Artificial intelligence system for automatic tooth detection and numbering in the mixed dentition in CBCT



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Abstract

Background Identifying and numbering teeth, the initial step in treatment planning, demands an efficient method.

Aim To evaluate the effectiveness and accuracy of artificial intelligence (AI) by automating tooth segmentation in CBCT volumes of paediatric patients with mixed dentition, using nnU-Netv2 algorithm.

Study Design In 49 CBCT scans, automatic segmentation and numbering of erupted/unerupted teeth of mixed dentition patients were performed using the CranioCatch labelling software (Eskisehir, Turkey). The dataset was randomly split into training (90%) and test (10%) groups. The developed model was trained with 1000 epochs using CBCT volumes and labelling. The performance of the model in numbering deciduous and permanent teeth was evaluated using several parameters, Dice Coefficient (DC), Jaccard index (Intersection over Union [IoU]).

Results The accuracy, precision, and recall values for the successful numbering of deciduous and permanent teeth in CBCT scans were determined to be 0.99, 0.86, and 0.84, respectively. The values for the DC, Jaccard index, and 95% HD were calculated as 0.81, 0.81 and 1.93, respectively.

Conclusion AI models offer a promising approach in the mixed dentition period and play a valuable role in dentists' planning in terms of time and effort.

KEYWORDS Artificial intelligence, tooth detecting, CBCT, paediatric dentistry, mixed dentition.

Introduction

The progress of modern dentistry, and particularly dentomaxillofacial radiology, has been keyed to the acquisition and segmentation of three-dimensional images [Polizzi et al., 2023]. Cone beam computed tomography (CBCT) has made it possible to obtain three-dimensional images of the relevant structures in the region of interest in dentomaxillofacial radiology with isotropic resolution and high dimensional accuracy at a low cost and low radiation dose [American Dental Association Council on Scientific Affairs, 2012] when compared with computed tomography, which was previously used to obtain a three-dimensional image of the region of interest. However, CBCT has a higher radiation dose than conventional two-dimensional dental radiographs. This is particularly important for use in paediatric patients due to the higher risk levels associated with X-ray exposure in younger age groups [Horner et al., 2020]. Conventional two-dimensional dental radiographs may cause some limitations in image interpretation due to anatomical superpositions and natural image distortions, which may cause difficulties in diagnosis especially in paediatric patients with mixed dentition. This period brings with it difficulties such as the complexity of the mixed dentition, overlapping teeth, differences in tooth shapes and sizes, and the presence of unerupted teeth [Bumann et al., 2024]. Therefore, in certain cases such as detecting and evaluating unerupted and impacted teeth, assessing oral and maxillofacial pathologies, and planning orthodontic treatment, three-dimensional imaging may be necessary for this patient group [Oenning et al., 2018]. Identification and numbering of teeth, which is the first step of treatment planning, requires a precise and effective approach [American Dental Association Council on Scientific Affairs, 2012]. Particularly in cases of mixed dentition, tooth detection and numbering on CBCT radiographs plays a central role in unraveling the complexities of this stage, guiding treatment decisions and ensuring optimal outcomes [Vishwanathaiah et al., 2023]. However, extracting two-dimensional features from three-dimensional tomography scans causes the loss of critical information, reducing the three-dimensional dataset. Therefore, segmentation of teeth, bones, and anatomical or pathological structures in CBCT images has become increasingly popular [Maschio et al., 2023]. In addition, interpreting CBCT volumes and manually segmenting certain features of paediatric patients in the mixed dentition period can be challenging and time-consuming due to the complex anatomical structures and the close proximity of teeth. Furthermore, these evaluations are highly susceptible to individual variations, particularly when not assessed by a specialist paediatric dentist or oral and dentomaxillofacial radiologist [Galibourg et al., 2018]. Advanced technology is required to decrease the error rate and facilitate precise and prompt analysis and planning

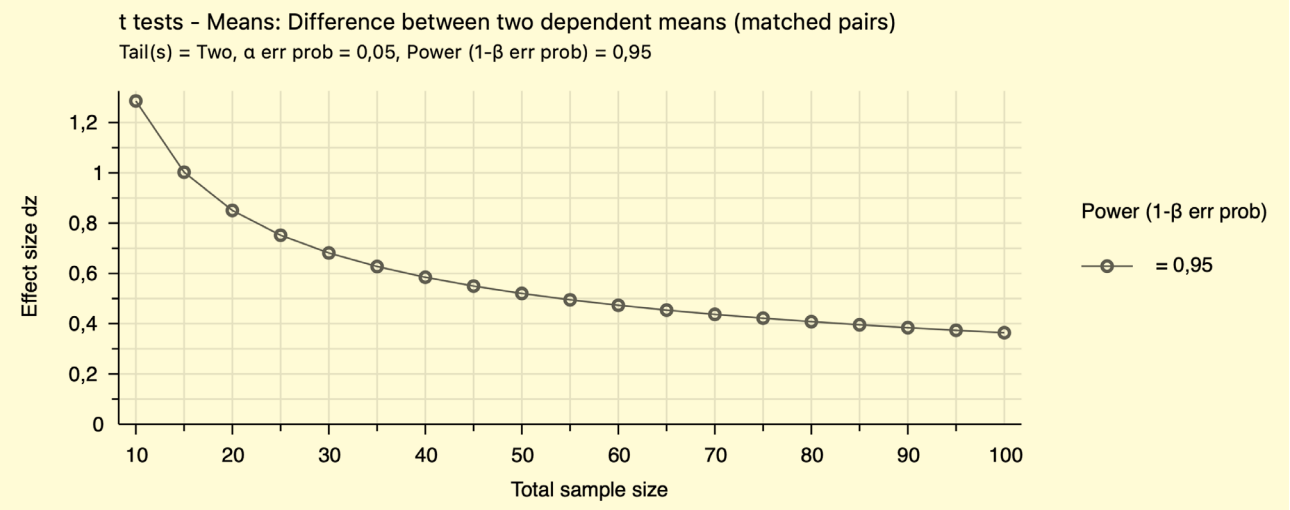


FIG. 1 Effect size configuration

[Azhari et al., 2023]. Artificial intelligence (AI) is a system that imitates human learning experiences. In recent years, AI has significantly impacted various fields, including healthcare [Shetty et al., 2024]. One such application is the use of AI in dentistry, particularly in dental imaging [Ding et al., 2023]. Deep learning (DL) is a subset of AI that mimics the learning function of neurons through multiple layers of neural networks [Chandrashekar et al., 2022]. Convolutional Neural Networks (CNN) are a type of DL network that specialises in processing grid-like topology data, such as two-dimensional and three-dimensional images [Al-Sarem et al., 2022]. AI models developed using CNNs aim to overcome the disadvantages and limitations of manual segmentation by providing automatic tooth segmentation. In this context, researchers are focusing on the development of algorithms capable of performing fully automatic segmentation without manual intervention, enabling radiologists to identify and categorise radiographs and teeth in a precise and time-efficient manner [Polizzi et al., 2023]. The objective is to prevent human errors caused by insufficient training, inattentiveness during diagnosis, or fatigue. An ideal tooth segmentation should accurately classify teeth while also providing fast and precise single-tooth segmentation [Fenster and Chiu, 2005]. Although many DL algorithm-based models have been developed by researchers for automatic tooth segmentation in two-dimensional radiography images, there are very few studies on the implementation of automatic tooth segmentation in CBCT volumes [Hwang et al., 2019]. To our knowledge, this is the first study to demonstrate the use of three-dimensional DL algorithms for automatic tooth segmentation and numbering in CBCT volumes of mixed dentition paediatric patients. NnU-Net is a CNN algorithm that makes three-dimensional biomedical image segmentation accessible to biomedical research applications by automatically adapting to arbitrary datasets. It provides standard segmentations by formulating the pipeline optimisation problem in terms of a data fingerprint and a pipeline fingerprint, and by condensing domain knowledge into a set of heuristic rules that generate a high-quality pipeline fingerprint from the corresponding data fingerprint. Unlike many other algorithms,

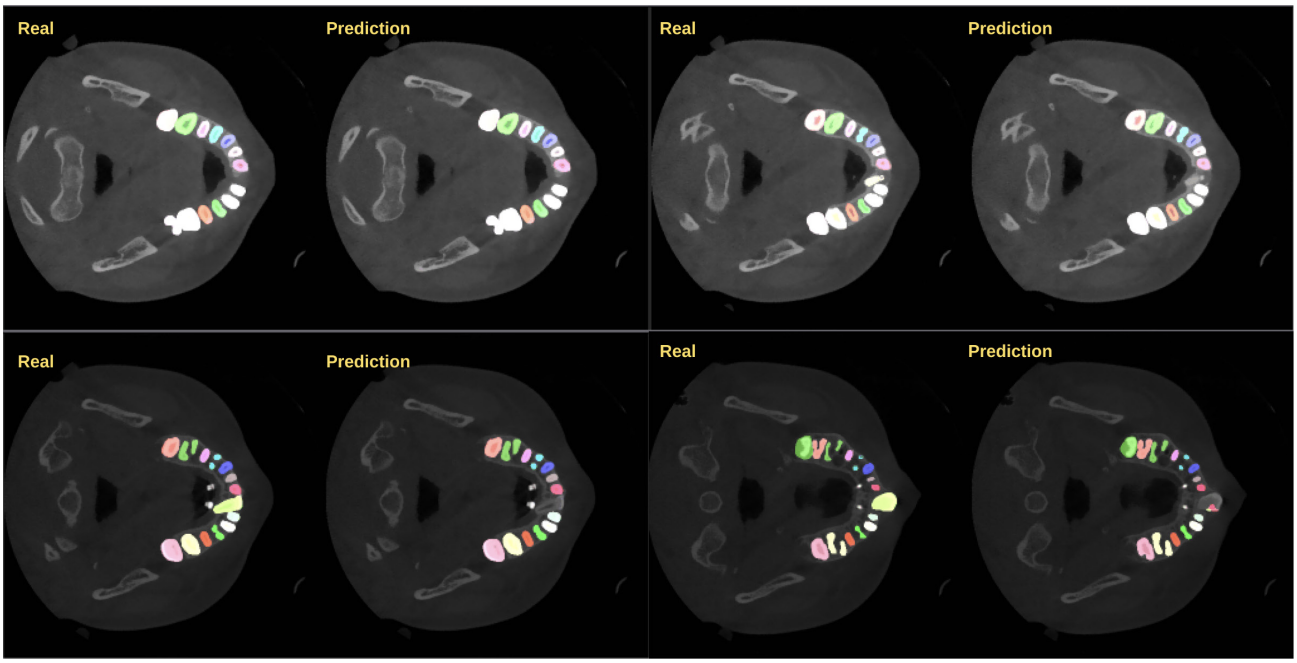


FIG. 2 Intersection in voxels of permanent and deciduous teeth

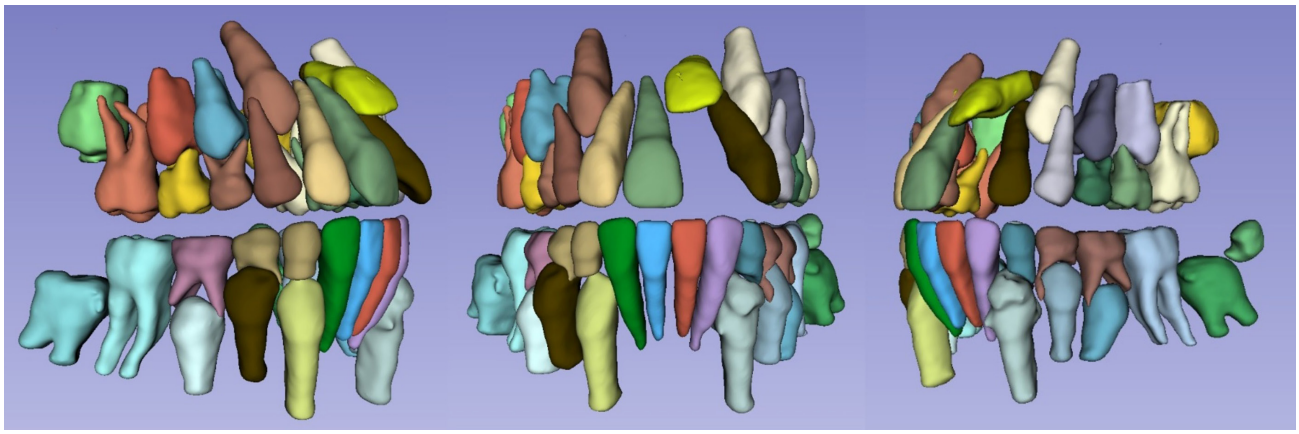


FIG. 3 3D segmentation results with different colors for different teeth

nnU-Net applies systematic rules to generate deep learning methods for datasets that the model encounters for the first time, without requiring further optimisation [Isensee et al., 2021]. nnU-Net v2 does not show any progress in terms of segmentation performance compared to nnU-Net, but it does introduce a number of improvements in terms of the ease of use of the model.

The objective of this study is to assess the effectiveness and accuracy of integrating AI into dental imaging by attempting to provide automatic tooth segmentation using the nnU-Netv2 algorithm in CBCT volumes of mixed dentition paediatric patients.

Materials And Methods

Study Design

In this retrospective study, an nnU-net v2-based algorithm for automatic segmentation and numbering of erupted/unerupted teeth of mixed dentition patients in CBCT volumes was developed using Pytorch library in Python programming language. To prepare the manuscript, Checklist for Artificial Intelligence in Medical Imaging (CLAIM) and Standards for the Reporting of Diagnostic Accuracy Studies (STARD) checklist were followed in this study. The study protocol (decision no.04.10.2022/22) was confirmed by the non-interventional Clinical Research Ethical Committee of Eskisehir Osmangazi University. The study was conducted in accordance with the principles of the Declaration of Helsinki. CBCT volumes that met the inclusion criteria and were previously taken for any reason were used in this study.

Sample Size Calculation

After conducting a power analysis to determine the necessary sample size, it was concluded that including 49 cases and using a paired two-sample t-test would result in a robust dataset. This configuration was designed to achieve a 95% power level with a 5% margin of error, based on an effect size of dz = 0.53 [Cohen, 1988; Gibson et al., 2017] (Figure 1).

Patient Selection

This study retrospectively analysed CBCT volumes of mixed dentition patients, available in the archive of the Department of Oral and Maxillofacial Radiology of Eskisehir Osmangazi University. The inclusion criteria required patients to be in the mixed dentition period with both permanent and deciduous teeth, and to have artefact-free tomography volumes taken in the appropriate position. Exclusion criterion was defined as the presence of any condition that could impede tooth segmentation. The volumes were anonymised prior to uploading to the marking system, and no differences were observed based on gender or ethnicity.

Acquisition of CBCT Volumes

The volumes were obtained using a NewTom 5G CBCT device (Verona, Italy) with a field of view (FOV) of 15 x 12 cm and 0.400 mm voxel size. The acquisition parameters were 110 kVp, 1-11 mA, 360° rotation and 3.6 s exposure time. The patient data was converted to volumetric data and exported in DICOM file format, and could be displayed in sagittal, coronal, and axial slices. The DICOM files were turned into the Neuroimaging Informatics Technology Initiative (NIfTI) format using a special code developed by the CranioCatch Software Team in Python programming language, with Pydicom, Nibabel, and Opencv libraries.

Ground Truth

The CranioCatch Annotation Tool (CranioCatch, Eskisehir, Turkey) via three-dimensional mask (3D Mask) was used to the numbering of deciduous and permanent teeth on the axial CBCT volumes using a polygonal box segmentation technique. The ground truth was carried out by the consensus of three senior paedodontist (S.O., E.G and F.N.K) with at least 3 years of experience on CBCT and one oral and maxillofacial radiologist (E.B.) with at least 5 years of experience on CBCT. The teeth were labelled using the FDI numbering system. After all annotation process, labels were checked by seniors (at least 10 years' experience) oral and maxillofacial radiologist (I.S.B) with the exact agreement on all labels.

Development of the nnU-Net v2 Based CNN Model

A total of 49 anonymised CBCT volumes with DICOM files were converted to NIfTI file format. The dataset was randomly split into training (90%) and test (10%) groups. The nnU-Net v2 based CNN model for automatic segmentation and numbering of deciduous and permanent teeth was developed in Python (v.3.6.1; Python Software Foundation, Wilmington, DE, USA) using the PyTorch library. The developed model was trained with 1,000 epochs using CBCT volumes and labelling. Mathematical processing in the model's training was performed with a Dell PowerEdge T640 Calculation Server (Dell Inc., Round Rock, TX, USA), Dell PowerEdge T640 GPU Calculation Server (Dell Inc., Round Rock, TX, USA), and a Dell PowerEdge R540 Storage Server (Dell Inc., Round Rock, TX, USA) at the XXXXX University Dentistry Faculty, Dental-AI Laboratory (Appendix A).

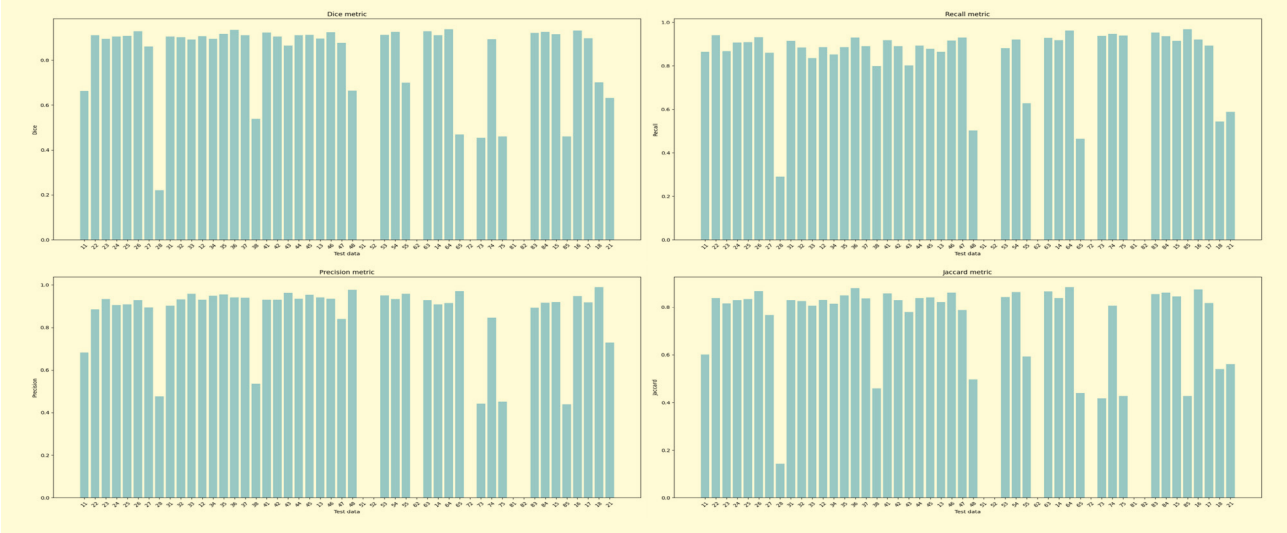


FIG. 4 Values of recall, precision, Dice Coefficient (DC), Jaccard index (Intersection over Union [IoU])

nnU-Net v2 workflow

nnU-Net v2 is a model designed to automate three-dimensional semantic segmentation tasks in biomedical image analysis. The model's strong performance is not due to innovations in network architecture, loss function, or training scheme, but rather to a systematic approach based on heuristic rules. This approach makes the complex nature of the manual pipeline optimization process clear and interpretable. nnU-Net v2 a segmentation tool that can be applied to a wide variety of biomedical imaging datasets without requiring user intervention and is ideal for users who need access to semantic segmentation methods but lack the expertise, time, or computational resources to manually adapt existing solutions to their needs. Model's workflow consists of Data Preparation, Pre-processing, Architecture, Training, Post-processing, Evaluation.

- Data Preparation: The initial stage of the workflow involves collecting the dataset. Depending on the research subject, data can be collected from various medical images in different ways. To increase data multiplicity, various data enhancement methods such as rotation, scaling, translation, intensity changes can then be applied. Once the data is prepared, it can be divided into training, validation, and test sets, or just training and test sets. The training set is utilized to train the model, whereas the validation set is used to set hyperparameters and monitor performance during training. The test set is used to evaluate the success of the model.
- Pre-processing: At this stage, the pixel intensities in the image can be normalised to have zero mean and unit variance, ensuring numerical stability during training. Additionally, the dataset can be resized to ensure consistency in image size and labelling, making it easier for the model to process the data during training. As pixel density may vary in radiographic images from different centres, density standardisation can be applied to improve the model's accuracy.
- Architecture: The nnU-Net model shares similarities with U-Net's legacy model as it employs an encoder-decoder architecture. The encoder gradually reduces the spatial dimensions of the input image while capturing hierarchical features, and the decoder increases the feature maps to the original resolution while incorporating skip connections to preserve spatial information. The skip connections act as a bridge between the encoder and decoder and facilitate the transfer of even low-level details.
- Training: At this stage, nnU-Net calculates the difference between the ground truth and the model's predictions and aims to minimise this difference using a loss function. The most used loss functions are the Dice coefficient, cross entropy, or a combination of the two.
- Post-processing: To enhance the model's success, post-processing techniques such as morphological and conditional random fields can be employed. Morphological procedures can smooth the segmentation markings predicted by the model and eliminate small artifacts or noise through dilation and erosion. Conditional random fields can improve the model's performance by modelling spatial dependencies between adjacent pixels.
- Evaluation: Metrics such as Dice Similarity Coefficient, Intersection over Union, accuracy, sensitivity, specificity, and Hausdorff distance are used to evaluate the performance of the trained nnU-Net model. These metrics enable the determination of the segmentation quality of the model through concepts such as overlap between ground truth and model prediction, border accuracy, and false positive/negativity.

The advantages of the nnU-Net v2 compared to older models

nnU-Net v2 is a deep learning model that incorporates critical innovations, including curvy paths, dense curvy paths, adaptive skip connections for larger scales, and loss functions at the image and voxel level. The use of curvy paths shortens the path between input and output, allowing for better flow of gradients and more successful results. To achieve further densification of the curly paths and higher performance with more features, dense curly paths are employed. nnU-Net improves model performance by providing adaptive skip connections for larger scale images and feature maps that cover a wider area for higher resolution images, unlike previous models. This is due to the implementation of loss functions that can provide precise results not only at the image level but also at the pixel or voxel level and are utilised at both image and voxel levels. Furthermore, nnU-Net v2 is expected to

yield superior outcomes compared to its previous versions. These characteristics allow nnU-Net v2 to surpass its predecessors.

Metrics for the Model's Performance

The performance of the model in numbering deciduous and permanent teeth on axial CBCT scans was evaluated using accuracy, precision, recall, area under the curve (AUC) and receiver operating characteristic (ROC) curves. In addition, the Dice Coefficient (DC), Jaccard index (Intersection over Union [IoU]) and the 95% Hausdorff distance (95% HD) were measured. The result of the model was considered successful if the prediction and the ground truth overlapped by more than 50% in each individual image slice. The true positive (TP), false positive (FP) and false negative (FP) results were determined to calculate the performance metrics.

Results

The algorithm based on nnU-Net v2 successfully predicted voxels belonging to the permanent and deciduous teeth with more than 50% intersection in most samples (Figure 2). Figure 3 shows the 3D segmentation results with different colours for different teeth for tooth segmentation and tooth identification. The nnU-Net v2 algorithm achieved DC values of 0.95, with the highest score observed on the tooth number 64, and 0.22, with the lowest score recorded on the tooth number 28. Recall metric values were 0.95, with the highest score achieved on tooth number 85, and 0.28, with the lowest score observed on tooth number 28. Precision metric values were found to be 0.95, with the highest score recorded on tooth number 18, and 0.43, with the lowest score observed on tooth number 85. Jaccard index values were reported as 0.95, with the highest score obtained on tooth number 64, and 0.18, with the lowest score recorded on tooth number 28 (Figure 4) (Table 1). AUC values were determined to be 0.98, with the highest scores observed on teeth numbered 64, 83, and 85, and 0.28, with the lowest score recorded on teeth numbered 28 (Figure 5). However, the nnU-Net v2 based algorithm could not determine the DC, AUC, recall, precision, and Jaccard Index values for teeth numbered 51, 52, 62, 72, 81, and 82. The accuracy, precision, and recall values for the successful numbering of deciduous and permanent teeth in CBCT scans were determined to be 0.99, 0.86, and 0.84, respectively. The values for the DC, Jaccard index, and 95% HD were calculated as 0.81, 0.81 and 1.93, respectively (Figure 6).

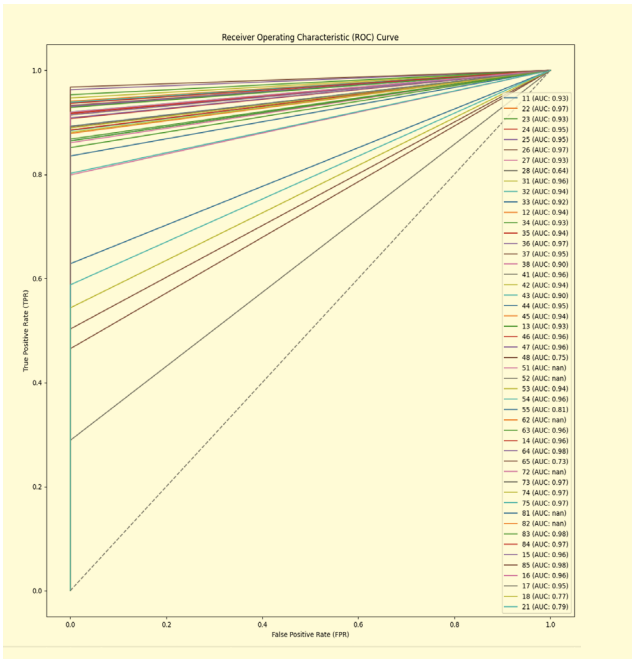


FIG. 5 Values of area under the curve (AUC)

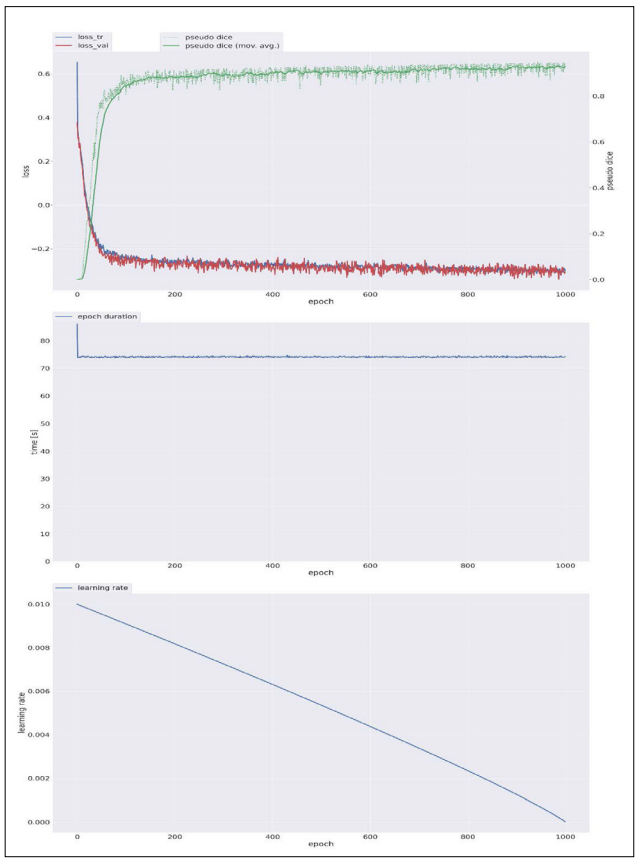


FIG. 6 Dice Coefficient (DC), Jaccard Index (Intersection over Union [IoU]), Hausdorff distance (95% HD) values.

Discussion

While CBCT have the advantage of emitting less radiation than CT, this can also lead to a disadvantage in image interpretation due to poorer contrast and increased noise. These factors contribute to the difficulty in tooth segmentation in CBCT volumes [Liang et al., 2010; Polizzi et al., 2023]. Furthermore, the similarity in densities between tooth and alveolar bone structures often results in blurred boundaries between the two. Segmenting the tooth in the alveolar bone in an image where these two structures have similar grey scale intensity can be a challenging process [Lee et al., 2020]. Another challenging situation is the overlapping of the occlusions of the upper and lower arch teeth due to the fact that the tomography image is taken in natural occlusion. This closeness can make the segmentation process more difficult, especially when combined with teeth crowding. Another challenging scenario arises from the overlapping occlusions of upper and lower arch teeth, stemming from the natural occlusion captured in tomography images. This proximity, compounded by crowding, can complicate the segmentation process. Moreover, the presence of a high number of teeth per arch exacerbates these challenges. Segmentation of teeth in CBCT volumes can be a challenging and time-consuming task, especially in mixed dentition patients where both permanent and primary teeth

	Dice Coefficient		Recall		Precision		Jaccard Index	
	Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest
Metric Value	0.95	0.22	0.95	0.28	0.95	0.43	0.95	0.18
Tooth number	64	28	85	28	18	85	64	28
Mean Metric Value	0.81		0.84		0.86		0.81	

TABLE 1 The performance of tooth segmentation

coexist in the jaw, mainly when dealing with closely positioned and overlapping teeth [Polizzi et al., 2023; Shaheen et al., 2017]. Numerous studies have been conducted on AI-assisted automatic tooth segmentation in CBCT images. However, none of these studies have focused on patients in the mixed dentition period, nor have they used an nnU-Net v2 based model in the models they developed. Therefore, this study represents the first attempt to automatically segment both permanent and deciduous teeth in CBCT volumes of mixed dentition patients using the nnU-Net v2. A number of different methods have been tried for the automatic segmentation of teeth in computed tomography images. These include the watershed algorithm, level set methods, thresholding, and deep learning algorithms. However, the most commonly used method for three-dimensional automatic tooth segmentation is DL algorithms that employ CNNs due to their near-perfect results. U-Net, V-Net, V-Net + hierarchical morphology-guided network, Toothnet, UDS-Net (U-Net + dense block + spatial dropout), AttU-Net (Attention U-Net), BDC_lstm, Hierarchical multi-step deep learning method, Feature pyramid network, Novel DBA, 3D U-Net three-step approach, 3.5D U-Nets, MS-D (mixed scale dense), DenseASPP-UNet, TSDNet (tooth segmentation deep learning network), Combination of deep CNN and level set method are various deep learning algorithms previously used for automatic tooth segmentation in CBCT images [Polizzi et al., 2023]. Duan W et al. [2021] developed a two-stage U-Net-based DL algorithm to segment teeth on CBCT scans before endodontic treatment and visualise their internal anatomy to obtain information about root canal configuration. The DC values of the model were 95.7 ± 0.5% for single-rooted tooth segmentation, 96.2 ± 0.2% for multi-rooted tooth segmentation, 88.6 ± 2.5% for pulp segmentation in single-rooted teeth, and 87.6 ± 2.5% for pulp segmentation in multi-rooted teeth. Cui et al. [2022] reported that their network model, which consisted of multiple V-Net networks, achieved DC values of 91.5% and 93% for tooth segmentation and alveolar bone segmentation, respectively. The model's performance remained excellent even in difficult dental anomaly cases. Hsu et al. [2022] hypothesised that the use of majority voting in the old versions of 3.5D U-Net could reduce false positive results and improve dental segmentation performance in this new version. In their study, they determined the DC, accuracy, sensitivity, and specificity values of 3.5D U-Net to be 91.1%, 99.9%, 88.8%, and 100%, respectively. Overall, they reported that 3.5D U-Net achieved the best segmentation performance among all U-Nets. Jang et al. [2022] developed a hierarchical multi-step deep learning model to identify and segment individual teeth in three dimensions from CBCT images. The success of their model was demonstrated with an F1-score of 93.35% and a DC value of 94.79%. Lahoud P et al. [2021] reported an IoU value of 87.7 ± 3.6% and a DC value of 93.4 ± 0.02% in an artificial intelligence-driven tooth segmentation algorithm based on a feature pyramid network developed to automatically detect and segment teeth, replacing manual user contour placement. In their study of a total volume of 186 tomographs obtained from two CBCT machines with different acquisition settings, Shaheen et al. [2021] segmented teeth using a three-step approach. The first step involved sub-sampling and coarse tooth segmentation. In the second step, the whole tooth image was cropped and transformed into the bounding box region of individual teeth. The third step involved performing fine-tooth segmentation for each tooth. The success of the model was evaluated using several performance metrics. The precision value obtained was 98 ± 2%, recall value was 83 ± 5%, IoU value was 82 ± 5%, and DC value was 90 ± 3%. Liu et al. [2023] reported the highest DC value of 89.74% on a custom dataset of 9651 CBCT images with ToothSegNet, which improves the dataset using generated degraded images and uses them during training. ToothSegNet utilises a channel cross-fertilisation module to combine information from high and low quality images and improves the shape of tooth estimates with a structurally constrained loss function. The detection and segmentation of teeth in CBCT radiography can be challenging due to various limitations, including the number of teeth per jaw, density differences within the tooth, and tooth development. These challenges are further compounded during the mixed dentition period, where primary and permanent teeth coexist, some permanent teeth have limited visibility, and teeth are positioned differently on the surface or below. These limitations may impact the performance of deep learning. Despite these challenges, the present study achieved an impressive accuracy rate of 0.99. Identifying, numbering, and segmenting teeth are essential tasks for automated analysis of radiographic images to take full advantage of their benefits. Currently, there are no studies or datasets in the literature that simultaneously consider primary and permanent teeth in CBCT images. To address this gap, this work presents a new, challenging, and highly variable public dataset that has been labelled from scratch. The DC index is a commonly used metric to evaluate the performance of segmentation methods. A DC value of over 0.700 is recommended for good overlap, although clinical dentistry applications may require higher values [Zijdenbos et al., 1994]. Polizzi et al. [2023] conducted a systematic review of studies on automatic tooth segmentation in CBCT scans using deep learning algorithms and found that the DC values in the literature ranged from 90 ± 3% to 97.9 ± 1.5%. In this study, we found a DC value of 0.81. However, due to the complex nature of dental structures during the mixed dentition period in paediatric patients, not all teeth were present, resulting in a lower value compared to studies conducted in adult patients in the literature. Performing this study in a population with evenly distributed teeth will yield healthier results in future studies. However, the limited use of CBCT in paediatric patients due to the high radiation dose makes it difficult to collect homogeneous data. Despite these limitations, the obtained DC value of 0.81 is promising for automatic tooth segmentation in CBCT volumes for this patient group. This value is higher than the accepted good ratio of DC >0.70 in the literature.

Bullet Points

- By automatically charting CBCT radiographs with deep learning-based artificial intelligence models, it allows dentists to save time in diagnosis and treatment planning in their daily routine.
- It also helps speed up the interpretation and detailing of dental reports obtained from CBCTs.

Author Contribution

S.O, İ.S.B. and E.B. conceived the ideas; S.O., E.G., T.M., F.K. and I.T.G collected the data; A.K., A.F.A. and O.C. analysed the data; and S.O., I.T.G. and I.S.B. led the writing.

Conflict of interest

The authors declare no conflict of interest.

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