and mechanical complications such as screw loosening, implant or screw fractures, low implant stability, and peri-implantitis.[2] During this serviceability, several information is required about the implant, for instance, manufacturer, implant system, fixation method, and abutment type used.[3] The difficulty of identifying implant systems is augmented when information needs to be exchanged across different regions and countries. Since there is no information network across regions to identify implant systems, the problem gets complex.[1] In an attempt to identify the system and treat the complication, clinicians might end up in invasive treatment modalities and further to the extent of making a new prosthesis, thus increasing the cost of treatment.[4]

Currently, patient previous records and radiographs are the only tools in identifying implant systems. Patient records may not be available all the time, and using radiographs requires a significant amount of human effort and experience as the procedure involves processing of larger data, i.e., implant features such as shape, size, threads, connection, apex, and collar, to draw a meaningful conclusion about the type of implant used.[1] Every clinician may not be experienced enough to identify the implant system that he encounters. There is a continuous thrust in the process of identification of various implant brands. However, there is a limited research on methods and techniques that allow the identification of dental implant systems clearly.[2]

Artificial intelligence (AI) has made a tremendous impact in solving problems of every field, particularly medicine. Over the last few decades, AI has made tremendous progress in empowering the machines to automatically process and categorize complex data[1] and has shown good competence and positive outcomes when ventured into various medical and dental fields. One of the AI technologies, machine learning method, is appropriate for classification, object detection, and prediction and proved to be close to or superior to that of humans. In dental field, diagnosis using radiographs, predicting prognosis, tumor classification, and various other domains has been addressed using a machine learning method.[3] If this system can be adopted for identifying implant systems, it will help dentists and prevent from missing problems or making errors. Considering the scope of AI, this study was undertaken with intent to evaluate the efficacy of machine learning in identification of different dental implant systems. We hypothesize that machine learning is efficient in identifying different dental implant systems from radiographs.

Review of literature

Several studies have documented the basic design of implants, based on these specific designs; dentists can identify different implants from radiographic images.[5,6] Based on the radiographic identification, Michelinakis *et al*.[7] proposed, if a database can be created of known implant systems, then several leading questions concerned with the dental implant being identified will minimize the number of possibilities remarkably, and the database is known as implant recognition software. However, the database comprises implant features based on the particulars given by the implant manufacturer in the brochure. To recognize a dental implant, particulars in each of the drop-down menus that include implant details should be entered manually. Furthermore, the software does not directly analyze the images. The database provides matching implants based on answers to these queries, and then, a dentist has to match them with that of the patient.[7] This system requires dentists to verify if two images of the implant are matching to identify implant system. In contrast, in the current study, AI model (computer) itself identifies the implant based on radiographic image.

Rami Jandali developed a miniature radiofrequency chip that can be fitted into screw hole of the dental implant, and the chip would be loaded with information about the implant system. A wireless reader can be used to communicate with the chip, and useful information can be extracted.[8] A wireless reader sends electromagnetic waves to activate the chip which could be hazardous to human health, and every clinician may not have this specialized device at clinic.

Basically, till today, a dentist has to read the features of implant system from radiograph and make an appropriate guess about the type of implant used. These methods have several limitations such as knowledge of dentists about different implant systems, time consumed in process, and accuracy of identification. Considering the rapid growth of implant dentistry as a prosthetic option, there is a need for an appropriate and quick scientific method for identification of implant systems. Contribution of this paper is proposing a method for identification of dental implant systems with standard techniques of computer vision based on the shape.

MATERIALS AND METHODS

Study design
A dataset of digital panoramic radiographs was obtained. Several machine learning algorithms were trained to classify implant systems from radiographs, and their classification accuracy was assessed. Performance of the algorithms

was primarily evaluated by its classification accuracy that corresponds to correct classifications. The accuracy and receiver operating characteristic (ROC) curve were calculated to analyze the AI model performance.

Data preprocessing

The study was approved by the Institutional Review Board (KAHER/EC/21-22/D-290721002). The study was conducted at KAHER's KLE VK Institute of Dental Sciences and Gogte Institute of Technology, Belagavi, Karnataka, India. Anonymized digital panoramic radiographs of patients who underwent implant treatment were obtained from the Department of Oral Radiology during the period January 2021 to April 2021. Ethical clearance was obtained from KAHER University Ethical Committee. As the study was a noninterventional design and anonymized data were collected, individual informed consent was waived by the Ethical Board. Radiographs with unknown implants, haziness, distortion, blur, and several other conditions that hinder the clinical recognition and classification of dental implant systems were excluded. Images were segmented (cropped) to focus on implant image and exported as PNG images. Types of dental implant systems and corresponding number of images were categorized and labeled based on patient records from a department ledger. Images were divided into two datasets: one for the training (80%) and the other for testing (20%). Training dataset was used to train the model by learning, and testing dataset was independent of the training dataset which was used to analyze the performance of model. The dental implant systems considered in the study were Osstem TS III SA Regular, Osstem TS III SA Medium, and Noris Medical Tuff.

Training of the AI model

The machine learning model was trained to identify the dental implant systems based on feature extraction, i.e., shape of the implant (geometry of the implant) using Hu and eigenvalues. Supervised machine learning techniques, support vector machine (SVM), K-nearest neighbor (KNN), X boost, and logistic regression classifiers, were tested in the study.

Feature extraction using Hu moments and eigenvalues

After preprocessing of images, features were extracted using Hu and eigenvalues. Hu moments basically describe, distinguish, and quantify the object shape in an image, thus helping to define the shape of an object. When using eigenvalues, for an unknown input image, the algorithm subjects the image to eigenspace and is recognized utilizing space partitioning method, which determines the object and its location in space in accordance with the number of images that describe position from the image set.

Machine learning entails predicting and classifying the data. For this, various algorithms/classifiers are employed according to the dataset. Supervised learning techniques were used to classify implant systems through Hu and eigenvalue based on feature extraction.

In SVM, the algorithm generates a hyperplane or a line known as a decision boundary that separates data into classes. Here, the chore is to find that ideal line which separates the dataset into classes. Advantage of SVM approach is that they are accurate, robust, and effective even with smaller training dataset. In linear regression, the goal is to train algorithm with input features and output labels and achieve best-fit line or curve amid data to separate the classes. KNN algorithm presumes the similarity among available data and new data and then puts the new data into a category that is most similar to available categories. KNN functions, by finding the distance between query and the nearest neighbour in the existing data, based on the threshold value it chooses the most frequent label or class. The basic principle behind X boost classifier is that it generates multiple weak learners and combines their predictions to devise one strong rule. Following multiple iterations, weak learners are integrated to form one strong learner which will predict an outcome that is most accurate.

Prediction

Once the algorithm was trained, the model was analyzed with a test dataset; the algorithm will predict the likelihood of particular implant system as an output.

Testing of the artificial intelligence model

Figure 1 depicts the schematic illustration of training and testing of the AI model. The trained AI model was tested for its validity and performance using the test dataset. In testing, a number of implant systems identified correctly (true positive; TP) and those identified as other implant systems (false positive; FP), false negative (FN; misdetection), and true negative (TN) were identified. Accuracy was calculated based on the following formula, and ROC curve was plotted. These values interpreted the performance of the trained AI model.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}$$

RESULTS

The image classification performance of all the classifiers tested is shown in Table 1.

Classification accuracy of classifiers

Table 1 shows the classification accuracy of classifiers based on Hu moments and eigenvalues. Based on Hu moments,

the logistic regression model attained the top performance with the highest accuracy followed by SVM classifier. KNN, an X boost classifier, showed similar performance in implant recognition. All the classifiers showed similar accuracy when trained, based on eigenvalues except KNN classifier which showed lesser accuracy in comparison to the rest classifiers.

Receiver operating characteristic curves

ROC curve is a statistical tool to measure the performance of trained model and is plotted between false-positive rate (FPR) upon x-axis and true-positive rate (TPR) upon y-axis. TPR is the percentage of actual positive classes that are correctly identified. FPR denotes the percentage of classes that are incorrectly identified to be positive.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{TN + FP}$$

A classifier with random performance shows a straight line from origin which is considered as baseline where FPR = TPR. Anything above this baseline is measured to be good performance and below is bad performance. Classifiers that display a curve closer to the top left indicate better performance. The closer the curve to 45° diagonal of ROC area, the lesser is the accuracy.

Hu moments based receiver operating characteristic curves of classifiers

Logistic regression model

Figure 2 shows the ROC curve for logistic regression classifier based on Hu moments. Class 0 depicts Osstem TS III SA Regular, class 1 depicts Osstem TS III SA Medium, and class 2 depicts Noris Medical Tuff implant systems. Logistic regression showed the highest accuracy for class 2 implant systems followed by class 0 and class 1.

K neighbor classifier

Figure 3 depicts that KNN classifier showed the highest accuracy for class 0 implant system followed by class 2 and class 1 implant systems.

Support vector model

Figure 4 illustrates that SVM classifier showed the highest accuracy for class 2 implant system followed by class 0 and class 1 implant systems.

Gradient boosting (X boost) classifier

Figure 5 shows the performance of X boost classifier for classification of implant systems and did not display any difference.

Eigenvalue based receiver operating characteristic curves of classifiers

Logistic regression model

With respect to Figure 2 logistic regression model showed the highest classification accuracy for class 2 implant systems followed by class 0 and class 1; the performance was similar to performance of the same classifier based on Hu moments.

K neighbor classifier

With respect to Figure 3 KNN classifier showed the highest accuracy for class 0 implant system followed by class 2 and class 1 implant systems; this performance was similar to performance of the same classifier based on Hu moments.

Support vector model

With respect to Figure 4 SVM classifier showed the highest accuracy for class 2 implant system followed by class 0 and class 1 implant systems; this performance was similar to performance of the same classifier based on Hu moments.

Gradient boosting (X boost) classifier

With respect to Figure 5 the performance of X boost classifier for classification of each implant system was similar and did not show much difference; this performance was similar to performance of the same classifier based on Hu moments.

Among the classifiers tested, logistic regression gave the best performance followed by SVM classifiers, followed by X boost and KNN classifiers in identifying dental implant systems. In regard to the implant systems, classifiers showed good accuracy with Noris Medical Tuff (class 2) implant
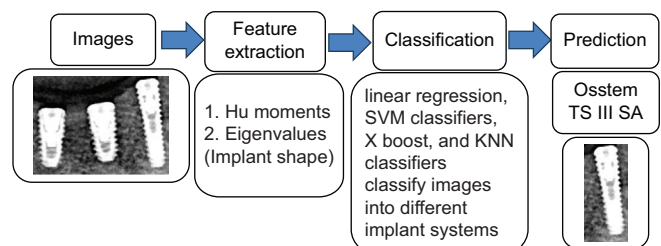
Table 1: Classification accuracy of classifiers

Machine learning model	Classification accuracy of classifiers based on Hu moments	Classification accuracy of classifiers based on eigenvalues
SVM classifiers	0.47	0.67
KNN	0.33	0.17
Logistic regression	0.50	0.67
X boost	0.33	0.67

SVM: Support vector machine, KNN: K-nearest neighbor

Figure 1: Schematic illustration of artificial intelligence model

system followed by Osstem TS III SA Regular (class 0), followed by Osstem TS III SA Medium (class 1).

DISCUSSION

Over the years, dental implants have become the standard treatment alternative for restoring missing teeth; yet biologic and mechanical, technical, and esthetic complications associated with these dental implants are inevitable.[9] Dental implants will need maintenance as long as they remain in patients' oral cavity. Due to lack of network for sharing information, clinicians face difficulty in identifying the implant system[1] and challenge is not only scientific but also professional and ethical.[10] Armamentarium required for maintenance of each implant system is different and is a critical issue in post implant treatment.[11] Hence, an automated system to identify the dental implant system will assist clinicians in instant identification and save chairside time, improving the patient care. Considering these issues, AI-based technology was adopted to formulate an algorithm to identify different implant systems.

A study was conducted on i3 processor and performed with Python comprising OpenCV, PIL, and sklearn libraries. A dataset of digital panoramic images was acquired and divided as training and testing datasets. Algorithms were trained using preprocessed images by extracting the shape features based on Hu and eigenvalues. Trained algorithms were tested for their performance using test dataset.

Digital radiographs are the starting point for evaluation of different implant brands across regions.[12,13] Radiographs are the most effective and convenient ways in daily clinical setting as a method for identifying the dental implant systems. Panoramic radiographs offer the advantages of being standardized to certain extent, hence the implant shapes are also standardized regardless of the patient, although some images were unclear due to overlapping of shadows in the maxillary anterior and sinus region. This may cause misdetection; in such cases, periapical radiographs would be useful.[3] It was observed that the number and quality of images play a crucial role in accuracy of AI model. The most commonly used implant
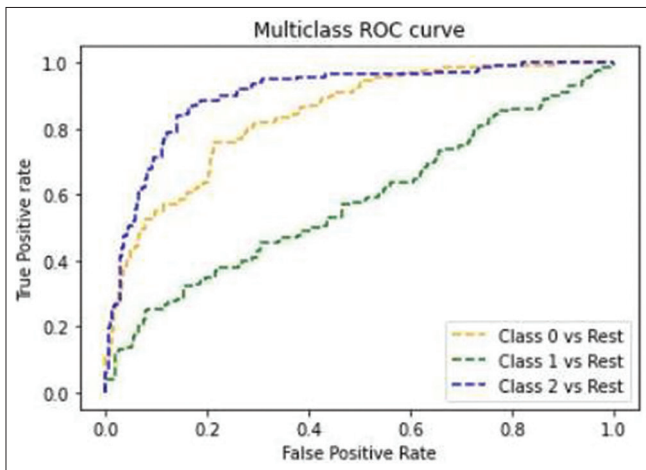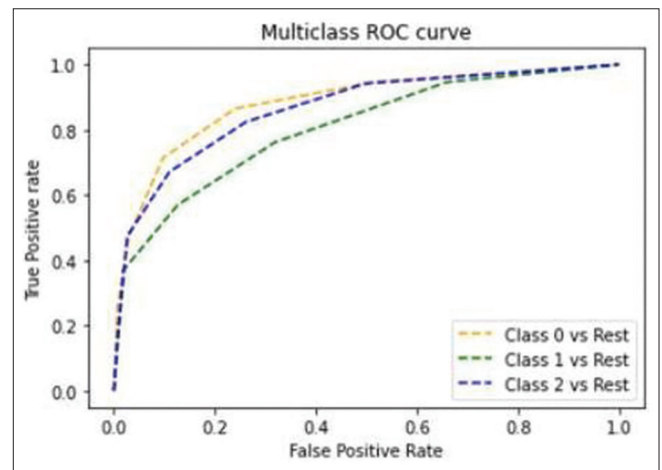

Figure 2: Logistic regression model
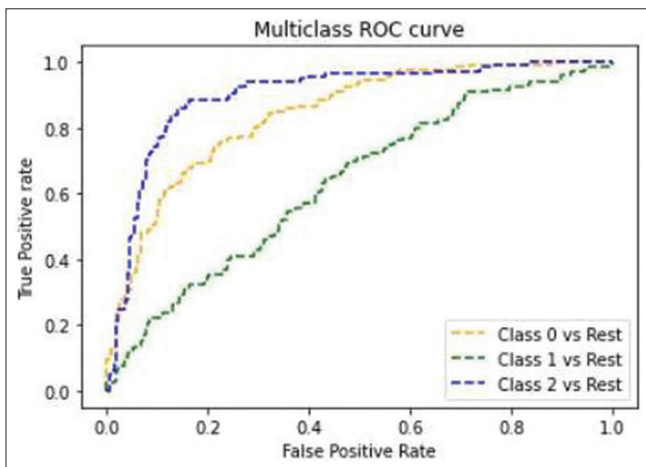

Figure 3: K neighbor classifier
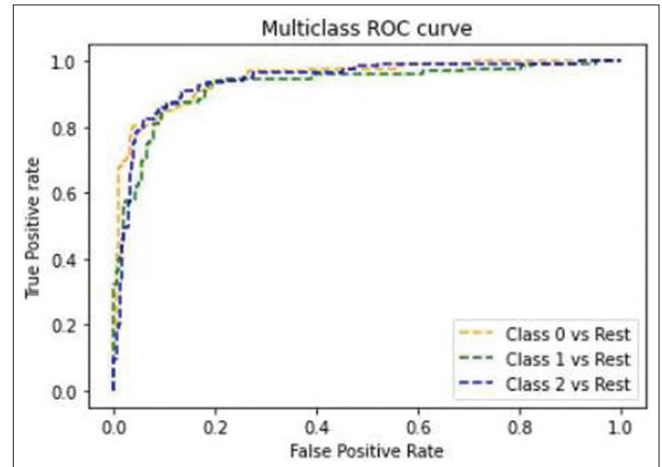

Figure 4: Support vector model

Figure 5: Gradient boosting (X boost) classifier

systems, Osstem and Noris, were considered to evaluate identification accuracy, and the algorithms used in the current study were able to identify these implant systems with an acceptable accuracy.

In computer vision and image processing, object recognition is a task of identifying the object and labeling it in an image. An object is identified by feature extraction such as color, shape, texture, or other features. Based on these features, objects are classified and each class is assigned a name.[14] In the present study, feature extraction was done based on the geometric shape (outline) of the implant. It was possible to train the classifiers for implant identification with relatively small dataset available, and classifiers could identify the implants accurately. Herein, we are proposing this method of machine learning for identifying the implants and can be generalized with a larger dataset which would improve the accuracy of the classifiers, and practical application of the AI can be attained. In the present study, classifiers were trained based on implant shape; further, different features can be extracted such as edges, corners, pixels, and apex to train the model. The proposed method can be tested with various other algorithms available, to different implant systems being used with a large and accurate database. This will create stronger implant classification methods using AI techniques.[1] In this study, we have made an attempt to apply AI technology to help solve the implant identification problem; the results showed that this objective can be achieved with good accuracy. The proposed method will assist clinicians in instant identification of implant systems saving patient and clinician time and also prevents missing problems and making errors in implant identification. This will preclude the trial and error method for implant identification, possibility of invasive treatment modalities, and treatment expenses associated with errors in implant identification.

Several studies[1-4,15,16] have applied deep learning and convolutional neural networks for identifying dental implant systems and achieved an accuracy of 0.80–0.95 in identifying the implant systems. Sukegawa *et al*.[1] used 5 CNN models which are basic CNN, VGG16, VGG19 transfer learning models, finely tuned VGG16 and VGG19 to identify implant systems and achieved accuracy in the range of 0.860–0.935. Lee *et al*.[2] used automated DCNN utilizing Neuro-T version 2.0.1 for implant recognition, and the accuracy (area under curve [AUC]) of 0.945 was achieved with this model. Lee and Jeong[15] tested deep CNN architecture (GoogLeNet Inception-v3) for implant identification and achieved accuracy (AUC) of 0.971with these models. In the current study, SVM classifiers, KNN, X boost, and logistic regression were tested. To the best of our knowledge, this is the first study to use these classifiers in implant recognition.

In medical field, AI techniques have been used to address the issues of arthroplasty implants identification. Jaret *et al*. analyzed the performance of deep learning algorithms in identifying arthroplasty implants of the knee and hip from plain radiographs. They could achieve a near-perfect accuracy of 99% and inferred that these methods constitute a significant opportunity in providing cost-efficient treatment for revision arthroplasty.[17,18]

The present pilot study had few limitations; images were taken from a single source, and different X-ray setups and devices can be considered for image acquisition to test the applicability of these algorithms. This will discern the real-life implication of machine learning in implant recognition as patients do come from across different regions, and dental implant systems and radiography devices vary in each region of the world. The second limitation was smaller dataset; an accurate and large dataset will build a stronger classification method. Third, various other machine learning models can be tested considering different features of the dental implant.

Digitalization in dentistry is on its peak in these modern times. These AI techniques can be beneficial in overcoming critical challenges in dentistry. Machine learning in particular will push forward the diagnostic measures and simplify the treatment planning minimizing the errors and eventually enhance the efficiency of entire health system. Although very limited studies are being done in this area, more systems with broader applications in implant recognition are required in this concern.[19,20]

CONCLUSION

In the current study, we illustrated that the classifiers tested were able to identify dental implant systems extracted from digital panoramic radiographs with good accuracy, even with a smaller dataset. In particular, logistic regression and SVM classifiers showed excellent classification performance. Hence, we conclude that machine learning technology is efficient in identifying the dental implant systems from radiographs and will play a significant role in assisting the clinician in implant identification, thus saving the chairside time.

Conflicts of interest
There are no conflicts of interest.

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