Journal of Dentistry 122 (2022) 104139

Contents lists available at ScienceDirect

Journal of Dentistry

journal homepage: www.elsevier.com/locate/jdent

Automated detection and labelling of teeth and small edentulous regions on cone-beam computed tomography using convolutional neural networks☆

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ARTICLE INFO

Keywords:
Artificial Intelligence
Deep Learning
Cone-Beam Computed Tomography
Tooth Detection
Digital imaging/radiology
Digital Dentistry

ABSTRACT

Objective: To assess the accuracy of a novel Artificial Intelligence (AI)-driven tool for automated detection of teeth and small edentulous regions on Cone-Beam Computed Tomography (CBCT) images.
Materials and Methods: After AI training and testing with 175 CBCT scans (130 for training and 40 for testing), validation was performed on a total of 46 CBCT scans selected for this purpose. Scans were split into fully dentate and partially dentate patients (small edentulous regions). The AI Driven tool (Virtual Patient Creator, Relu BV, Leuven, Belgium) automatically detected, segmented and labelled teeth and edentulous regions. Human performance served as clinical reference. Accuracy and speed of the AI-driven tool to detect and label teeth and edentulous regions in partially edentulous jaws were assessed. Automatic tooth segmentation was compared to manually refined segmentation and accuracy by means of Intersetion over Union (IoU) and 95% Hausdorff Distance served as a secondary outcome.
Results: The AI-driven tool achieved a general accuracy of 99.7% and 99% for detection and labelling of teeth and missing teeth for both fully dentate and partially dentate patients, respectively. Automated detections took a median time of 1.5s, while the human operator median time was 98s (P<0.0001). Segmentation accuracy measured by Intersection over Union was 0.96 and 0.97 for fully dentate and partially edentulous jaws respectively.
Conclusions: The AI-driven tool was accurate and fast for CBCT-based detection, segmentation and labelling of teeth and missing teeth in partial edentulism.
Clinical Significance: The use of AI may represent a promising time-saving tool serving radiological reporting, with a major step forward towards automated dental charting, as well as surgical and treatment planning.

1. Introduction

The speedy improvement in computer technology, the capacity of storing large amounts of information have allowed the gathering of data with greater variety and the formation of big databases, also known as "Big Data", for dental and medical researches in general [1]. Big Data together with the increasing computer performance have brought Artificial Intelligence (AI) back to the arena. AI is a general term coined to describe the development of computer systems aiming to perform tasks that require human cognition, enhancing the human-machine interaction. New AI techniques, such as Machine Learning (ML), are able to learn through inputs, analyze and extract statistical patterns in complex

☆ The researchers Maurício do Nascimento Gerhardt and Rocharles Cavalcantes Fontenele were supported by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001
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https://doi.org/10.1016/j.jdent.2022.104139
Received 28 October 2021; Received in revised form 4 April 2022; Accepted 20 April 2022
Available online 21 April 2022

data and accomplish tasks, such as detection of diseases, image segmentation and enhancement [2–7].

Deep Learning (DL) is a subset of AI that allows computational models composed by multiple processing layers to learn the complex statistical pattern in data with multiple levels of abstraction. DL is structured as a nested hierarchy of concepts in which the underlying composition is made of artificial neural networks (ANN). ANN are layers of processing units known as neurons, sequentially organized via weighted connections. There are plenty of types of deep neural networks. The ones specialised in dealing with grid-like topology data, such as 2D and 3D images, are called Convolutional Neural Networks (CNN) [5,7–9]. Currently, computer-aided diagnosis may assist radiologists to interpret images in order to attain precise and time saving identification and classification of teeth, meanwhile avoiding incorporation of human errors associated with either lack of specialised training, or lack of attention to detailed diagnosis, or fatigue [4,10,11].

AI-based tools have proven to be accurate and fast for detection, segmentation and classification of teeth on 2D imaging, even in the presence of dental treatment such as dental fillings and root canal treatment. It has also been implemented for detection, classification, or disease diagnosis, as well as classification of jaw bone morphology [12–15].

Also some notable AI applications on 3D images found in the literature include the detection, segmentation and classification of the teeth, mandibular canal, pharyngeal airspace and mandibular bone [16–19].

Cone-Beam Computed Tomography (CBCT) has replaced Multi-Slice Computed Tomography (MSCT) due to its major advantages over the latter, such as three-dimensional view of the maxillofacial structures at reasonable dose of radiation, low cost, ease-of-use and more comfortable for patient and operator. Its 3D reconstruction and spatial information provided has been used for planning purposes in many fields of dentistry [20–26].

As a resource for dental assessments, diagnoses and outcomes evaluation, the CBCT scans need to be interpreted by a radiologist who will then elaborate the report. If the computer could identify and label the oral condition correctly prior to the radiologist's reading, it would reduce the time necessary for image interpretations. Accurate detection, segmentation and labelling of teeth and edentulous regions might contribute to further development of computer-assisted and automated dental charting and dental treatment planning. However, scientific reports on computer-assisted detection and labelling of teeth on CBCTs are scarce. If present, these often lack challenging situations, such as in partial edentulism [27,28].

Thus, the aim of this study was to assess the performance and clinically validate a novel AI-driven tool for accurate detection and classification of teeth and small edentulous areas on CBCT. Accuracy of the system to detect and classify teeth/missing teeth were the primary outcomes, time analysis and accuracy of tooth segmentation were secondary outcomes. The hypothesis of the present study was that this novel AI-driven tool would be accurate for detecting and labelling teeth and small edentulous regions with minimal time consumption.

2. Materials and methods

The present study was designed as an observational study to test accuracy of an AI-based tool for tooth classification and segmentation on CBCTs of fully and partially dentate patients. CBCT data used in this study were retrieved from the Center of Dentomaxillofacial Radiology of the University Hospitals, from March 2016 to January 2021. This study was approved by the Medical Ethical Committee of the UZ Leuven (B322201525552) and was conducted according to the ICH-GCP principles and the Declaration of Helsinki (2013). Image data were anonymized prior to analysis.

This study followed the STARD guideline. The STARD guideline, from the Equator Network, is a checklist of essential items for reporting diagnostic accuracy studies (https://www.equator-network.org/reporting-guidelines/stard/)

2.1. Image dataset

A total of 175 CBCT scans were used for training of the detection model. This was split into 140 scans for training and 35 for testing. Images from the training dataset were preprocessed using three different data augmentation techniques, with the aim to virtually enlarge the dataset. In first, the dataset was extended with the application of spatial augmentations (rotation, scaling and elastic deformation) on each individual image. Secondly, the dataset was extended using mixup, a technique that takes a linear combination of a random pair of images. In the third place, the dataset was further enlarged with the application of cutout to an individual image, where the grey values of a randomly-selected small cube of voxels were put to zero.

For the clinical validation of the tool in this study, a total of 46 CBCT scans were used to assess accuracy of the system to detect teeth and small edentulous regions. The scans were obtained using two CBCT units, 3D Accuitomo 170 (Morita, Kyoto, Japan) and NewTom VGI EVO (Cefla, Imola, Italy), which were used to acquire 32 and 14 CBCTs respectively. The sample was split into "Fully Dentate" (23 scans) and "Partially Dentate" (small edentulous areas - 23 scans). This sample had never been seen by the AI (see sample composition in Fig. 1).

The inclusion criteria were a) patients with permanent dentition; b) Healthy natural dentition or presence of low density restorative materials; c) up to two consecutive missing teeth (or three if the consecutive missing teeth were next to the missing third molar); d) CBCT scans comprising both maxilla and mandible. The exclusion criteria were a) edentulous patients; b) complex cases with crowns, bridges and/or dental implants or great amount of artefacts; c) large edentulous areas (more than two consecutive missing teeth); d) patients with mixed dentition; e) patients with impacted and/or supernumerary teeth.

The acquisition parameters used for each CBCT unit were as follows: 110kV, 3-20 mA and Field of Views (FOVs) varying among 8×8, 10×10, 12×8, 16×16 and 24×19cm for the NewTom VGI EVO and 90kV, 5mA and FOV varying among 8×8, 10×10, 14×10 and 17×12cm for the 3D Accuitomo 170.

2.2. Human tooth detection and labelling

For the human tooth detection and labelling, the first author (MNG) visualized the CBCTs scans on a clinical workstation (1920×1200 pixels, MDRC-2124, Barco N.V., Kortrijk, Belgium) using the Impax viewer (Agfa Healthcare v6.5.5, Mortsel, Belgium) and classified teeth according to the International Standards Organization Designation System (ISO System) [29] or annotate as absent in case of a missing tooth (Fig. 2). The time needed to assess and label was recorded using a stopwatch. The information from each case were filled in a Microsoft Excel spreadsheet. The analysis performed by the specialist was considered as the ground truth.

2.3. Automated tooth detection and labelling

This study used Virtual Patient Creator (Relu BV, Leuven, Belgium - https://creator.relu.eu - 2021), an interactive platform for AI-driven segmentations of dentomaxillofacial anatomy. This platform uses a deep learning algorithm that detects and segments the teeth in two subsequent networks, both based on the 3D U-Net architecture [30]. In a first network the teeth are detected in a down sampled image and rough segmentation is provided. The rough segmentation allowed the proposal of regions of interest (ROI), which were cropped and down-sampled to a fixed resolution (0.7×0.7×0.7 mm) enabling the use of a deep neural network for multi-class classification (33 classes: 32 teeth classes and background class representing structures not belonging to a tooth class) and subsequent 3D segmentation (Fig. 3). An Adam optimizer optimizes the hyperparameters with an initial learning rate of 1.25e-4 which

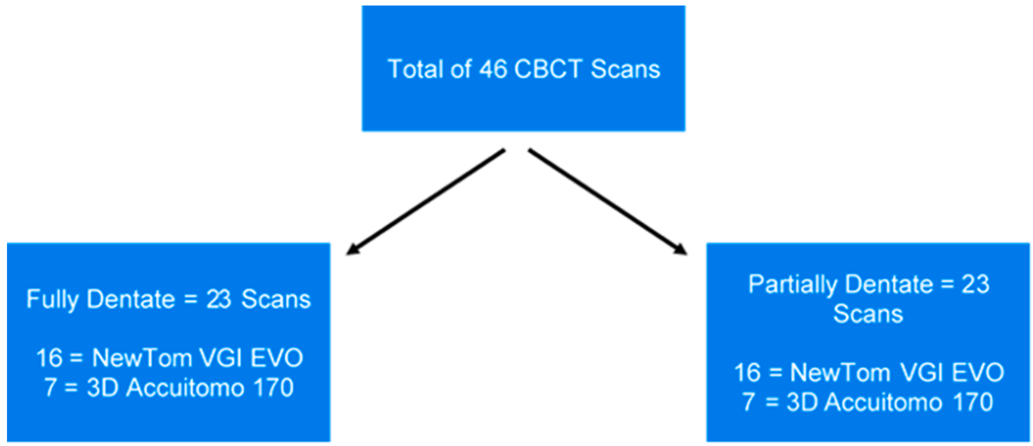

Fig. 1. CBCTs Dataset sample distribution.

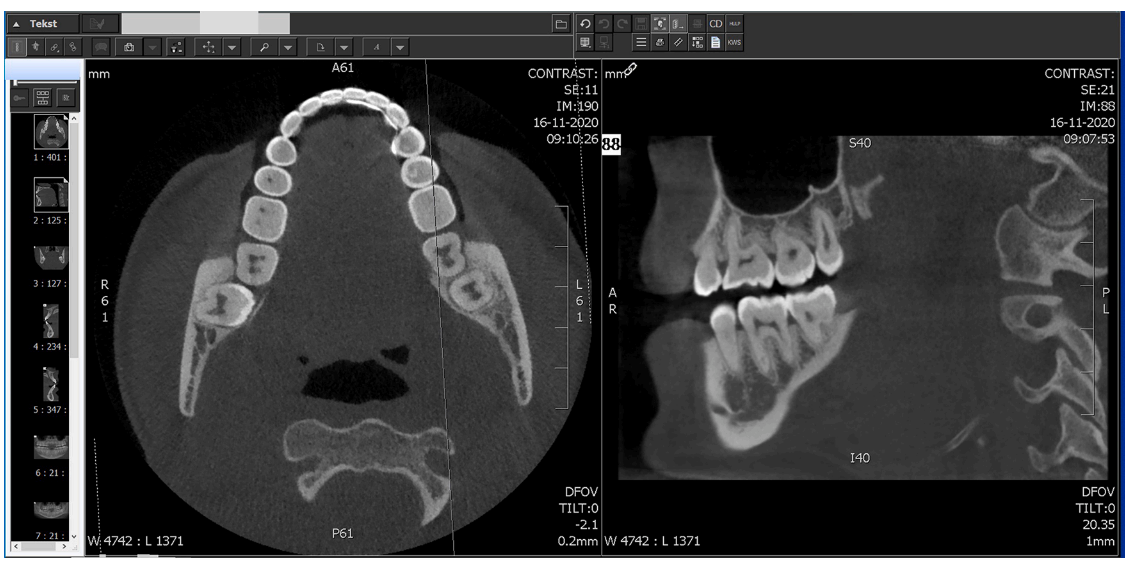

Fig. 2. Human visualisation of the CBCT for detection and labelling of teeth and edentulous areas navigating on the Impax viewer.

halved 7 times over 300 epochs. Early stopping is determined on a validation set containing 10% of the scans.

All CBCT scans were uploaded in the platform that automatically segmented the teeth providing individual 3D models in Standard Triangle Language (STL) (Fig. 4). Automated tooth segmentations were all judged by an expert (MNG) and those needing adjustments were manually refined using the same aforementioned platform and its tools, such as the brush (adds or removes pixels of the segmentation map) and smart brush (groups pixels together according to their tonal intensities). The manually refined 3D models were opposed to automatically segmented models to allow for accuracy assessment of the AI segmentation. The time needed to display detection and labelling were provided by the platform. Tooth labelling of each case was verified and noted in a Microsoft Excel spreadsheet.

2.4. Statistical analysis

Statistical data were analyzed with GraphPad Prism 7.00 (GraphPad Software Inc., La Jolla, CA, USA).

For the automated detection, the following metrics were used: accuracy = TP+TN/TP+TN+FP+FN, recall = TP/TP+FN and precision = TP/TP+FP, where TP, TN, FP and FN represent true-positive, true negative, false-positive, and false-negative results, respectively. The TP represented correctly labelled teeth by the AI algorithm compared to the ground truth. The TN represented the missing teeth correctly labelled, while the FP represented the misinterpreted teeth or other structure identified as tooth, and the FN results were the present teeth that were not annotated, thus representing an edentulous area (Fig. 5).

The normality of the data regarding the time needed for the human versus machine detections were assessed with a Shapiro-Wilk test. As the data followed a non-normal distribution, the Mann Whitney test was used to compare the groups. The level of significance was set at 5%.

The accuracy of segmentation was reported using two different metrics: Intersection over union (IoU), which is the amount of overlapping voxels between the predicted model and the adjusted model and, the 95% Hausdorff Distance (95HDmm), which is the 95 percentile of the maximal distance between the predicted model and the ground truth.

3. Results

Considering the validation dataset consisting of 46 CBCT scans, 1.472 labels were established as a ground truth by a dental specialist (tooth number or missing tooth).

For fully dentate patients, 736 labels were established. The system was capable of agreeing with the dental specialist on 734 and failed in 2. There were 2 FN. Therefore, the system achieved a general accuracy of 99.7%, 99.7% of recall and 100% of precision.

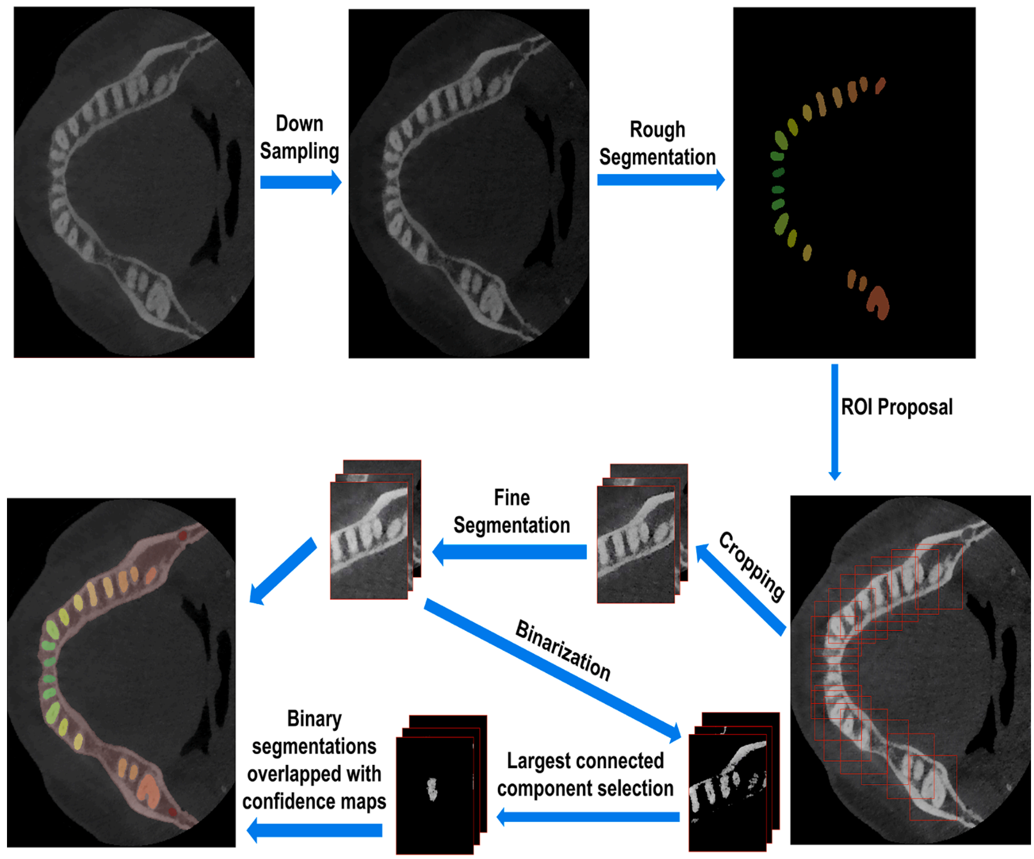

Fig. 3. Workflow of the 3D-net for tooth identification and segmentation. Firstly, the CBCT file is down-sampled and teeth are detected. Rough segmentation is provided, allowing the identification of ROIs, which are cropped and down-sampled to a fixed resolution where multi-class tooth classification and final segmentation are done by a deep neural network.

Also 736 labels were established for patients presenting small edentulous areas. The artificial intelligence tool agreed with the professional on 729 and failed in 7. There were 7 FP. Thus, the general accuracy achieved in patients presenting small edentulous areas was 99%. Recall was 100% and precision was 98.7%.

Descriptive statistics regarding the time needed to perform the analysis are shown in Table 1. The dental specialist took a median time of 98s to perform the analysis while the AI had a median time of 1.5s to do the same task. Results of the Mann Whitney test were statistically significant (p-value < 0.001).

Table 2 reports on the accuracy of tooth segmentation by means of Intersection over Union (IoU) and 95% Hausdorff Distance (mm) for both fully and partially dentate groups respectively.

4. Discussion

Applications of Artificial Intelligence in dentistry have been investigated considering its potential for fast, accurate and consistent performance of clinical tasks, such as detection, classification and segmentation of orofacial structures and to provide accurate diagnoses. However, currently, the use of AI in clinical dentistry is still limited to specific tasks, such as automatic detection of diseases, image segmentation and imaging resolution enhancement. 3D segmentation of oral structures is still an innovative application [2,6,16–19].

The present study relates on the development and validation of a novel AI-driven tool to automatically detect and label teeth and small edentulous areas on CBCT with high levels of accuracy and speed. The automated detection of teeth on 2D and 3D radiological images represents a time-saving task and a first step towards the automatization of dental charts and reports based on these exams. Furthermore, towards the future, dental software applications may incorporate AI-tools trained to perform specific tasks meanwhile dealing with patient-specific situations. This may hold the potential to automatically provide personalized treatment plans based on a highly enriched scientific evidence. In this context, automated detection of teeth and edentulous areas is a potential time-saving tool for software applications aiming to provide (automated) design of removable partial dentures or presurgical treatment plans involving (automated) implant placement, for example.

Prior studies on automated 2D tooth detection/labelling, such as the study by Zhang et al. [31] and Chen et al. [32] who applied CNN to recognise teeth in periapical radiographs achieved a precision rate of 95% and 90% respectively. Periapical radiographs are taken with intraoral films that only fit few teeth given their limited size. So, the system only needs to classify the present teeth in 2 or 3 classes, but based on scarce references. The studies by Tuzoff et al. [12] and Leite et al. [14] which applied subclasses of AI to detect and number teeth in panoramic radiographs achieved high levels of accuracy. In this trend, our study showed that the automated classification of teeth/missing teeth performed by the AI can also achieve excellent accuracy metrics on 3D imaging modalities such as CBCTs.

The present results showed 99.7% of general accuracy, 99.7% of recall and 100% of precision for tooth detection and labelling in scans of fully dentate patients. In patients presenting small edentulous areas, the accuracy was 99%, recall was 100% and precision was 98.7%. These high levels of accuracy are comparable and show that, even in the absence of some teeth, the AI network is competent to overcome this challenging situation and to correctly classify the present dentition. Also, these results are higher than those reported by Miki et al. [27] who achieved 88.8% in classification accuracy. When they applied data augmentation, the results improved to 93.8%. However, they excluded

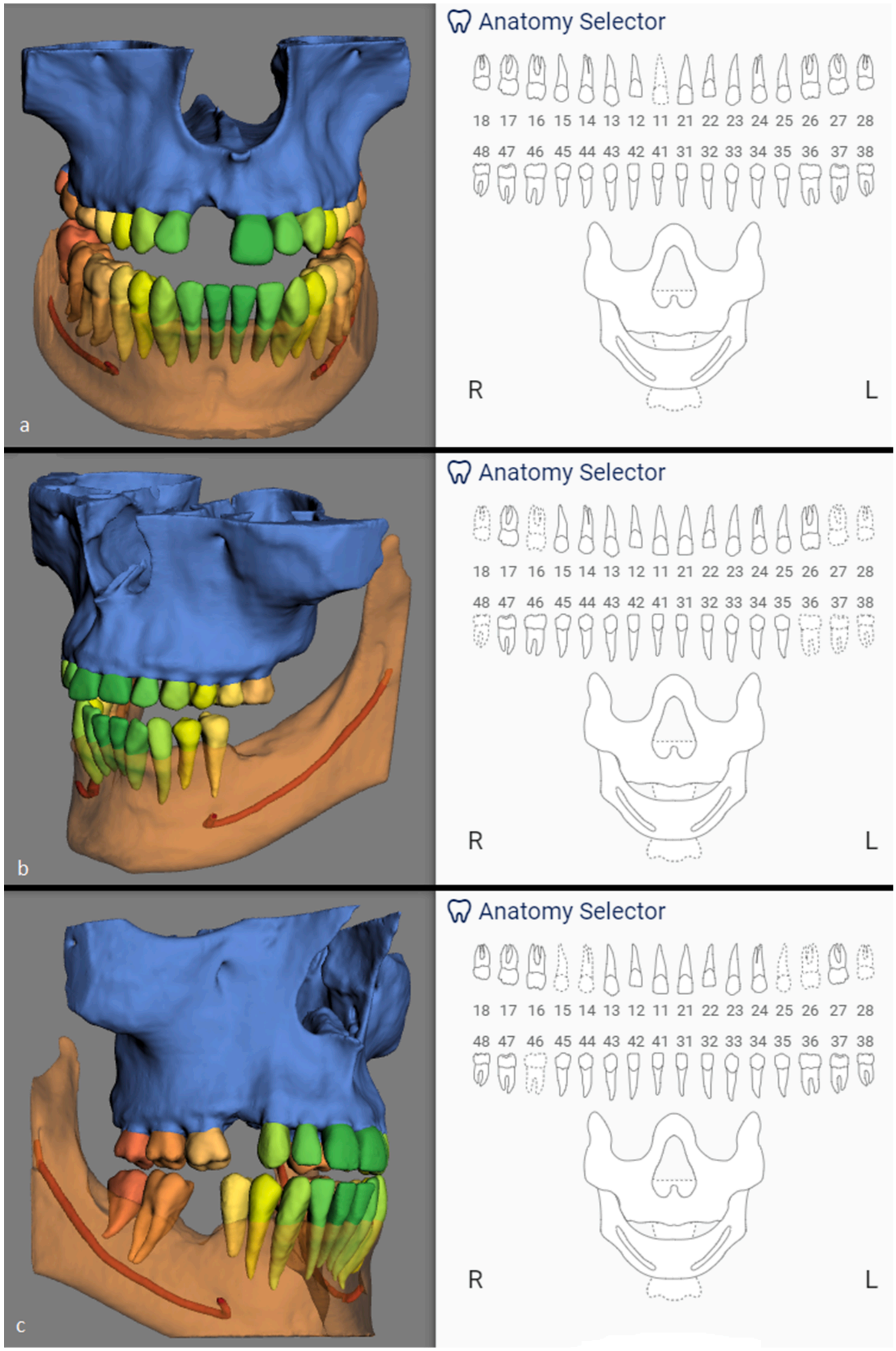

Fig. 4. Correct automated detection and labelling of teeth and edentulous regions done by the AI algorithm on Virtual Patient Creator (Relu BV, Leuven, Belgium) - 3D models on the left side and correspondent dental charting on the right side: a) anterior missing tooth; b) consecutive missing upper molars (27 and 28) and lower molars (36, 37 and 38); c) missing upper premolars (14 and 15) and missing lower molar (46).

cases with third molars because of the small sample size. Cui et al. [28] also checked the accuracy of detection and labelling of teeth on CBCTs. They used a Spatial Relation Component in their two-stage network and achieved accuracy of 99.5% in tooth detection and 96.8% in identification. They did not train the system with third molars and, although these teeth were correctly segmented, they were always mislabelled.

In the present study, there were 7 FP in cases of partially dentate patients. That means that some particular structure present in the region, such as dense areas within the trabecular bone, was detected as being a tooth. The Virtual Patient Creator (http://creator.relu.eu) is an

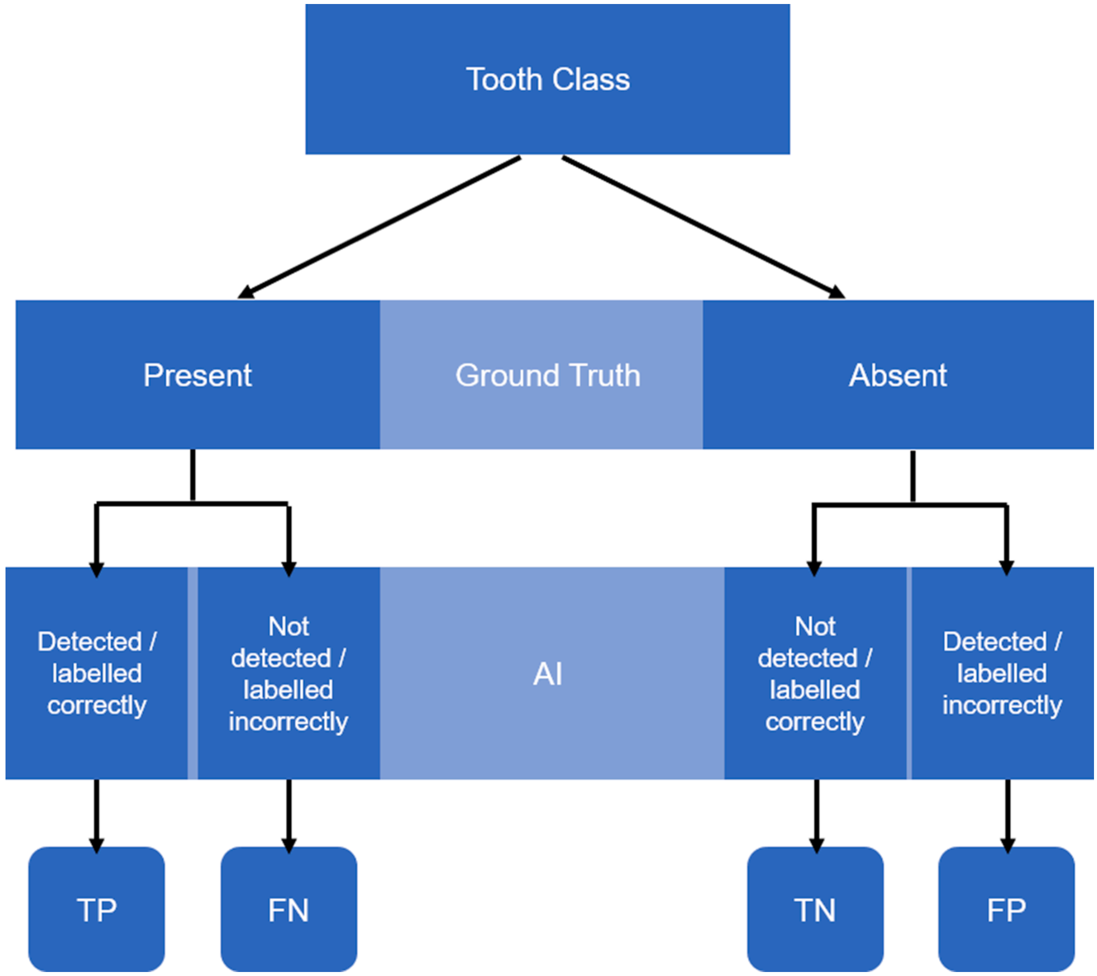

Fig. 5. Schematic representation of automated tooth/edentulous areas accuracy analyses. The classification done by the expert was considered as the ground truth. Present tooth correctly labelled by the AI was considered as a true positive (TP). Present tooth not detected by the AI and consequently mislabelled as an edentulous area was considered as a false negative (FN). Absent tooth correctly detected was considered as a true negative (TN). Edentulous areas that were detected but assigned to the wrong tooth space were considered as a false positive (FP).

Table 1
Median time for detection and labelling.

Observer	Median	Min	Max	Significance
Dental Specialist	98s	47s	165s	
Artificial Intelligence	1.5s	1.2s	2.9s	P < 0.0001

Table 2
Accuracy of tooth segmentation by comparing the AI model and the ground truth per group.

Metrics	Fully Dentate	Partially Dentate
Intersection over Union (IoU)	0.96	0.97
95% Hausdorff Distance (mm)	0.33	0.15

interactive platform and the user can easily change a tooth's classification or remove it, and, thus, correct the automated dental charting. Besides that, our tool has not been trained for bone segmentation and classification yet, which we believe can improve our results.

The consistency of the system was also tested by uploading the same cases another time. The platform was 100% consistent, meaning that the outputs were exactly the same as in the first time. Thus, one advantage of the system is that it avoids human (intra and inter-subject) variability.

The automated labelling of teeth was 65x faster than human detection. This showed how the aid of AI can be time-saving in the daily routine of an oral radiologist and general dentist as well, helping to speed up the interpretation and elaboration of dental reports from CBCTs. Leite et al. [14] analyzed the time needed for segmentation of tooth in dental panoramic radiographs, but this process comes one step earlier in the development of an AI system. Lahoud et al. [33] analyzed the accuracy performance and time needed for AI-driven tooth segmentation on CBCTs. Overall, the accuracy of the automated segmentations did not differ from the clinical reference, but the average time needed for user segmentation was 6.6 mins while the fully automated segmentation took a mean time of 0.5 mins (p-value < 0.05).

It is worth mentioning that the AI-driven tool used in this study not only detected and labelled the teeth, but also segmented them. The AI took a median time of 15s for complete detection and segmentation of the full dentition. The difference between the AI and a human operator for full dentition detection and segmentation would be a lot greater. The 6.6 mins mean reported by Lahoud et al. [33] is related to the segmentation of single rooted teeth (incisors, canines and premolars). Thus, one can assume that it would take even more time for a human operator to segment all single rooted teeth and molars. To the best of our knowledge, there is still no study in the literature reporting on the difference in time needed to identify and label teeth on CBCTs between a dental specialist and an AI-tool.

This study represents the first step in the development of a more robust system that will be able to detect and label a wide variety of situations, aiming to accelerate the reports of dental imaging accurately, and also to provide automated dental planning based on identification of the oral condition, such as detection of edentulous areas.

However, we do recognize some limitations that need to be overcome in order to apply this technology in clinical dentistry. The system needs to be trained and validated for different radiological machines and various patient samples with a more complex dental status, such as more missing teeth, more dental restorations, prostheses and dental implants. The same holds true for CBCT images with motion or metal artefacts. These limitations are closely related to the richness of the training dataset and some of them are tackled with the help of data augmentation, to virtually expand the dataset and, in that way, to introduce more variability. If the AI is exposed to more variability, it becomes better in generalizability. The AI under study has been updated on a consistent basis with the inclusion of more data to improve its robustness/generazability. In addition, the cloud-based system used in this study processed CBCT scans in digital imaging and communication in medicine (DICOM) files (single file or folder) with a current maximum of 2 gigabytes (GB). Uploading depends on user's internet processing speed capacity and CBCT file size.

Although the system is capable of processing CBCT scans with smaller and larger FOVs than the range reported, the accuracy for such cases was not checked due to the inclusion criteria of this study.

We have to realise that even after proper training and validation of all the aforementioned variables, time and accuracy analysis might deviate from the currently reported values. The system should always be used by trained professionals, once it aims to augment their capacity, not to replaced them.

5. Conclusions

The AI-tool presented in this study is accurate and fast for automatic detection and classification of teeth and small edentulous areas on CBCT scans. Its performance is comparable to a human expert, yet more consistent.

CRediT authorship contribution statement

Maurício do Nascimento Gerhardt: Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Rocharles Cavalcante Fontenele:** Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing. **André Ferreira Leite:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – review & editing. **Pierre Lahoud:** Conceptualization, Methodology, Validation, Investigation, Data curation, Writing – review & editing. **Adriaan Van Gerven:** Methodology, Software, Validation, Resources, Formal analysis, Writing – review & editing. **Holger Willems:** Conceptualization, Methodology, Software, Validation, Resources, Writing – review & editing, Funding acquisition. **Andreas Smolders:** Methodology, Software, Validation, Resources, Writing – review & editing. **Thomas Beznik:** Methodology, Software, Validation, Resources, Writing – review & editing. **Reinhilde Jacobs:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Acknowledgments

This publication was made possible with the support of a Development Project of VLAIO (Flanders Innovation & Entrepreneurship).

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