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A novel deep learning system for multi-class tooth segmentation and classification on cone beam computed tomography. A validation study

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A R T I C L E I N F O

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A B S T R A C T

Objectives: Automatic tooth segmentation and classification from cone beam computed tomography (CBCT) have become an integral component of the digital dental workflows. Therefore, the aim of this study was to develop and validate a deep learning approach for an automatic tooth segmentation and classification from CBCT images.
Methods: A dataset of 186 CBCT scans was acquired from two CBCT machines with different acquisition settings. An artificial intelligence (AI) framework was built to segment and classify teeth. Teeth were segmented in a three-step approach with each step consisting of a 3D U-Net and step 2 included classification. The dataset was divided into training set (140 scans) to train the model based on ground-truth segmented teeth, validation set (35 scans) to test the model performance and test set (11 scans) to evaluate the model performance compared to ground-truth. Different evaluation metrics were used such as precision, recall rate and time.
Results: The AI framework correctly segmented teeth with optimal precision (0.98±0.02) and recall (0.83±0.05). The difference between the AI model and ground-truth was 0.56±0.38 mm based on 95% Hausdorff distance confirming the high performance of AI compared to ground-truth. Furthermore, segmentation of all the teeth within a scan was more than 1800 times faster for AI compared to that of an expert. Teeth classification also performed optimally with a recall rate of 98.5% and precision of 97.9%.
Conclusions: The proposed 3D U-Net based AI framework is an accurate and time-efficient deep learning system for automatic tooth segmentation and classification without expert refinement.
Clinical significance: The proposed system might enable potential future applications for diagnostics and treatment planning in the field of digital dentistry, while reducing clinical workload.

1. Introduction

Tooth segmentation is of vital importance in a daily clinical practice. The identification of teeth with their exact shapes and boundaries on two-dimensional (2D) and three-dimensional (3D) images can guide dental practitioners by allowing an improved precision for early disease detection and diagnosis, treatment planning and outcome prediction [1]. Furthermore, an accurate tooth segmentation for the creation of a 3D tooth model from cone beam computed tomography (CBCT) images is a prerequisite for digital dental workflows [2,3].

An accurate digital model of individual tooth geometry could be beneficial for a number of clinical applications, such as, prosthetic evaluation, orthodontic analysis, orthodontic treatment planning, computer-aided digital implant planning, follow-up of root resorption after orthodontic treatment, canine eruption assessment and tooth autotransplantation [4–7]. Additionally, correct tooth detection and segmentation on CBCT images is also crucial for diagnosing pathologies, allowing morphological and positional visualization of teeth to aid the clinical decision-making process [1]. However, an accurate segmentation of individual teeth is an extremely challenging and a

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time-consuming process.

The conventional image processing techniques for performing tooth segmentation on CBCT images are semi-automated in nature as these require manual intervention and are prone to human error [8]. Similarly, template-based fitting approaches lack robustness for segmenting multi-rooted teeth, and level-set methods need numerous mathematical operations. Furthermore, the vague edges between tooth root and alveolar socket and image intensity inhomogeneity could lead to false segmentation [9]. The aforementioned classical segmentation approaches require laborious manual corrections for achieving an accurate segmentation and are considered as highly time-consuming, operator-dependent and inaccurate especially in the presence of artifacts related to high-density materials [10].

Recently, convolutional neural networks (CNNs) have been widely employed in the field of dentistry for overcoming the limitations associated with the conventional segmentation approaches. Deep neural networks trained end-to-end have the ability to outperform classical pipeline-based systems. These networks have been applied in various fields of image processing, such as, feature extraction, image classification, and semantic segmentation [11]. In context to dentistry, deep learning has allowed detection and segmentation of teeth based on 2D radiography, prediction of third moral eruption, detection and diagnosis of dental caries, and cyst and tumor classification [1,12–16]. However, lack of evidence exists related to the application of deep learning for the segmentation and/or classification of teeth from CBCT images [2,3,10,11,17–21].

A successful tooth segmentation from a clinician's perspective should exhibit the following; accurate segmentation of complete 3D individual teeth, correct classification of each tooth, and fast segmentation and classification [22]. Failure of any of these measures would result in an unsuccessful segmentation task. Additionally, previous evidence also suggests the necessity of further research with more robust, accurate and fast systems, capable of achieving a high segmentation and classification performance for all the teeth groups with images acquired from different devices and protocols [21].

Therefore, the aim of the following study was to develop and validate a clinically operational CNN-based system allowing an accurate and time-efficient segmentation and classification of 3D teeth from CBCT images.

2. Materials and methods

This study was conducted in compliance with the World Medical Association Declaration of Helsinki on medical research. Ethical approval was obtained from the Ethical Review Board (reference number: S57587). Informed consent was not required for this retrospective study as patient-specific information was kept anonymous.

2.1. Dataset

The artificial intelligence (AI) networks were developed based on CBCT scans. All images were recruited from the Hospital's database which were utilized for the diagnostics and/or treatment planning of patient with dentomaxillofacial deformities and diseases. No additional scans were taken specifically for this study. The inclusion criteria involved, high quality images, sufficient field of view (FOV) for visualizing all upper and lower jaw teeth (with or without restorative filling) with the exception of missing wisdom teeth. Scans with metal artifacts from implants or brackets, motion artifacts and partial edentulism were excluded.

Two CBCT devices were utilized in this study: 3D Accuitomo 170 (J Morita, Kyoto, Japan) and NewTom VGi evo (NewTom, Verona, Italy). The acquisition settings were; 90 kV, voxel size: $0.25\times0.25\times0.25$mm^3, FOV: $100.75\times100.75\times100$ mm^3 or $170.25\times170.25\times120$ mm^3 for 3D Accuitomo 170 and 110 kV, voxel size: $0.2 \times 0.2 \times 0.2$ mm^3, FOV: $122.8 \times 122.8 \times 80.2$ mm^3 or $103.2 \times 103.2 \times 100.8$ mm^3 or $244.8 \times 244.8 \times 188.7$ mm^3 for Newtom VGi evo.

The total dataset consisted of 186 CBCT scans and was split into the following subsets:

- Training set (scans=140, teeth=400), to train the AI model where individual teeth were segmented from each scan. The selection of teeth was random, however, covering the 32 teeth classes.
- Validation set (scans=35, teeth=100), to test the model performance based on the training set. The selection of teeth was random, however, covering the 32 teeth classes.
- Test set (scans=11, teeth=332) to evaluate the model performance by comparing with ground-truth segmented teeth where all teeth per scan were segmented.

The training and test ground-truth datasets were prepared by segmenting the CBCT Digital Imaging and Communications in Medicine (DICOM) images using a previously validated AI tool [3] which allowed segmentation of individual teeth instead of the complete arch. The CBCT DICOM images were taken as an input and the user manually cropped the image around each tooth individually for segmentation. Thereafter, 3D contours were suggested automatically as described in a previous study [23]. The tool also allowed the user to manually adjust contours for optimally segmenting the teeth. The segmentation process for training and testing was performed by a single expert and later verified by another expert.

2.2. AI framework

The two main tasks required from the AI framework as an output involved; segmentation of each individual tooth and classification to a particular tooth class.

Segmentation of individual teeth was achieved using a three-step approach as the size of the image (full CBCT DICOM scan) was usually too large to be used in a deep neural network. In the first step, the original image was down-sampled to a fixed size ($96 \times 128 \times 128$). All teeth were segmented as a single class on the down-sampled image for producing a binary image to overcome the variety of FOVs such as complete skull, all lower teeth or only a part of the teeth, since the model was trained with different FOVs.

In the second step, the dental region in the full resolution image was cropped based on the binary image then down-sampled to a fixed resolution of $0.7 \times 0.7 \times 0.7$ mm. The cropping and down-sampling allowed the use of deep neural networks and facilitated multi-class segmentation. The model in this step performed a multi-class segmentation of the image into 33 classes, with each tooth being a separate class (i.e. 32 classes) and a background class representing all structures not belonging to a tooth class.

The third step consisted of segmenting each of the 32 teeth classes individually. A crop was taken around each tooth which was bounded with a cuboid called the bounding box of the tooth. This small crop (i.e. bounding box) for each tooth was segmented in full resolution by a third network. Thereafter, the segmented teeth were inserted into a global label map with their class label corresponding to that of the bounding box. As the bounding boxes of the 32 teeth were axis-aligned, a significant overlap was usually observed between them. The overlap sometimes led to the false segmentation of the voxels as tooth by more than one bounding box. To resolve this issue, the confidence of the model, i.e., Sigmoid activation of the model output was applied to decide which label each voxel finally obtained.

All the three steps consisted of a 3D U-Net network structure composed of 4 encoding and 3 decoding blocks, where each block was made up of 2 convolutions followed by ReLU activation and group normalization with 8 feature maps [24]. The number of features after the first encoder was 64 which was doubled in each of the following encoders. All convolutions had a kernel size of $3 \times 3 \times 3$, stride 1 and dilation 1. Max pooling was applied after each encoder with kernel size

$2 \times 2 \times 2$ and stride 2, reducing the resolution with a factor 2 in all dimensions.

The training of the first and third models was performed with a Binary Cross Entropy loss, and the second model with Cross Entropy. All models were optimized using the Adam Optimiser with initial learning rate of 10^{-4}, which was reduced in several steps until 10^{-7} during the training for fast convergence. Random rotation, scaling, elastic deformation, and cropping were applied as data augmentation strategies. Fig. 1 explains step 2 and 3 of the AI framework for segmenting and classifying the teeth. The AI model is available via an online user-interactive cloud based platform, Virtual Patient Creator (relu, Leuven, Belgium)[25] that is accessible upon registration and allows users to import DICOM datasets, visualize, manually correct if required and export the segmented teeth in Standard Tessellation Language (STL) file format

2.3. Evaluation metrics

The evaluation metrics consisted of two sets, one for tooth segmentation and another for classification.

2.3.1. Evaluation metrics for segmentation

A confusion matrix (voxel-wise comparison) was used to compare the prediction of the AI model to the ground truth based on four variables: true positive (TP), true negative (TN), false positive (FP), false negative (FN), where TP are the correctly segmented voxels of a tooth. TN are the correctly not segmented voxels of a tooth. FP are the incorrectly segmented voxels and FN are missed from segmentation voxels. The following metrics were used for segmentation evaluation:

- Recall is the rate of correctly identified voxels in the predicted model compared to ground truth

$$\text{Recall} = \frac{TP}{\text{TP} + \text{FN}}$$

- Precision is the percentage of the accurately identified segmented region from the completely segmented region

$$\text{Precision} = \frac{TP}{\text{TP} + \text{FP}}$$

- Accuracy is the rate of correctly identified voxels to all the voxels

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

- Intersection over union (IoU) is the amount of overlapping voxels between the predicted model and the ground truth

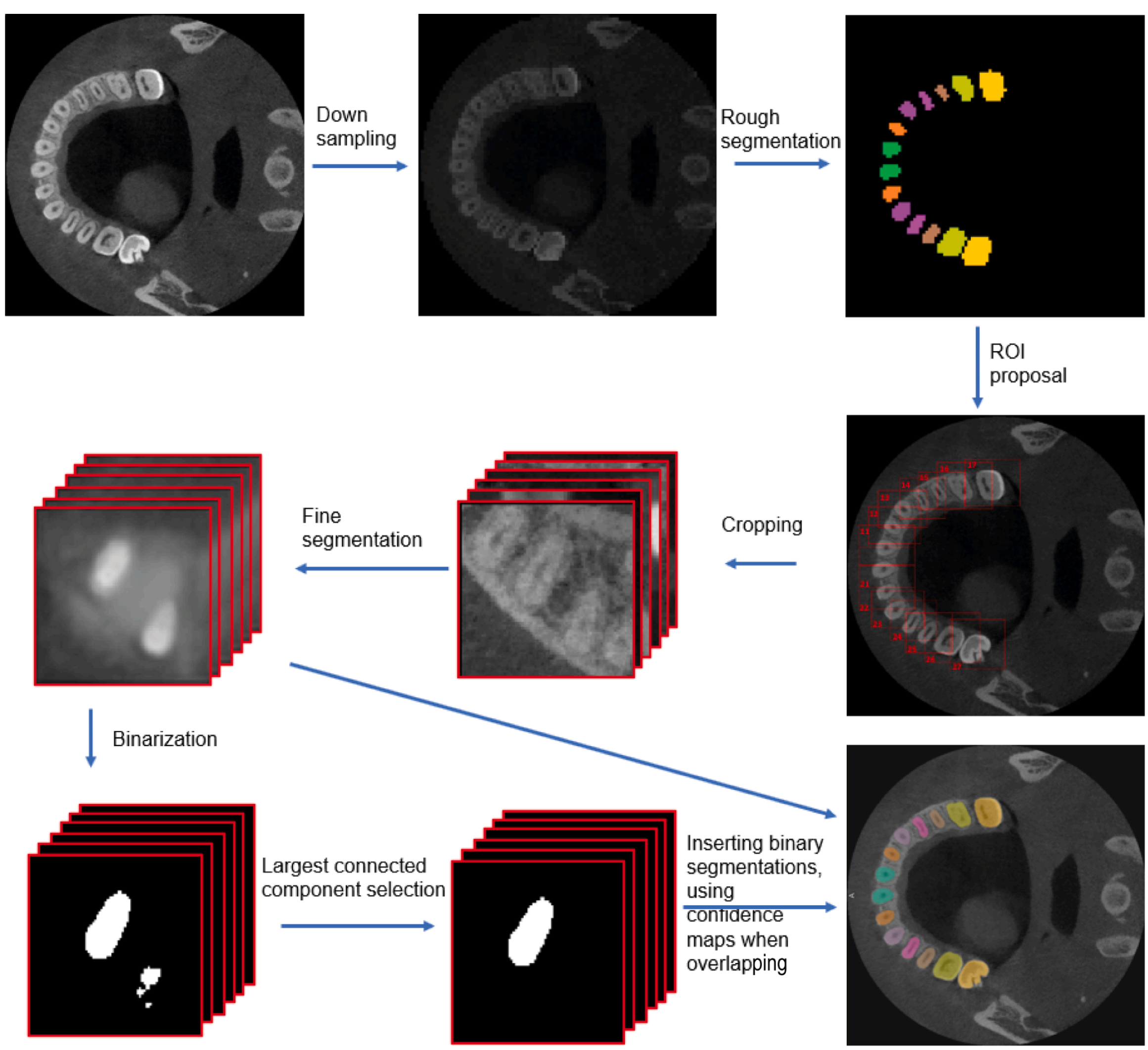

Fig. 1. Steps 2 and 3 of the AI framework for segmenting and classifying the teeth.

$$\mathrm{IoU} = \frac{TP}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}$$

- Dice similarity coefficient (DSC): is the score of similarity between the segmented region and the ground truth

$$\mathrm{DSC} = \frac{2*TP}{2*\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} = \frac{2*IoU}{1+\mathrm{IoU}}$$

- 95% Hausdorff Distance (HD) is the 95 percentile of the maximal distance between the predicted model and ground truth

$$p_{95}\left(\min_{g\in G}\| p-g\|^2 \cup \min_{p\in P}\| p-g\|^2\right)$$

- Time is the number of seconds to segment all teeth from a CBCT image whether using the expert or AI method. For the expert method the timing was calculated from the point when the DICOM data was opened in the segmentation software till a STL file was produced. For the AI method, timing was automatically recorded by the algorithm by calculating the number of seconds needed to produce a multi-class segmentation map excluding the DICOM data upload.

2.3.2. Evaluation metrics for classification

Fig. 2 illustrates the tooth classification pipeline, where TP, TN, FP and FN variables are defined differently from that of segmentation, TP is correctly identified tooth class compared to ground truth with IoU > 50%, TN is a correctly identified tooth as not present, FP is a non-existing identified tooth, FN is a non-identified existing tooth (IoU < 50%). The equations for accuracy, precision and recall rate remained the same as mentioned above.

2.3.3. Evaluation of subgroups

Data were analyzed using MedCalc Statistical Software version 16.2.0 (MedCalc Software bvba, Ostend, Belgium). Mean and standard deviation (SD) values of the validation metrics were reported to evaluate the performance of the network for complete dataset segmentation, separate teeth sub-groups segmentation (incisors, canines, premolars and molars) and teeth classification. The comparison between segmented teeth subgroups was performed using Kruskal Wallis test with Bonferroni correction as the data had a non-parametric distribution. A p-value of <0.05 was considered as statistically significant.

3. Results

The timing of segmentation and classification of all the teeth based on the test dataset of a single scan ($n = 11$ scans with 332 teeth) with the AI model was 13.7 ± 1.2 s compared to that of an expert (25,353.6 ± 4284 s or 7 ± 1.2 h). Thereby, indicating that the AI performed more than 1800 times faster than an expert.

Table 1 describes the accuracy metrics which were calculated for the segmentation evaluation by comparing the AI model to the ground truth. Fig. 3 shows an example of segmentation from the AI model versus

Table 1
Accuracy results of segmentation by comparing AI model segmentations to the ground truth segmentations (Mean ± SD).

Accuracy metrics	Mean ± SD
IoU	0.82 ± 0.05
Precision	0.98 ± 0.02
Recall	0.83 ± 0.05
DSC	0.90 ± 0.03
95% HD (mm)	0.56 ± 0.38

IoU: intersection over union, DSC: Dice, HD: Hausdorff distance.

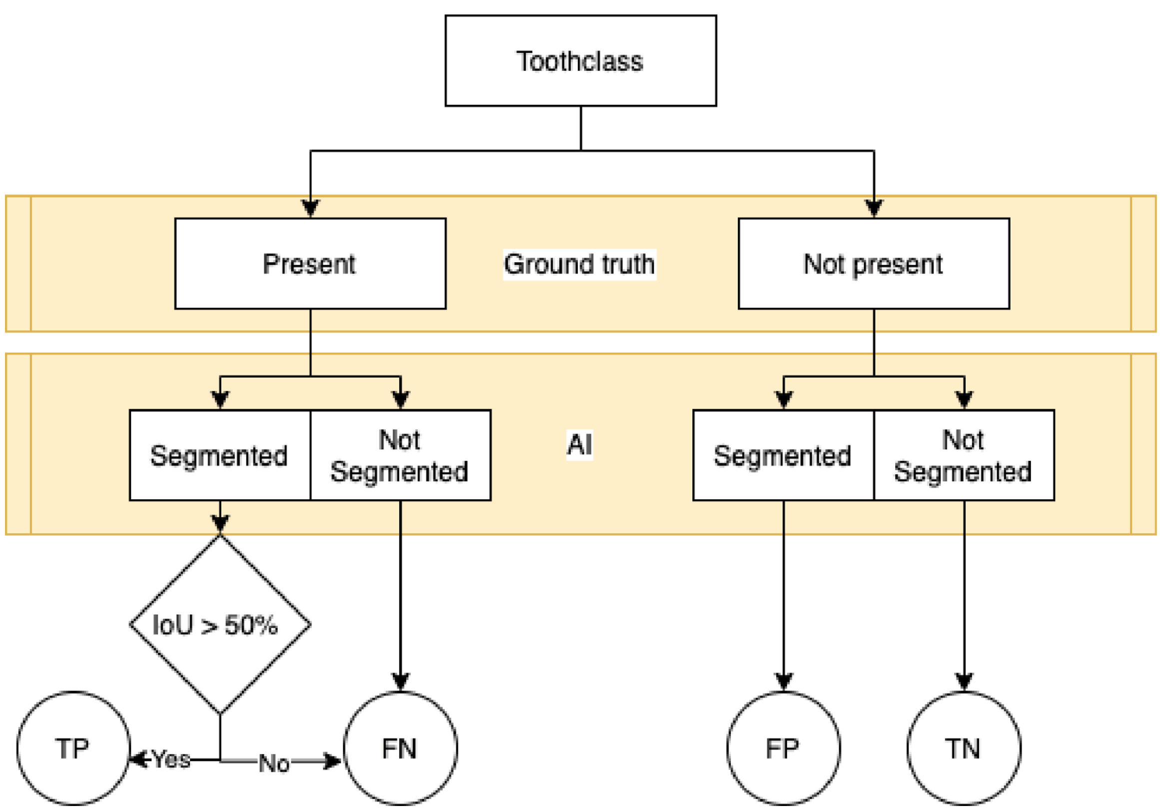

Fig. 2. Diagram explaining the tooth classification pipeline.

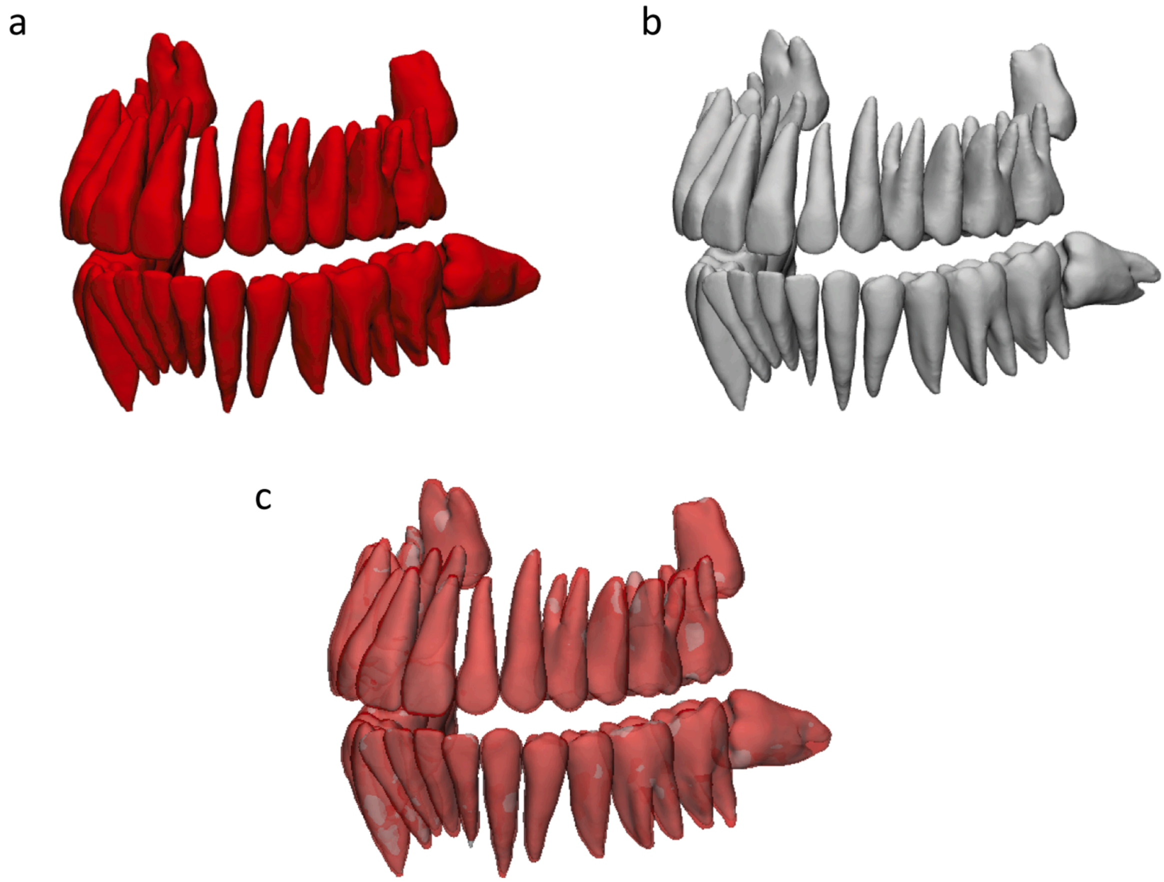

Fig. 3. An example from the validation dataset with a. Ground truth segmentation in red, b. AI model segmentation in gray, c. AI segmentation superimposed on Ground truth (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

ground truth.

The classification of teeth to the correct class (32 classes and 1 background class) performed well with an accuracy of 96.6%, recall rate of 98.5% and precision of 97.9%.

Table 2 and Fig. 4 show the IoU values for segmentation of different teeth sub-groups. The IoU values were within a similar range, however, the canine subgroup scored the highest followed by molar and premolar. The incisor sub-group had the lowest IoU with a statistically significant difference compared to all other sub-groups ($p<0.05$). No other significant differences were observed.

The AI system was incorporated with several tools that allowed refinement of the automatic segmentation. However, this study only investigated the fully AI-based task without any manual correction. Fig. 5 demonstrates some cases requiring minor corrections.

Table 2
IoU of segmentation of the different teeth subgroups.

Teeth subgroups	Number of teeth	Mean IoU ± SD
Average		
Incisor	87	0.80 ± 0.05
Canine	43	0.83 ± 0.05
Premolar	86	0.81 ± 0.09
Molar	116	0.82 ± 0.04
p-value		
Incisor vs Canine	0.003*	
Incisor vs Premolar	0.019*	
Incisor vs Molar	0.003*	
Canine vs Premolar	0.291	
Canine vs Molar	0.352	
Premolar vs Molar	0.926	

IoU: intersection over union.
* Indicates statistical significance ($p<0.05$).

4. Discussion

The 3D visualization and segmentation of human teeth has become an indispensable component for computer aided diagnostics and treatment planning in many fields of digital dentistry. The following study validated a new system for automatic tooth segmentation and classification based on CBCT images acquired by two different acquisition devices with a variety of FOVs and protocol settings. The use of three different CNNs yielded a high accuracy. Furthermore, the AI-driven system performed 1800 times faster compared to an expert-based segmentation. Additionally, the proposed method overcame some of the limitations associated with the existing deep learning-based algorithms. Recently, few studies have developed and validated CNN based tools for tooth segmentation [2,3,10,11,17–20]. However, comparison with the previous studies was limited due to the non-standardization in metrics, sample heterogeneity and lack of clinical applicability of some of the previously developed algorithms.

Fenster & Chiu stated that designing or choosing an appropriate effectiveness measure for an object segmentation is challenging [22]. For the purpose of providing information relevant to the task, the authors suggested categorizing the requirements of medical image segmentation evaluation into accuracy (the degree to which the segmentation results agree with the ground truth segmentation), precision (correct classification), and efficiency which is mostly related to time duration. In present study, all accuracy metrics demonstrated high values for segmentation and classification of teeth. Cui et al. relied on a 2D-stage approach with two 3D networks which required a specialized software and an advanced hardware to run efficiently [17]. Another

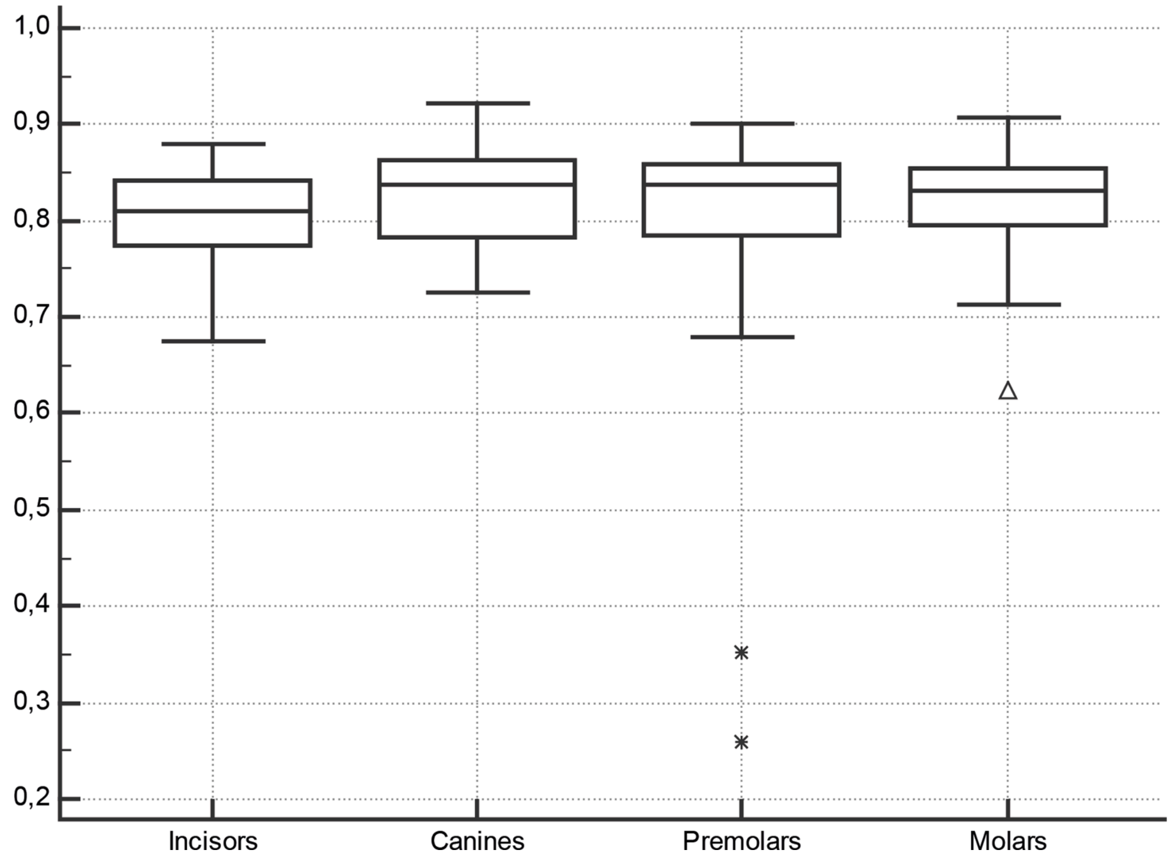

Fig. 4. Box plot comparing IoU resulting from segmentation for the different subgroups: incisors, canines, premolars and molars.

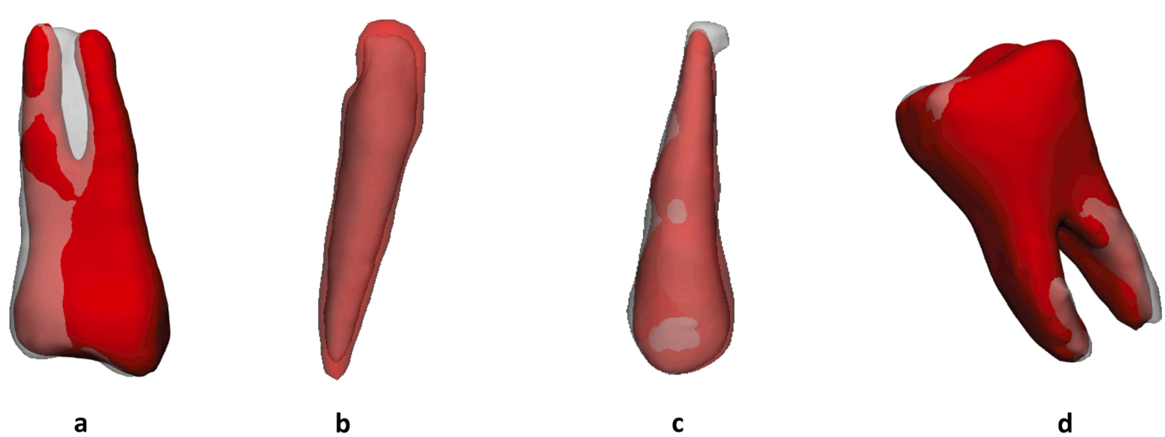

Fig. 5. Examples of cases requiring minor corrections based on the comparison of the AI segmentation (gray) versus Ground truth (red). a. Overestimation, b. Underestimation, c. and d. Deformed root (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

study also focused on segmentation using a multi-task 3D fully CNNs for predicting the tooth region and surface [19]. However, both studies failed to report the time taken for segmentation meanwhile requiring heavy processing.

Until now, three studies have been published related to the application of CNNs for individual 3D CBCT-based tooth segmentation [3,10,20], where only one study proposed a multiclass CBCT image segmentation system for automatically creating 3D surface models of the teeth in a preliminary dataset of 30 CBCT images of patients who underwent orthodontic treatment. Duan et al. developed a two-phase deep learning solution for tooth and pulp cavity segmentation [20]. However, only 20 CBCT images were recruited as the dataset and were acquired from a single device with similar acquisition parameters. Lahoud et al. assessed the performance of an innovative CNN-based algorithm for performing tooth segmentation but segmentation of molar sub-group was precluded [3]. To the best of our knowledge, as the preceding study was the first to test all the performance metrics proposed by Fenster et al., which included: accuracy, precision and efficiency [22]. Hence, serving as a groundwork for the present study where a newly developed multiclass system was employed for automatically generating 3D models of all the teeth.

The efficiency of image segmentation algorithm provides information related to its practical use, which is often measured as the segmentation time and should include all aspects of user interaction and whether the approach could be suitable for all images [22]. Unfortunately, majority of the previous studies did not evaluate this metric.

Some of the algorithms allowed only single tooth segmentation at a time-point following complete image upload, which could be considered a time-consuming and less robust method. In contrast, a multi-class tooth segmentation approach was utilized in the present study which allowed segmentation of the complete arch at the same time-point. Furthermore, the algorithm was deployed onto a cloud-based platform in order to serve a wider audience for digital dental applications independent of the hardware specifications of the personal computers.

The CBCT scans were acquired from young patients without dental implants or orthodontic devices to avoid the influence of metal artifacts. Nonetheless, slight artifacts due to dental fillings were present. In a daily clinical practice, the findings of the current study should be interpreted with caution, as the presence of such artefacts might degrade the quality of segmentation. So far, the system has proven to be highly accurate and consistent, considering training with data from two CBCT devices with different FOV and acquisition settings. Further training remains mandatory, which can be achieved by allowing the system to master more CBCT artifacts generated by high-density materials such as, dental implants and/or orthodontic brackets. Additionally, inclusion of more CBCT devices with different scanning parameters might allow to increase the generalizability of the system.

5. Conclusions

This study developed and validated a new cloud-based deep learning system for automatic tooth segmentation and classification without expert refinement.

The proposed system is accurate and time-efficient, enabling potential future applications in the digital workflows of dental diagnostics and treatment planning while reducing clinical workload.

CRediT authorship contribution statement

Eman Shaheen: Conceptualization, Methodology, Validation, Formal analysis, Visualization, Writing – original draft. **André Leite:** Conceptualization, Data curation, Validation, Writing – original draft. **Khalid Ayidh Alqahtani:** Validation, Data curation, Writing – review & editing. **Andreas Smolders:** Conceptualization, Methodology, Software, Validation, Writing – original draft. **Adriaan Van Gerven:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – review & editing. **Holger Willems:** Conceptualization, Methodology, Software, Validation, Writing – review & editing. **Reinhilde Jacobs:** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A.F. Leite, A. Van Gerven, H. Willems, T. Beznik, P. Lahoud, H. Gaêta-Araujo, M. Vranckx, R. Jacobs, Artificial intelligence-driven novel tool for tooth detection and segmentation on panoramic radiographs, Clin. Oral Investig. 25 (2021) 2257–2267, https://doi.org/10.1007/s00784-020-03544-6.

[2] Q. Li, K. Chen, L. Han, Y. Zhuang, J. Li, J. Lin, Automatic tooth roots segmentation of cone beam computed tomography image sequences using U-net and RNN, J. Xray. Sci. Technol. 28 (2020) 905–922, https://doi.org/10.3233/XST-200678.

[3] P. Lahoud, M. EzEldeen, T. Beznik, H. Willems, A. Leite, A. Van Gerven, R. Jacobs, Artificial intelligence for fast and accurate 3-dimensional tooth segmentation on cone-beam computed tomography, J. Endod. 47 (2021) 827–835, https://doi.org/10.1016/j.joen.2020.12.020.

[4] T.J. Jang, K.C. Kim, H.C. Cho, J.K. Seo, A fully automated method for 3D individual tooth identification and segmentation in dental CBCT, IEEE Trans. Pattern Anal. Mach. Intell. (2021) 1–12, https://doi.org/10.1109/TPAMI.2021.3086072.

[5] C. Tanikawa, T. Kajiwara, Y. Shimizu, T. Yamashiro, C. Chu, H. Nagahara, Machine/deep learning for performing orthodontic diagnoses and treatment planning, in: C.-C. Ko, D. Shen, L. Wang (Eds.), Mach. Learn. Dent., Springer International Publishing, Cham, 2021, pp. 69–78, https://doi.org/10.1007/978-3-030-71881-7_6.

[6] K. Alqahtani, E. Shaheen, S. Shujaat, M. EzEldeen, T. Dormaar, M.C. de Llano-Pérula, C. Politis, R. Jacobs, Validation of a novel method for canine eruption assessment in unilateral cleft lip and palate patients, Clin. Exp. Dent. Res. 7 (2021) 285–292, https://doi.org/10.1002/cre2.397.

[7] M. EzEldeen, J. Wyatt, A. Al-Rimawi, W. Coucke, E. Shaheen, I. Lambrichts, G. Willems, C. Politis, R. Jacobs, Use of CBCT guidance for tooth autotransplantation in children, J. Dent. Res. 98 (2019) 406–413, https://doi.org/10.1177/0022034519828701.

[8] M. Chung, M. Lee, J. Hong, S. Park, J. Lee, J. Lee, I.-.H. Yang, J. Lee, Y.-.G. Shin, Pose-aware instance segmentation framework from cone beam CT images for tooth segmentation, Comput. Biol. Med. 120 (2020), 103720, https://doi.org/10.1016/j.compbiomed.2020.103720.

[9] Y. Wang, S. Liu, G. Wang, Y. Liu, Accurate tooth segmentation with improved hybrid active contour model, Phys. Med. Biol. 64 (2018), 015012, https://doi.org/10.1088/1361-6560/aaf441.

[10] H. Wang, J. Minnema, K.J. Batenburg, T. Forouzanfar, F.J. Hu, G. Wu, Multiclass CBCT image segmentation for orthodontics with deep learning, J. Dent. Res. 100 (2021) 943–949, https://doi.org/10.1177/00220345211005338.

[11] Y. Rao, Y. Wang, F. Meng, J. Pu, J. Sun, Q. Wang, A symmetric fully convolutional residual network with DCRF for accurate tooth segmentation, IEEE Access 8 (2020) 92028–92038, https://doi.org/10.1109/ACCESS.2020.2994592.

[12] M. Vranckx, A. Van Gerven, H. Willems, A. Vandemeulebroucke, A.F. Leite, C. Politis, R. Jacobs, Artificial intelligence (Ai)-driven molar angulation measurements to predict third molar eruption on panoramic radiographs, Int. J. Environ. Res. Public Health. 17 (2020), https://doi.org/10.3390/ijerph17103716.

[13] S.B. Khanagar, A. Al-ehaideb, P.C. Maganur, S. Vishwanathaiah, S. Patil, H. A. Baeshen, S.C. Sarode, S. Bhandi, Developments, application, and performance of artificial intelligence in dentistry – a systematic review, J. Dent. Sci. 16 (2021) 508–522, https://doi.org/10.1016/j.jds.2020.06.019.

[14] S. Kim, Y.H. Lee, Y.K. Noh, F.C. Park, Q.S. Auh, Age-group determination of living individuals using first molar images based on artificial intelligence, Sci. Rep. 11 (2021) 1–11, https://doi.org/10.1038/s41598-020-80182-8.

[15] R.H. Putra, C. Doi, N. Yoda, E.R. Astuti, K. Sasaki, Current applications and development of artificial intelligence for digital dental radiography, Dentomaxillofac. Radiol. (2021), 20210197, https://doi.org/10.1259/dmfr.20210197.

[16] M.C. Kılıc, I.S. Bayrakdar, Ö. Çelik, E. Bilgir, K. Orhan, O.B. Aydın, F.A. Kaplan, H. Sağlam, A. Odabaş, A.F. Aslan, A.B. Yılmaz, Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs, Dentomaxillofac. Radiol. 50 (2021), 20200172, https://doi.org/10.1259/dmfr.20200172.

[17] Z. Cui, C. Li, W. Wang, Toothnet: automatic tooth instance segmentation and identification from cone beam ct images, in: Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. 2019-June, 2019, pp. 6361–6370, https://doi.org/10.1109/CVPR.2019.00653.

[18] S. Lee, S. Woo, J. Yu, J. Seo, J. Lee, C. Lee, Automated CNN-Based tooth segmentation in cone-beam CT for dental implant planning, IEEE Access 8 (2020) 50507–50518, https://doi.org/10.1109/ACCESS.2020.2975826.

[19] Y. Chen, H. Du, Z. Yun, S. Yang, Z. Dai, L. Zhong, Q. Feng, W. Yang, Automatic segmentation of individual tooth in dental CBCT images from tooth surface map by a multi-task FCN, IEEE Access 8 (2020) 97296–97309, https://doi.org/10.1109/ACCESS.2020.2991799.

[20] W. Duan, Y. Chen, Q. Zhang, X. Lin, X. Yang, Refined tooth and pulp segmentation using U-Net in CBCT image, Dentomaxillofac. Radiol (2021), 20200251, https://doi.org/10.1259/dmfr.20200251.

[21] J.-.J. Hwang, Y.-.H. Jung, B.-.H. Cho, M.-.S. Heo, An overview of deep learning in the field of dentistry, Imaging Sci. Dent. 49 (2019) 1–7, https://doi.org/10.5624/isd.2019.49.1.1.

[22] A. Fenster, B. Chiu, Evaluation of segmentation algorithms for medical imaging, in: Proceeding 2005 IEEE, Eng. Med. Biol. 27th Annu. Conf., IEEE, Shanghai. China, 2005, pp. 7186–7189, https://doi.org/10.1109/iembs.2005.1616166.

[23] M. EzEldeen, G. Van Gorp, J. Van Dessel, D. Vandermeulen, R. Jacobs, 3-dimensional analysis of regenerative endodontic treatment outcome, J. Endod. 41 (2015) 317–324, https://doi.org/10.1016/j.joen.2014.10.023.

[24] Y. Wu, K. He, Group normalization, in: V. Ferrari, M. Hebert, C. Sminchisescu, Y. Weiss (Eds.), Comput. Vis. - ECCV 2018, Springer International Publishing, Cham, 2018, pp. 3–19, https://doi.org/10.1007/978-3-030-01261-8_1.

[25] relu, Virtual Patient Creator, Leuven, Belgium. (n.d.). https://creator.relu.eu/.