Automated Identification of Dental Implants: A New, Fast and Accurate Artificial Intelligence System

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ABSTRACT

Introduction: Prosthetic complications that occur to some implant prosthetics may require removal of the prosthesis for replacement or repair. Therefore, the presence of a technique to identify the type of dental implant is mandatory to provide the suitable components. Hence, the aim of the current study was to evaluate the accuracy of YOLOv8 object detection algorithm in automatic identification of the type of dental implant from digital periapical radiographs. Methods: YOLOv8m-seg object detection algorithm was used to build a model to automatically identify the type of dental implant. A set of 2573 digital periapical radiographs for six distinct dental implants manufacturers were used to train the model. The outcomes were evaluated using precision, recall, F1 score and mAP. Results: The overall accuracy of the YOLOv8m-seg model in terms of precision, recall, F1 score and mAP revealed values of 0.919, 0.98, 0.95 and 0.972 respectively. The average detection speed of the images was 1.3 seconds. The model was able to detect and identify multiple implants simultaneously on the same image. Conclusions: YOLOv8m-seg object detection algorithm is promising in identification of dental implants from periapical radiographs with high detection accuracy (97.2%), fast detection results and multi-implant detection from the same image. Clinical Significance: This AI system can accurately identify the type of osseointegrated dental implants enabling dentists to provide the appropriate prosthetic components even if different implant systems are used within the same patient. This can save tremendous amounts of time, effort and cost for both the dentist and the patient.

INTRODUCTION

Dental implantology has undergone rapid development since the introduction of osseointegration by Professor Brånemark in the 1960s. Today, it is a common and highly effective treatment option for both completely and partially edentulous patients. Continued developments in the field of dental implants have resulted in the availability of a wide range of implant systems in the market in the recent years. These implant systems are selected and placed based mainly on the preferences and familiarity of clinicians.

Although dental implants are considered as an effective and successful treatment option with high osseointegration rates, some complications can occur to the osseointegrated implants over time.[1] The most common type of complications that occur after successful osseointegration are the prosthetic complications such as screw loosening, screw fracture, fracture of the framework material or the veneering material... etc.[2] Such complications necessitate removal of the prosthesis for the repair process. This requires proper knowledge of the type of dental implant system used to be able to use the correct screwdriver and provide the compatible prosthetic parts.

Unfortunately, patient records may not always be available. Therefore, the presence of a technique to identify the type of dental implant is crucial for success of the treatment plan. The conventional identification of dental implants using periapical radiographs by a dentist or radiologist is a challenging task. It can also be inaccurate as they are prone to human error and requires massive expertise due to complexity of implant analyzing features such as thread design, threads number, implant connection and degree of implant taper. Inaccurate implant identification can impose significant costs on dentists if they order the incorrect abutment or any other prosthetic part.[3]

With the recent revolution in the aspect of artificial intelligence, it can be implemented in different fields including the dental field. Artificial intelligence (AI) depends on the utilization of intelligent, machine-based algorithms that closely resemble human brain processes to analyze and categorize complex data automatically.[4]

Object detection is a computer vision task that aims at determining where objects are located in a given image in a process called object localization and also determining which category each object belongs to, which is called object classification.[5] Object detection can be performed using either classic image processing techniques or by the newly developed deep learning networks. There are various object detection algorithms including: a) *two-stage object detection algorithms* such as convolutional neural networks (CNN), Region-Based Convolutional Neural Networks (R-CNN), and Fast R-CNN, (b) *one-stage object detection algorithms*: such as Single-shot detector, and YOLO (You Only Look Once). The two stage object detection algorithms perform the steps of object localization and object classification in two separate stages which achieve high accuracy at the expense of the performance fastness. On the other hand, the one-stage object detection algorithms perform both steps in one stage to achieve faster performance at the expense of the accuracy.[6]

The YOLO (You Only Look Once) framework has stood out for its remarkable balance of speed and accuracy enabling rapid and reliable identification of objects in images. YOLO object detection framework was first introduced in 2016 by Joseph Redmon and it was significantly faster than any other object detector. Since then, different versions of YOLO have been released. YOLO works by dividing an image into a grid, predicting bounding boxes and class probabilities for each grid cell. This approach allows YOLO to make detections with high accuracy and speed, even in cases where objects are partially obscured or small.[7] In 2023, the latest version of YOLO was released and named YOLOv8.

Therefore, the aim of the current study was to evaluate the accuracy of YOLOv8 in automatic identification of the type of dental implant from digital periapical radiographs.

MATERIALS AND METHODS

DATA PREPARATION

Digital periapical radiographs of six known dental implant systems were collected from different clinics in Egypt. The radiographs were categorized into six groups based on the implant manufacturer (Dentium, Fortis, NucleOSS, ROOTT, Straumann and Zimmer). Images with severe noise, blur, distortion, or any major artifact that could hinder the detection were excluded from the dataset. The approval of this study was granted by the institutional ethics committee. Informed consent was not required as all image data were anonymized and de-identified prior to analysis.[8]

DATA ANNOTATION

All of the implant systems used were manually annotated using Roboflow Annotate which is a web-based image annotation tool that can be used to label images for object detection, classification, and segmentation tasks. In order to proceed with the object detection task, the ground truth bounding boxes needed to be labeled to avoid false positives or incorrect detection results. The prosthetic suprastructure and the occlusal part of the abutment were excluded from the bounding box during labeling. The ground truth was focused on the outer implant's borders. (*Figure 1*). The last step in this stage was to generate corresponding labels for each ground truth for each implant type.

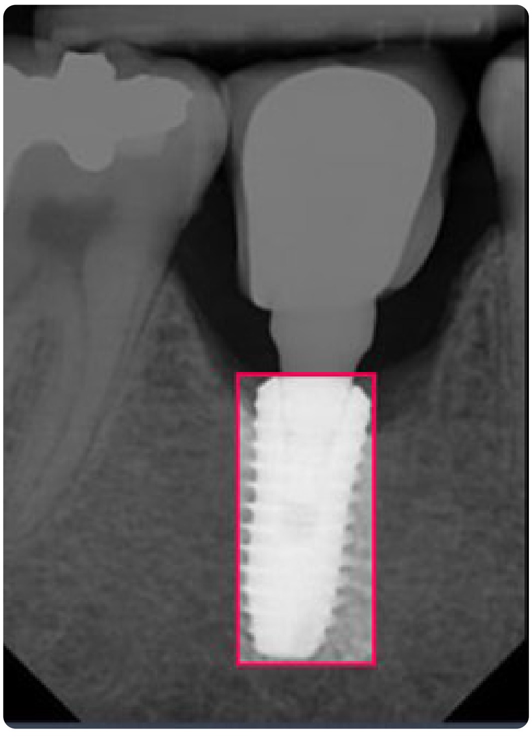

Figure 1: Annotation of the dental implant.

OBJECT DETECTION MODEL

YOLOv8m-seg object detection algorithm model was implemented. The YOLOv8m-seg architecture makes use of a few key components to perform object detection tasks. The Backbone is a series of convolutional layers that extract relevant features from the input image. The Spatial pyramid pooling-fast layer (SPPF) and the subsequent convolution layers process features at a variety of scales, while the up-sample layers increase the resolution of the feature maps. The Detection module uses a set of convolution and linear layers to map the high-dimensional features to the output bounding boxes and object classes.

MODEL TRAINING

All images were JPEG files, and the image size was fixed at (800 x 800) as larger images can provide better accuracy. This choice aligns with the recommendation in YOLO to use square images with the width and height set to be a multiple of 32 as the YOLO network down samples the input by 32.

Augmentation techniques were applied on the dataset including flipping (horizontal and vertical), 90° rotations (clockwise, counter-clockwise, upside down), and rotations between -28° and +28°. The total number of digital periapical radiographic images was 2573 images. The number of radiographic images used for each system were as follows: Dentium (482), Fortis (420), NucleOSS (430), ROOTT (418), Straumann (410) and Zimmer (413). The annotated images were randomly divided into three datasets: 80% for training (2059 images), 10% for validation (257 images), and 10% for testing (257 images). The training dataset is used to train the model, the validation dataset is used to tune the hyperparameters of the model, and the testing dataset is used to evaluate the final performance of the model.

The dataset was trained to detect implants. The training dataset was divided into 64 batches for each epoch, and a total of 100 epochs were conducted. For the validation set, the object confidence threshold for detection (conf) was set to 0.4, and the IOU threshold was set to 0.5.

ASSESSMENT OF THE LEARNING RESULT

The Precision, Recall, F1 score and mean average precision (mAP) were assessed to evaluate the detection accuracy of the trained model.

The algorithm classifies the images as true positive (TP), true negative (TN), false positive (FP), and false negative (FP). The prediction is considered true positive when it was identified and classified as a member of the true class. For example, when the algorithm detects a Zimmer implant and classifies it in the Zimmer dental implant class, it's considered positive. On the other hand, the prediction is considered true negative when the object in the image is classified as not being a member of the class we are trying to identify. For example, when the algorithm is searching for Zimmer implant and when it viewed a Straumann implant, it was able to identify that it's not a Zimmer implant and hence it is not a member of the Zimmer dental implant class.

False positive predictions occur when the algorithm falsely categorize an object in a certain class e.g., searching for a Zimmer implant and then wrongly categorizing Straumann implant in the Zimmer group. False negative predictions occur when the algorithm falsely omits an object out of a certain class e.g., searching for a Zimmer implant and then unable to identify an image with Zimmer implant in the Zimmer group.

Precision: is the ratio between the True Positives and all the Positives. A higher precision value (close to 1) indicates fewer false positives, meaning that the algorithm is more accurate in identifying objects.

$$Precision = \frac{Tp}{(Tp + Fp)}$$

Recall: is the measure of how the model correctly identifies True Positives. In other words, it measures the number of positive predictions that are correctly predicted positive, i.e., the true positives. The higher the precision and recall values, the better the detection performance.

$$Recall = \frac{Tp}{(Tp + Tn)}$$

The F1 score is a machine learning evaluation metric that combines precision and recall values of a model into a single score. This metric computes how many times a model made a correct prediction across the entire dataset. The closer the value of F1 score to 1.0, the more accurate the model is.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Mean average precision (mAP): it is machine learning metric that is used to measure the overall performance of object detection models. It measures the model's ability to accurately identify and localize objects in images, taking into account both the precision and recall of the model across all classes. The higher the mAP score, the more accurate is the model in its detection. In other words, high mAP value means that the model is able to accurately identify and localize objects in images with a high degree of precision and recall.

RESULTS

The model achieved overall high detection accuracy with mAP of 0.972 and F1 score of 0.95. The overall performance detection of the model has shown 0.919 precision and 0.98 recall. Considering successful detection, the model achieved the highest detection accuracy with F1 score of 0.995 and mAP of 0.995 for Zimmer dental implants. The least detection accuracy was obtained for NucleOSS dental implants with F1 score of 0.742 and mAP of 0.791. The detailed performance of YOLOv8m-seg model is presented in *(Table 1)*.

Table 1. Detection performance of YOLOv8m-seg model

Dental implant System	Precision	Recall	F1 score	mAP
Dentium	1	0.972	0.986	0.995
Fortis	0.915	0.727	0.810	0.965
Nucleoss	0.735	0.75	0.742	0.791
ROOTT	0.924	1	0.960	0.995
Straumann	0.93	0.778	0.847	0.943
Zimmer	0.991	1	0.995	0.995
Overall Accuracy	0.919	0.98	0.95	0.972

The number of epochs is a hyperparameter that defines the number of times that the learning algorithm will work through the entire training dataset. Each time a dataset passes through an algorithm, it is said to have completed an epoch. The progress of precision over epochs for each class is shown in (*Figure 2*).

The confusion matrix for the YOLOv8m-seg model is also shown in (*Figure 3*). The confusion matrix is a matrix of size 2×2 for binary classification with actual true values on the horizontal axis and predicted values on the vertical axis.

VISUALIZATION OF MODEL PREDICTION RESULTS

The output image shows the detection results in the form of a bounding box on the successfully detected dental implant, with the detection confidence value written above the bounding box. The average detection speed of the image was 1.3 secs. The model was able to detect more than one implant system within the same image. (*Figure 4*).

DISCUSSION

The aim of the current study was to evaluate the accuracy of YOLOv8m-seg as a computer vision algorithm for automatic identification of the type of dental implant from periapical radiographs.

Periapical radiographs were used in our study owing to its higher resolution for the implant part which would yield better recognition results than panoramic images.[9] In addition, the periapical radiographs are easy to take in the clinic due to the presence of intraoral x-ray device in every clinic. Moreover, Augmentation techniques were applied on the periapical radiographic images such as rotations and flipping to simulate all the possible angulations that the radiograph could be clinically taken with and to imitate the flipping conditions that the images could be inserted into the software by the dentist.

Based on the findings of our study, YOLOv8 model achieved high performance, with an overall F1 score of 0.95 and mAP of 0.972. This may be due to the large and complex structure of

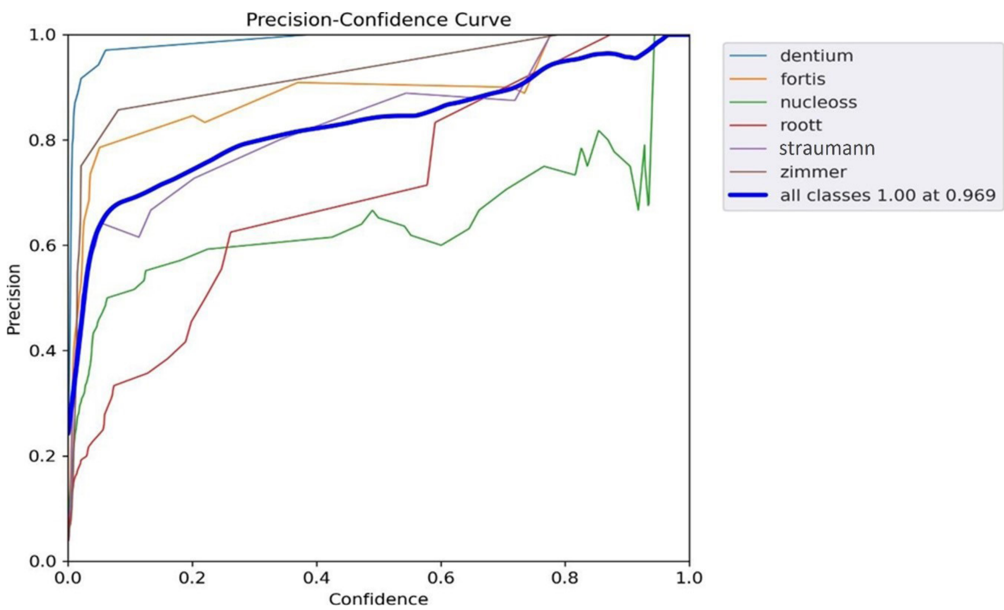

Figure 2: The progress of precision over epochs for each class.

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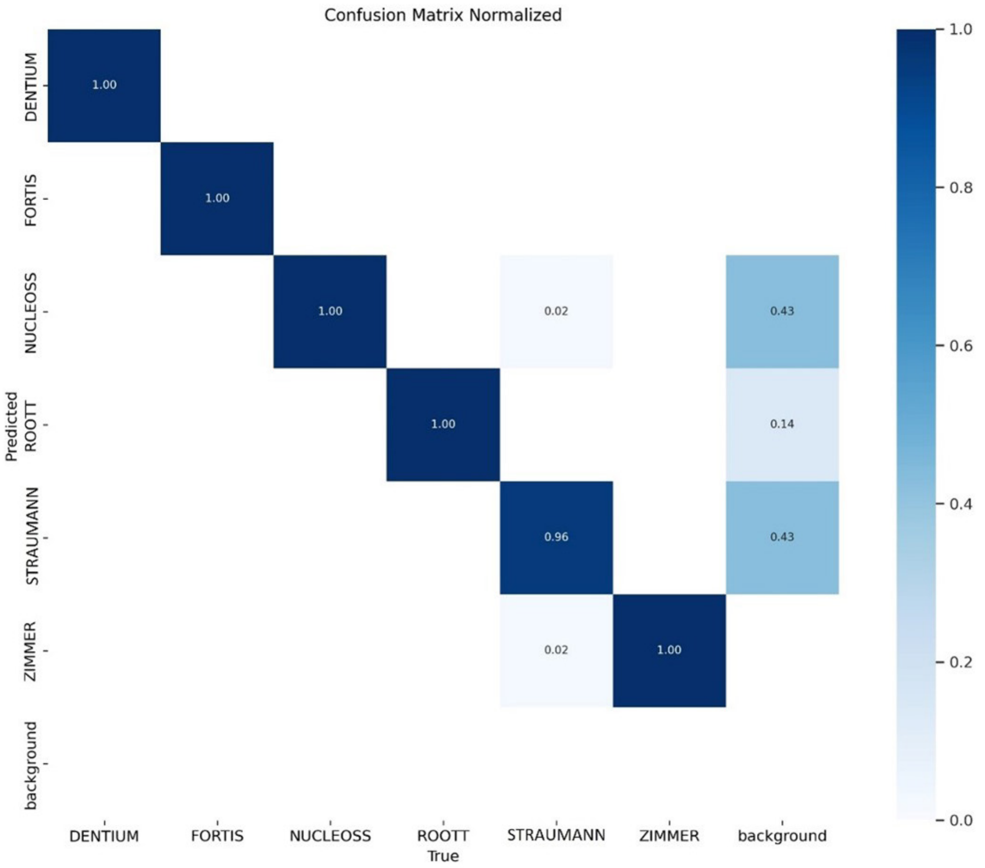

Figure 3: YOLOv8m-seg confusion matrix.

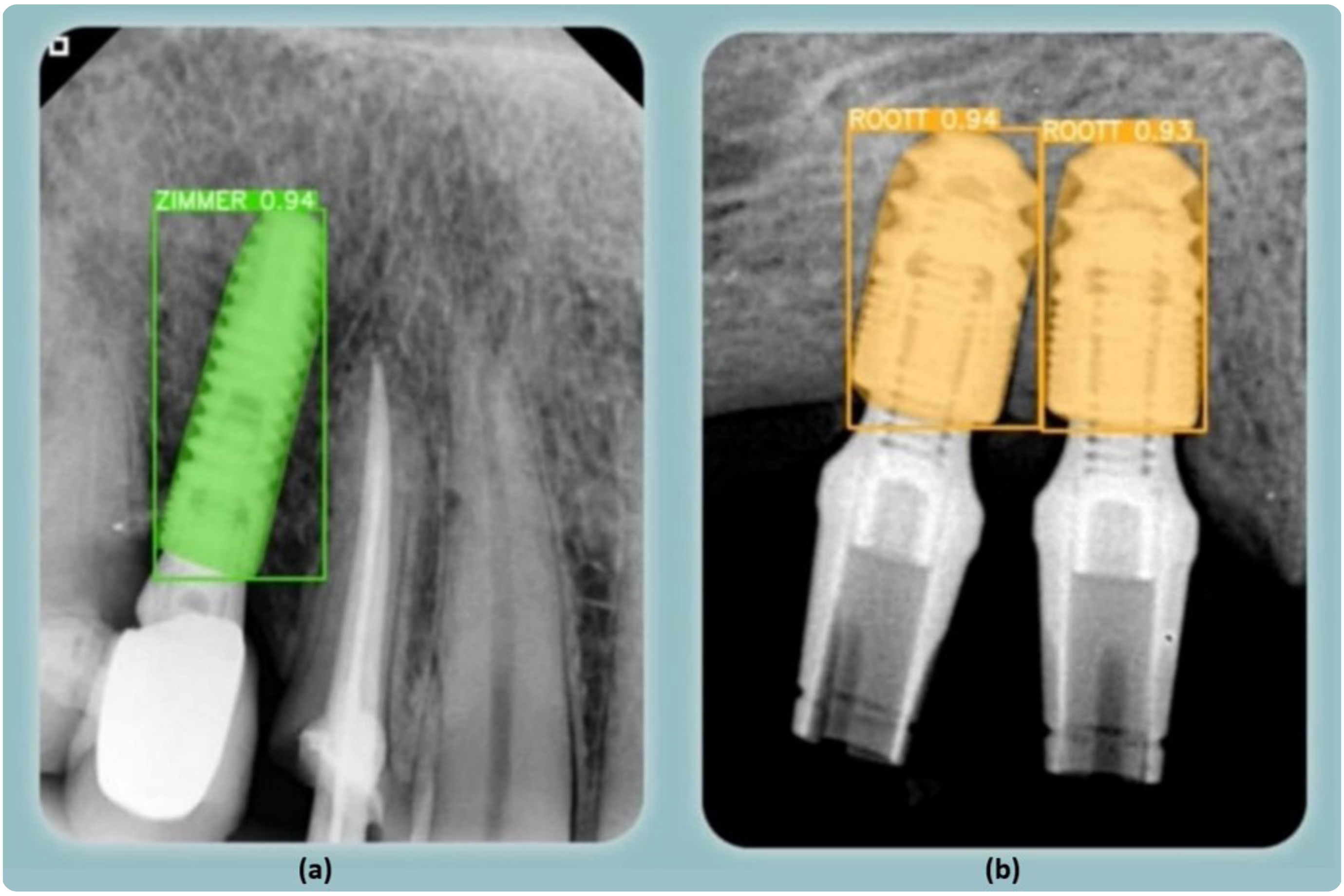

Figure 4: Examples of Output detection results showing: (a) the name of the implant system with the detection confidence value written above the bounding box (b) the ability of the model to detect two implants in the same image.

YOLOv8 framework which allows the model to learn more about the objects it is detecting, leading to high accuracy. In addition, the YOLOv8 framework uses a sophisticated loss function. This loss function helps the model to learn more effectively, which can enhance the accuracy of prediction.[10] A loss function is a mathematical function that quantifies the difference between predicted and actual values in a machine learning model. It measures the model's performance and guides the optimization process by providing feedback on how well it fits the data.[11]

The prediction shows up in an average of 1.3 seconds. This high speed of detection can be explained based on the working technique of YOLO framework which belongs to the one-stage object detection algorithms. It accomplishes the detection task with a single pass of the network, as opposed to other approaches that either used sliding windows followed by a classifier that needed to run hundreds or thousands of times per image or the more advanced methods that divided the task into two-steps, where the first step detects possible regions with objects or regions proposals and the second step run a classifier on the proposals.[7,12]

Another important feature in our study is the ability of the model to detect different types of implants within the same image simultaneously. This is due to the ability of YOLOv8m-seg model to perform multi-scale object detection. The model utilizes a feature pyramid network to detect objects of different sizes and scales within an image allowing the model to detect large and small objects within the same image.[13]

There are few studies available in the literature that evaluate different artificial intelligence systems in identification of the type of the implant system from radiographs. In a study performed by da Mata Santos *et al*., convolutional neural networks (CNN) were used to identify three different implant brands from periapical radiographs and the resultant test accuracy of the model was 85.29%.[14] In another study performed by Takahashi *et al*., YOLOv3 was used to identify six implant systems from panoramic radiographs. Their resultant model showed mAP value of 0.71.[15]

As far as we know, the present study is the first study that uses YOLOv8 algorithm to identify the type of dental implant system from periapical radiographs. The results of the present study suggest that YOLOv8 based system can assist dentists and contribute to accurate fast detection of the type of dental implants which can tremendously save much time and cost for both the dentist and the patient.

Nonetheless, there are some limitations of the present study. Although the study involved six types of dental implant systems, it's still insufficient for clinical practice. The implant systems under consideration in this study are still being used in clinical practice up till now. To expand the results of this study for future work, it is necessary to build a database comprising a wide variety of implant fixture systems. For the implant systems that has been discontinued, it's mandatory that the dentists develop lists for all those systems and gather radiographic images for such implants so that the newly developed software can easily detect and identify any type of dental implant even if it's discontinued. This will enable dentists to provide the prosthetic components compatible with the identified implant system.

CONCLUSION

YOLOv8m-seg Object detection algorithm is very promising in identification of dental implants from periapical radiographs with high accuracy, fast detection results and multi-implant detection from the same image.

CONFLICTS OF INTEREST

The present study was self-funded, and the authors report no conflict of interest.

REFERENCES

1. Pi-Anfruns, J. Complications in implant dentistry. *Alpha Omegan*. 2014; **107**.
2. Hanif, A., Qureshi, S., Sheikh, Z. and Rashid, H. Complications in implant dentistry. *Euro J Dent*. 2017; **11**:135-140.
3. Sharma, D., Jhingta, P. and Bathla, S.C. Challenges in Dental Implant Identification and Need of Universal Dental Implant Identification, Numbering, and Nomenclature System. Int J Prosthodont Restor Dent. 2020; **10**:146-150.
4. Lu, Y. Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of Management Analytics*. 2019; **6**:1-29.
5. Gupta, A.K., Seal, A., Prasad, M. and Khanna, P. Salient object detection techniques in computer vision—A survey. *Entropy*. 2020; **22**:1174.
6. Sharma, V. and Mir, R.N. A comprehensive and systematic look up into deep learning based object detection techniques: A review. *Computer Science Review*. 2020; **38**:100301.
7. Terven, J. and Cordova-Esparza, D. A comprehensive review of YOLO: From YOLOv1 to YOLOv8 and beyond. arXiv preprint *arXiv*. 2023;2304.00501.
8. Vinayahalingam, S., Goey, R.S., Kempers, S., Schoep, J., Cherici, T., Moin, D.A. and Hanisch, M. Automated chart filing on panoramic radiographs using deep learning. *J Dent*. 2021; **115**:103864.
9. Antony, D.P., Thomas, T. and Nivedhitha, M.S. Two-dimensional periapical, panoramic radiography versus three-dimensional cone-beam computed tomography in the detection of periapical lesion after endodontic treatment: A systematic review. *Cureus*. 2020; **12**:e7736.
10. Yin, Y., Li, H. and Fu, W. Faster-YOLO: An accurate and faster object detection method. *Digital Signal Processing*. 2020; **102**:102756.
11. Wang, Q., Ma, Y., Zhao, K. and Tian, Y. A comprehensive survey of loss functions in machine learning. *Annals of Data Science*. 2020: **9**:1-26.
12. Kaur, R. and Singh, S. A comprehensive review of object detection with deep learning. *Digital Signal Processing*. 2022:103812.
13. Kim, J.H., Kim, N. and Won, C.S. *High-Speed Drone Detection Based On Yolo-V8*. InICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2023 Jun 4 (pp. 1-2). IEEE.
14. da Mata Santos, R.P., Vieira Oliveira Prado, H.E., Aranha Neto, I.S., Alves de Oliveira, G.A., Vespasiano Silva, A.I., Gonçalves Zenóbio, E. and Ricardo Manzi F. Automated Identification of Dental Implants Using Artificial Intelligence. *Int JOral Maxillofac Implants*. 2021; **36**:918-923.
15. Takahashi, T., Nozaki, K., Gonda, T., Mameno, T., Wada, M. and Ikebe, K. Identification of dental implants using deep learning—pilot study. *Int J Implant Dent*. 2020; **6**:1-6.

