

An Artificial Intelligence model for implant segmentation on periapical radiographs

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Abstract

Objective: To segment dental implants on PA radiographs using a Deep Learning (DL) algorithm. To compare the performance of the algorithm relative to ground truth determined by the human annotator.

Methodology: Three hundred PA radiographs were retrieved from the radiographic database and consequently annotated to label implants as well as teeth on the LabelMe annotation software. The dataset was augmented to increase the number of images in the training data and a total of 1294 images were used to train, validate and test the DL algorithm. An untrained U-net was downloaded and trained on the annotated dataset to allow detection of implants using polygons on PA radiographs.

Results: A total of one hundred and thirty unseen images were run through the trained U-net to determine its ability to segment implants on PA radiographs. The performance metrics are as follows: accuracy of 93.8%, precision of 90%, recall of 83%, F-1 score of 86%, Intersection over Union of 86.4% and loss = 21%.

Conclusion: The trained DL algorithm segmented implants on PA radiographs with high performance similar to that of the humans who labelled the images forming the ground truth.

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Introduction

Branemark placed the first dental implant in a human volunteer in 1965, since then implantology has paved its way into dentistry to replace teeth.¹ Missing teeth can have serious functional and psychological consequences and therefore are preferably replaced by dentists to maintain the wellbeing of their patients. Although several modalities are available for replacement of teeth, including removable prostheses, fixed replacements are preferred.² Of the fixed replacement options, fixed partial dentures require preparation of adjacent teeth compromising their vitality, whereas dental implants have the advantage of being independent of the adjacent teeth.³

During placement of dental implants into the jawbone, a periapical (PA) radiograph is exposed which confirms the position of implant fixture as well as forming a baseline for future evaluations.⁴ With the advent of digitized

radiography in dentistry, extensive radiographic data is now available. And with more technological advancements this data is being used for automation of dental radiographic diagnoses using Artificial Intelligence (AI).⁵ Deep Learning (DL) models are dominating the field of computer vision especially in the medical and dental fields, aiding clinicians in diagnoses and treatment planning.⁶ DL is a subset of AI that consist of neural networks that allow these models to train independently and learn various features with limited need for manual human input.⁷ Various diagnostic DL models exist that aid dentists in teeth segmentation and numbering as well pathology detection on different types of radiographs used in clinical practice.⁵ Further research into the detection of all possible findings on dental radiographs will help in improving the efficiency of diagnoses and treatment planning in everyday clinical settings.

Several studies have trained DL models in dental implantology using radiographs, these appear as highly radio-opaque fixtures in bone.⁸ Some studies classify different types of dental implant systems whereas others perform implant detection.⁸ These tasks have been carried out on a range of radiographs, including PA, Orthopantomograms (OPGs) and Cone Beam Computed Tomography (CBCT) images.^{5,7,9} However, mere classification of dental implants has very limited application in helping dentists identify unknown implants placed outside of their practice in order to provide

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compatible restorations.^{5,7} Additionally, all existing studies that perform implant classification as well detection use bounding boxes to localise them on radiographic images.^{5,7} This technique of implant detection leads to incorporation of the background around implants, leading to a wider region of interest.⁷ A more advanced technique that allows precise delineation of the region of interest is segmentation.⁵⁻⁷ Therefore, for better localisation of implants via segmentation is better suited that identifies each pixel associated with the implant fixture for a more robust diagnostic process.⁷ There is lack of literature on DL models trained for implant detection on PA radiographs and this study aims to detect implants by performing pixel-wise segmentation.

Methods

This study was conducted at Aga Khan University Hospital, Karachi, Pakistan from May 2023 to August 2023. A total of 300 PA radiographs were retrieved from the database of dental clinics after obtaining exemption from the ethics review committee of the institution (ERC# 2023-8434-24001). The sample size was estimated arbitrarily to achieve optimal performance of the AI model for implant segmentation task, the authors aimed to increase the number of images in the dataset if the desired accuracy was not achieved.

PA radiographs were selected via the non-probability purposive sampling technique according to the set inclusion and exclusion criteria as follows. Good quality PA radiographs with at least one dental implant per image were included. Blurred PA radiographs or those with artifacts were excluded from the study. These radiographs were downloaded from SIDEXIS XG 2.63 software in Joint Photographic Experts Group (JPEG) format from the image database. Data confidentiality was maintained by assigning a serial number to each OPG, instead of using the patient's medical record number. The patient's identifiers were not disclosed at any point in the study. The data was kept in a password-protected database, only accessible to the authors of this study.

Dataset annotation and preprocessing

The dataset of 300 PA radiographs was annotated using the LabelMe annotation tool.¹⁰ Implants were localized using bounding boxes and all teeth present in the image were delineated using polygons, the labels included 'implant' and 'tooth'(figure 1). These annotations were carried out by two investigators (NHAD & FUMR) of this study. The annotations by the first investigator were checked by the second investigator and vice versa. All investigators were calibrated on the use of this software before beginning the annotation process. Any mistakes in

the annotations were corrected prior to the commencement of training. These annotations formed the ground truth for training the algorithm and against which the performance was evaluated in the test dataset.

The dental implants annotated with bounding boxes were converted into binary masks using the Roboflow toolbox (figure 1).¹¹ The dataset consisted of images of various dimensions including 1000x680, 1200x868, 668x1012, 455x679 and 636x679 pixels. All images as well as the binary masks were resized to 256x256 pixels for homogeneity in the dataset as well as to reduce the computational resources for training the model by lowering resolution. Since the number of images forming the dataset was relatively small, data augmentation techniques were applied to increase the total number of images in the dataset. These augmentations included flipping, rotation, and different brightness to produce variations of an image in the original dataset. Image augmentation is a widely used technique to increase the dataset size, without alerting the information content of the image. The enhanced dataset was then split into training, validation and testing sets. A total of 1294 augmented images were generated and consequently used to train, validate and test the DL model.

AI model training

The training set images along with their corresponding masks were then passed to the U-net model for implant segmentation.¹² The selection of U-net model was based on its efficient performance in the image segmentation tasks using encoder and decoder blocks.¹² Adam optimiser was used in this study to update network weights in the training stage of the model. The learning rate was set to 0.1 and the binary cross-entropy loss was used as network convergence. The model converged after 30 epochs, with a batch size of 32 images. The model performance was evaluated using different metrics, including accuracy, loss, and mean Intersection over Union (IoU). After successful training, the trained weights were saved, and the model was validated and tested using the test images set. These test images were not included in the training of the model and were passed as 'observe images' in run time. The model was trained on 1035 images, further validated on 129 images in 10 epochs with a batch size of 32 images per iteration. Consequently, its performance was gauged on 130 unseen images.

Results

The trained U-net carried out implant segmentation on PA radiographs with the following performance metrics: accuracy of 93.8%, precision of 90%, recall of 83%, F-1

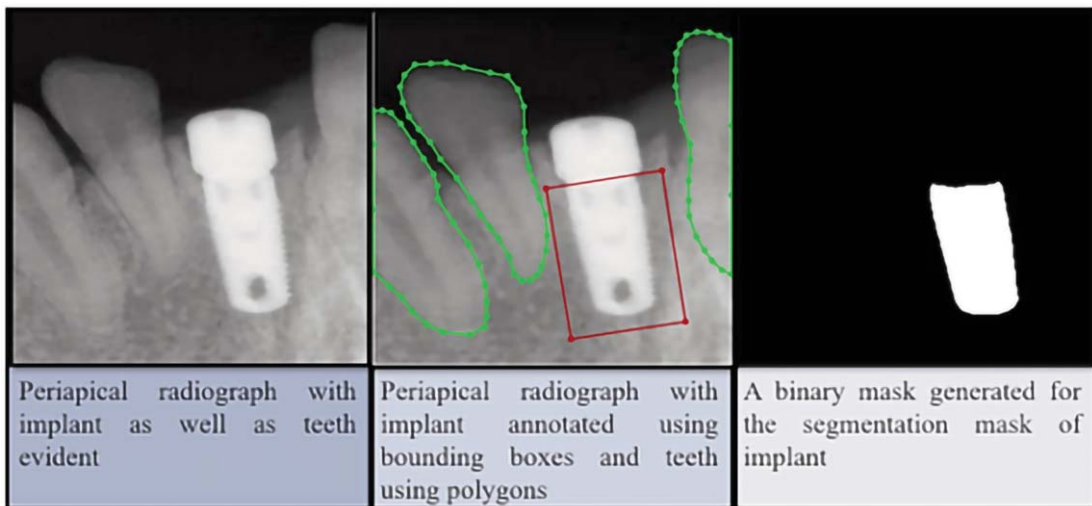


Figure-1: The unannotated image was labelled using the LabelMe annotation tool to localize implants using bounding boxes and teeth were denoted using polygons. Binary segmentation masks were generated to be used for training the AI model.

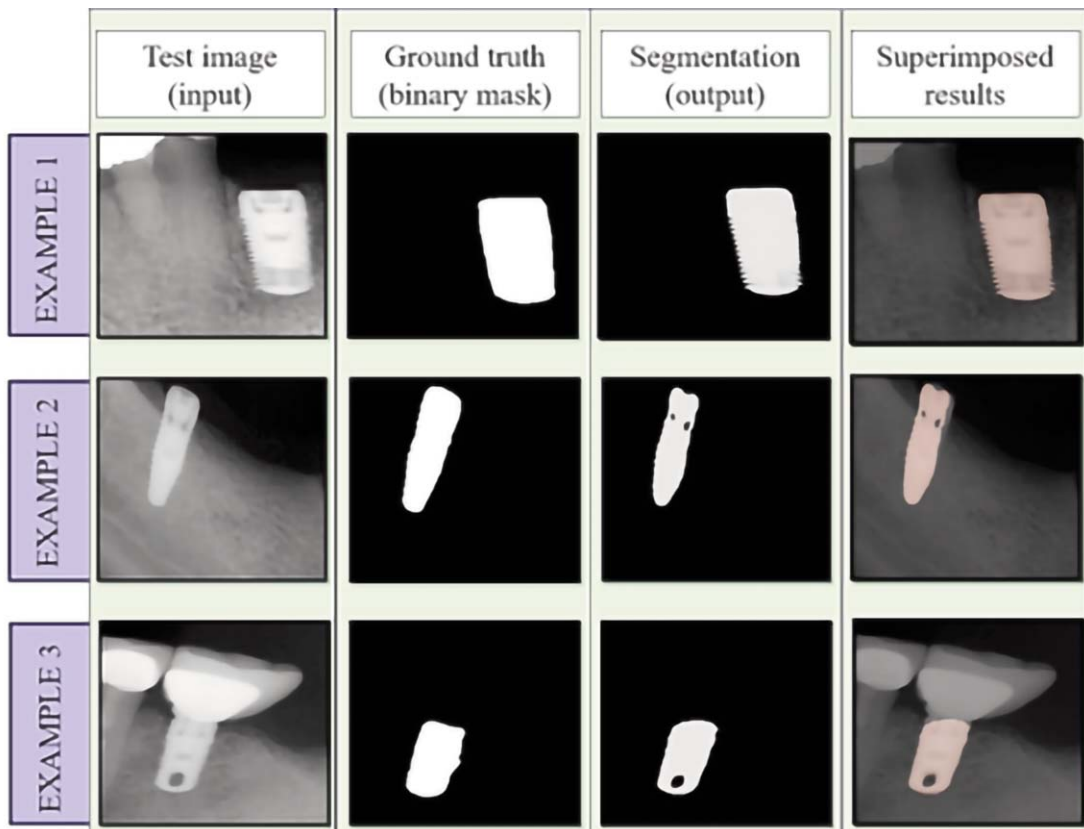


Figure-2: Three examples of the unseen test images and their binary masks forming ground truth are shown. The segmentation results of the trained U-net model show enhanced results with the screw indentations, screw channels and the vent being detected as well. Furthermore, the resulting segmented masks are shown superimposed on the unseen test images for better visualization of the results.

score of 86%, IoU of 86.4% and loss = 21%. The visual results are also shown in figure 2.

Discussion

The pixel-wise segmentation of a feature in an image is considered to be a superior method for localising of the region of interest.⁵⁻⁷ It has the advantage of separating the background in the image and each pixel of the feature

is precisely classified, leading to a detailed understanding of the image.⁷ In this study, the DL U-net model accurately identified and closely delineated implants on PA radiographs.

The annotations formed the ground truth against which the performance of the U-net model was gauged on unseen images. The initial labels were in the form of bounding boxes localising the implant as well as segmentation masks to delineate the teeth in the image. These were pre-processed to form binary segmentation masks, which were consequently used to train the model. The masks allowed for the segmentation technique to be carried out for implant detection as opposed to bounding boxes that incorporate the redundant background pixels in the training dataset. This technique leads to increased computation costs and a lack of precise delineation of the region of interest, i.e., implants.

In the visual results, the outcome of the model seems to be an improvement on the binary masks used for training. In the segmentation masks, the implants are not labelled according to the screw indentation, and the screw vents are labelled as a part of the implant. The testing masks show extremely precise labelling of implants with the screw indentations meticulously delineated as well as identification of the radiolucent screw vents that were not annotated as such. The U-net model was able to identify the radiolucent serrations associated with the screw indentation as well as the radiolucent screw vent as separate from the actual implant fixture. This is due to the black box nature of AI that allows these models to learn information independently and make accurate predictions based on that knowledge.¹³

This striking visual performance may be under-represented by the numerical performance metrics. Since the implant was trained to identify implants as smooth structures, in the mathematical sense it 'mis-classified' pixels to create the serrations in its prediction masks. Similarly, the model assumed that it 'mis-classified' the screw vents and screw channels by identifying it separately from the implant since it was not trained to do so.

This is the first study to carry out implant segmentation on PA radiographs, a study by Elgarba et al. performed implant segmentation on CBCT.⁹ In this study, the model achieved a mean accuracy of 96.5%, mean precision of 89.5%, mean recall of 97.7% and mean IoU of 88%.⁹ The performance of this 3D U-net is comparable to the U-net in this study but the results cannot be compared due to the different radiographic modalities used in both studies. CBCTs have a high radiation dose as well as

higher costs and are not the radiograph of choice after implant placement and at follow-up. PA radiographs have the advantage of being cheaper, low radiation exposure and widely available in dental clinics. Other studies have performed implant classification to identify the different types of implant systems on PA radiographs as well as OPGs.¹⁴⁻¹⁷ These models were developed with the aim to help dentists identify unknown implant systems placed outside of their practices, in order to restore them.¹⁸ These models do not provide other diagnostic information moreover these do not utilize segmentation technique to delineate implants.

However, the trained U-net in this study is not generalisable on radiographs obtained from different institutions. To improve its performance, further training on a dataset from various centres need to be included.⁶ The number of images used for training was relatively smaller and to mitigate this issue, image augmentation techniques were applied to inflate the total number of images from 300 to 1294. This still does not overcome limited generalisability of this model and a wide variety of images exposed from different machines are still required. Due to the lack of access to a graphics processing unit, the authors had to limit the resolution of the images causing a limitation in the performance of this model. Furthermore, the implant segmentation model needs to be incorporated with AI models in dentistry performing other tasks such as teeth segmentation and numbering and pathology detection, etc to be deployable in dental clinics as adjunctive softwares.⁵

Conclusion

The U-net in this study performs the task of implant segmentation with results comparable to the annotator who labelled the images. Further training of this model on a heterogenous dataset is required before this model can be used in daily clinical practice. The performance of an AI model should be gauged by its applicability in the real world rather than the performance metrics and in this study the trained U-net model exhibited significant real-life applicability. This model can be integrated with other DL algorithms trained to perform different dental diagnostic tasks on radiographs to develop an all-encompassing dental diagnostic model. (The code of the following can be found at: <https://github.com/Niihhaa/implant-segmentation.git>).

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