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A nnU-Net Based Deep Learning Approach for Detection and Positional Classification of Maxillary Impacted Canines in Cone Beam Computed Tomography Images: A Pilot Study

SUMMARY

Background: Maxillary impacted canines represent one of the most clinically significant eruption disturbances due to their association with severe complications such as root resorption and complex orthodontic treatment requirements. Accurate three-dimensional localization is therefore essential for diagnosis and treatment planning. The aim of this study was to develop and evaluate a deep learning-based automated decision support system using a nnU-Net architecture for the detection, segmentation and positional classification of impacted maxillary canines on cone-beam computed tomography (CBCT) images. **Materials and Methods:** This retrospective study included 49 CBCT datasets obtained from the archive of the Department of Oral and Maxillofacial Radiology. All datasets were anonymized and converted from DICOM to NIfTI format. A total of 44 datasets were used for training and 5 for testing. Manual segmentation of impacted canines was performed using CranioCatch annotation software (CranioCatch, Eskişehir, Türkiye) to establish ground-truth annotations. The nnU-Net v2 architecture was used for model training and automatic segmentation. Model performance was evaluated using the Dice similarity coefficient, Jaccard index, Hausdorff distance, and confusion matrix-based metrics, including precision, recall, and F1 score. **Results:** The model demonstrated variable performance across different classes. The highest segmentation performance was observed in palatal impactions (Dice = 0.685, recall = 0.744), whereas horizontal and vestibular impactions showed poor segmentation (Dice = 0). Despite very high overall accuracy values (>0.999), high false negative rates were observed in underrepresented classes, indicating significant class imbalance. **Conclusion:** The nnU-Net model demonstrated promising performance in detecting and segmenting palatal impacted canines; however, its performance was limited in other classes due to dataset imbalance and anatomical variability. Future studies with larger and more balanced datasets are required to improve clinical applicability.

Keywords: Impacted maxillary canine; Cone-beam computed tomography; Deep learning; nnU-Net; Artificial intelligence; Dental radiology

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Introduction

Maxillary canine teeth play a pivotal role in maintaining occlusal stability, anterior guidance, facial aesthetics, and preservation of dental arch integrity. Due to their long eruption pathway, delayed eruption timing, and development within anatomically complex regions, they are particularly prone to impaction¹⁻⁴. Clinically, maxillary canines represent the most frequently impacted teeth after third molars and constitute a critical decision point in orthodontic and surgical treatment planning^{1,5}.

Failure to detect impacted canines in a timely and accurate manner may lead to severe complications, including displacement of adjacent teeth, loss of arch length, cyst formation, ankylosis, infection, and most importantly, root resorption of adjacent incisors^{1,5-7}. Among these, incisor root resorption is considered the most critical and often irreversible complication, typically progressing asymptotically in early stages and thereby delaying diagnosis^{6,7}. Therefore, comprehensive evaluation of impacted canines requires not only identification of their presence but also precise assessment of their three-dimensional spatial position, eruption direction, proximity to adjacent structures, and associated pathological changes^{8,9}.

Cone beam computed tomography (CBCT) has emerged as an advanced imaging modality in dentistry, providing high-resolution three-dimensional visualization with relatively low radiation dose compared to conventional computed tomography¹⁰⁻¹³. Unlike two-dimensional imaging techniques, CBCT eliminates anatomical superimposition and enables accurate localization of impacted teeth and their relationship with adjacent anatomical structures^{6,10}. Consequently, CBCT is widely accepted as the gold standard imaging modality for evaluating impacted maxillary canines^{11,13}. Furthermore, CBCT allows detailed assessment of buccal–palatal localization, eruption axis, and associated pathological conditions such as root resorption and cystic changes, which are essential for treatment planning^{4,9}.

In recent years, artificial intelligence (AI) and deep learning (DL) techniques have significantly transformed medical imaging workflows. AI-based systems have demonstrated performance comparable to experienced clinicians in tasks such as image classification, detection, and segmentation¹⁴⁻¹⁷. In dentistry, deep learning applications have been successfully utilized in detecting periapical lesions, segmenting anatomical structures, and classifying oral mucosal diseases¹⁵⁻¹⁸. These technologies offer advantages such as increased speed, reproducibility, and objectivity, thereby reducing operator dependency and diagnostic variability.

Machine learning (ML) and DL as subfields of AI, enable automated analysis of complex imaging data using

artificial neural networks (ANNs), which learn hierarchical representations through multiple interconnected layers¹⁹⁻²². In medical imaging, these systems rely on annotated ground truth datasets for training and validation, ensuring reliable performance evaluation¹⁹. Recent studies have demonstrated the feasibility of deep learning approaches in detecting and classifying impacted maxillary canines using both panoramic radiographs and CBCT images²³⁻²⁵. In particular, nnU-Net has emerged as a self-configuring framework for biomedical image segmentation, achieving state-of-the-art performance across various datasets²⁶. These developments highlight the growing potential of AI-based systems as clinical decision support tools, improving diagnostic accuracy and efficiency in the evaluation of impacted teeth.

The aim of the present study was to evaluate the performance of an nnU-Net–based deep learning model for the automatic segmentation and classification of impacted maxillary canines on CBCT images, and to assess its effectiveness across different impaction types (horizontal, palatal, and vestibular). Additionally, the study aimed to investigate the model's reliability in terms of segmentation accuracy and its potential applicability as a clinical decision support tool in dental radiology.

Materials and Methods

Study Design and Ethical Considerations

This retrospective observational study was conducted using cone-beam computed tomography (CBCT) datasets obtained from the institutional archive of the Department of Oral and Maxillofacial Radiology. The study protocol was reviewed and approved by the Marmara University Faculty of Medicine Non-Drug and Non-Medical Device Research Ethics Committee (Protocol No: 09.2026.26-0112; Approval Date: 20 February 2026), and all procedures were performed in accordance with the principles of the Declaration of Helsinki. All imaging data were anonymized prior to analysis to ensure patient confidentiality. As the study involved retrospective analysis of archived imaging data, no additional radiation exposure or intervention was required for the participants. The study design aligns with previous CBCT-based research methodologies in dentomaxillofacial radiology.

Study Population and Dataset Characteristics

A total of 49 CBCT datasets were included in the study, selected according to predefined inclusion and exclusion criteria to ensure data quality and consistency. The inclusion criteria comprised the presence of at least one impacted maxillary canine, availability of high-resolution CBCT images suitable for segmentation, complete visualization

of the maxillary region, and absence of severe motion artifacts. The exclusion criteria included CBCT images with significant motion artifacts, incomplete anatomical coverage, presence of large pathological lesions obscuring anatomical structures, and previous surgical intervention in the maxillary canine region. The final dataset consisted of 49 CBCT scans, of which 44 were allocated to the training set and 5 were reserved for independent testing. This patient-level separation was implemented to prevent data leakage and to ensure an unbiased evaluation of model performance.

Imaging Protocol and Acquisition Parameters

All CBCT scans were acquired using a standardized imaging protocol to minimize variability and ensure consistency across datasets. Imaging was performed using a Planmeca ProMax 3D Mid CBCT system, which is widely used in dentomaxillofacial radiology.

The imaging parameters were as follows:

- Tube voltage: 90 kVp
- Tube current: 12 mA
- Exposure time: 12–27 seconds
- Voxel size: 0.4 mm³
- Field of view: sufficient to include the maxillary region

These parameters were selected to provide optimal image quality while maintaining radiation exposure within acceptable limits, consistent with established CBCT imaging guidelines^{9–11}.

CBCT imaging provides high spatial resolution and three-dimensional visualization, making it particularly suitable for evaluating impacted teeth and their relationship with adjacent anatomical structures^{7–9}.

Data Preprocessing and Format Conversion

All CBCT datasets were initially stored in Digital Imaging and Communications in Medicine (DICOM) format. For compatibility with deep learning frameworks, the datasets were converted into Neuroimaging Informatics Technology Initiative (NIFTI) format.

The conversion process included:

- Standardization of voxel spacing
- Intensity normalization
- Removal of non-relevant anatomical regions

Preprocessing plays a critical role in deep learning performance, as variations in image intensity and resolution can significantly affect model training^{24,25}.

Ground Truth Annotation and Segmentation Protocol

Manual segmentation was performed by B.L.Ç. using CranioCatch annotation software (CranioCatch, Eskişehir, Türkiye) to generate ground-truth annotations for model training. The segmentation process was carried out on axial CBCT slices, and the boundaries of impacted maxillary

canines were delineated using a polygon-based annotation approach. The dataset consisted of 44 CBCT volumes for training and 5 CBCT volumes for testing, corresponding to approximately 4,400 annotated training slices and 500 annotated test slices in which the impacted maxillary canines were visible. All annotations were independently reviewed and verified by G.K. and F.N.P. to ensure accuracy and consistency. Any discrepancies were resolved through consensus evaluation. This approach is consistent with previous studies emphasizing the importance of expert annotation in medical image segmentation.²³

Classification of Impacted Canines

Impacted maxillary canines were categorized into three positional classes based on their spatial orientation:

- Class 1: Horizontal impaction
- Class 2: Palatal impaction
- Class 3: Vestibular impaction

This classification system is widely used in clinical practice and reflects the anatomical positioning of impacted canines relative to the dental arch^{3–5}.

The classification labels were integrated into the segmentation masks, enabling the model to perform both segmentation and classification tasks simultaneously.

Deep Learning Architecture: nnU-Net Framework

The nnU-Net (no-new-U-Net) framework was employed for automated segmentation. nnU-Net is a state-of-the-art deep learning architecture specifically designed for biomedical image segmentation tasks. Unlike traditional models, nnU-Net automatically configures the network architecture, preprocessing pipeline, training strategy, and hyperparameters based on the characteristics of the input dataset²³. This self-configuring capability eliminates the need for manual tuning and enhances reproducibility and robustness across different datasets.

Model Training Strategy

Model training was performed using the three-dimensional full-resolution configuration of nnU-Net. The training process included:

- Automatic normalization of image intensities
- Resampling to standardized voxel spacing
- Patch-based training approach
- Data augmentation techniques

The model was trained for 1000 epochs using a high-performance computing environment with GPU acceleration. Data augmentation techniques included:

- Rotation
- Scaling
- Translation
- Intensity variation

These techniques were applied to increase dataset diversity and improve model generalization, as

recommended in previous deep learning studies^{24,25}.

Evaluation Metrics

Model performance was evaluated using both segmentation and classification metrics. The segmentation performance was assessed using:

- Dice Similarity Coefficient (DSC)
- Jaccard Index (Intersection over Union)

These metrics evaluate the overlap between predicted segmentation and ground truth and are widely used in medical image analysis^{25,26}. Additionally, boundary accuracy was evaluated using:

- Hausdorff Distance (HD)
- Average Surface Distance (ASD)

These metrics provide information on the spatial accuracy of segmentation boundaries.

Classification performance was evaluated using confusion matrix-based metrics, including accuracy, precision, recall (sensitivity), and F1 score, which collectively provide a comprehensive assessment of model performance, particularly in imbalanced datasets²⁷.

Results

A total of 49 CBCT datasets were included in the study, comprising 44 datasets for training and 5 datasets for

independent testing. All cases involved impacted maxillary canines and were categorized into three positional classes: horizontal (Class 1), palatal (Class 2), and vestibular (Class 3).

The distribution of samples across these classes was imbalanced, with palatal impactions representing the majority of cases. This imbalance is known to significantly affect deep learning model performance, particularly in segmentation tasks. For Class 2 (palatal impactions), the model demonstrated the highest segmentation performance. The Dice similarity coefficient reached 0.685, while the Jaccard index was calculated as 0.612. Precision and recall values were 0.665 and 0.744, respectively, indicating a relatively balanced performance. The Hausdorff distance was measured at approximately 11.59 mm, reflecting moderate boundary agreement. In contrast, Class 1 (horizontal impactions) demonstrated extremely poor segmentation performance. The Dice and Jaccard values were both 0.0, indicating complete failure in overlap between predicted and ground truth masks. Despite this, the overall accuracy was calculated as 0.9999, which was misleading due to the overwhelming number of true negative predictions. Similarly, Class 3 (vestibular impactions) also showed poor segmentation performance, with Dice and Jaccard values of 0.0. The absence of true positive detections in this class resulted in a recall value of 0.0. However, the true negative rate reached 1.0, again indicating severe class imbalance. The quantitative performance of the nnU-Net model across

Table 1. Comprehensive Performance Evaluation of the nnU-Net Model for Impacted Maxillary Canine Segmentation and Classification

Class	Impaction Type	Dice	IoU (Jaccard)	Precision	Recall	F1-score	Accuracy	AUC	HD95 (mm)	ASD (mm)
1	Horizontal	0.000	0.000	0.000	0.000	0.000	0.9999	0.50	39.05	30.77
2	Palatal	0.685	0.612	0.665	0.744	0.702	0.9998	0.87	11.59	3.10
3	Vestibular	0.000	0.000	–	0.000	–	1.0000	0.50	–	–

AUC: Area Under the Receiver Operating Characteristic Curve

HD95: 95th percentile Hausdorff Distance

ASD: Average Symmetric Surface Distance

“–” indicates non-computable values due to absence of positive predictions

different impacted canine classes is summarized in Table 1.

Axial CBCT slices in Figure 1 are demonstrating comparison between manually annotated ground truth (Real) and model predictions (Prediction). The highlighted regions represent segmented impacted maxillary canines. The upper row shows a representative case with relatively

accurate segmentation, particularly in palatal impaction, where the model prediction closely corresponds to the ground truth. The lower row illustrates a case with reduced segmentation performance, demonstrating discrepancies between the predicted and actual regions. These examples reflect the variability in model performance across different impaction types and are consistent with the quantitative

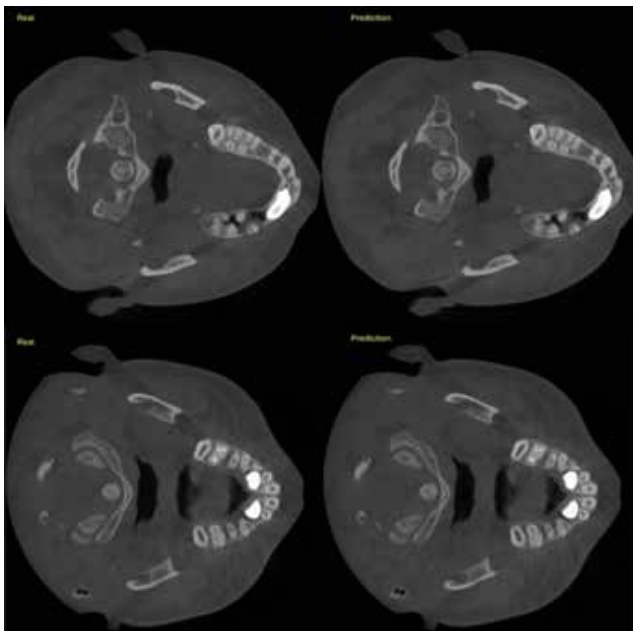


Figure 1. Representative examples of ground truth and nnU-Net-based segmentation results for impacted maxillary canines on CBCT images.

findings reported in this study.

Receiver operating characteristic (ROC) curves are presented in Figure 2. The AUC value for palatal impactions was 0.87, indicating strong discriminative performance. In contrast, horizontal and vestibular classes demonstrated AUC values of 0.50, corresponding to random classification

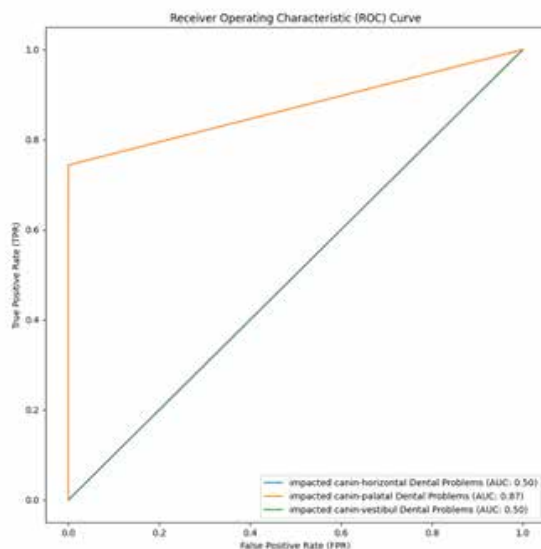


Figure 2. Receiver Operating Characteristic (ROC) curves of the nnU-Net model for classification of impacted maxillary canine

performance.

Discussion

The present study evaluated the performance of an nnU-Net-based deep learning model for the automatic segmentation and classification of impacted maxillary canines on CBCT images. The findings demonstrate that while the model shows promising performance in certain impaction types, particularly palatal cases, its overall performance remains heterogeneous and highly dependent on data distribution and class representation.

CBCT is widely accepted as the gold standard imaging modality for the evaluation of impacted maxillary canines due to its ability to provide high-resolution three-dimensional anatomical information without superimposition^{10,11}. Previous studies have demonstrated that CBCT significantly improves the detection of root resorption and spatial localization compared to conventional two-dimensional imaging methods^{6,7}. The use of CBCT in the present study ensured high-quality volumetric data, which is essential for training deep learning algorithms and achieving reliable segmentation outcomes.

Despite these advantages, CBCT interpretation remains time-consuming and operator-dependent, which has led to increasing interest in artificial intelligence-based solutions in dental radiology^{16,17}. Deep learning models, particularly convolutional neural networks, have demonstrated high performance in medical image analysis tasks such as classification and segmentation^{14,17}. Studies by Esteva et al.¹⁴ and Rajpurkar et al.²⁷ have shown that deep learning systems can achieve performance comparable to experienced clinicians, supporting their integration into diagnostic workflows.

In the field of dental imaging, several studies have reported successful applications of deep learning in the detection and classification of impacted canines. Aljabri et al.²⁴ and Alenezi et al.²³ demonstrated effective classification of impacted canines using panoramic radiographs, while Swaitly et al.³ reported successful CBCT-based segmentation using deep learning approaches. Furthermore, Pirayesh et al.²⁵ emphasized the potential of AI systems in detecting root resorption associated with impacted canines, highlighting their clinical relevance.

A particularly important comparison can be made with the study conducted by Ünal et al.⁴, who developed a deep learning-based framework for automatic three-dimensional segmentation of impacted maxillary canines using CBCT images. Their study reported consistently high segmentation performance across different anatomical variations, suggesting that deep learning models can achieve robust and clinically reliable results when trained on sufficiently

large and well-balanced datasets. In contrast, the findings of the present study revealed marked variability across different impaction classes, with acceptable performance observed primarily in palatal cases, whereas horizontal and vestibular impactions demonstrated near-zero segmentation performance. This discrepancy is most likely attributable to differences in dataset size, class imbalance, and annotation consistency. Ünal et al.⁴ emphasized the importance of dataset diversity and optimized preprocessing strategies, which likely contributed to their more stable outcomes. Additionally, their dataset appears to include a more balanced representation of impaction types, whereas the present study was limited by a relatively small training dataset and uneven class distribution. These findings underscore that although nnU-Net-based architectures are highly promising, their performance is strongly dependent on the quality, size, and heterogeneity of the training data.

The heterogeneous performance observed in this study may also be explained by inherent challenges in medical image segmentation. Class imbalance is a well-recognized limitation in deep learning, leading to poor model generalization in underrepresented categories²⁸. Moreover, the complex anatomical variability of impacted canines, differences in bone density, and variations in spatial orientation further increase the difficulty of segmentation tasks, particularly in atypical cases. Similar challenges have been reported in previous studies evaluating AI-based detection of impacted teeth and associated complications^{25,29}.

Despite these limitations, the integration of AI into CBCT analysis offers significant clinical advantages. AI-based systems can reduce interpretation time, improve diagnostic consistency, and function as supportive tools in clinical decision-making processes^{15,16}. In the context of impacted canines, accurate segmentation and classification are essential for determining surgical approaches and orthodontic traction strategies^{4,5}. Therefore, even partially successful models may still provide valuable assistance to clinicians by highlighting regions of interest and supporting diagnostic evaluation.

From a broader clinical perspective, the integration of deep learning-based systems into CBCT analysis has the potential to substantially improve diagnostic efficiency and reduce inter- and intra-observer variability, which remains a well-recognized limitation in dental radiology^{5,14}. Automated segmentation and classification of impacted canines may facilitate more standardized treatment planning, particularly in complex cases involving multiple anatomical variables and spatial considerations. However, before such systems can be routinely implemented in clinical workflows, it is essential to ensure consistent and reliable performance across all impaction types. This necessitates addressing key challenges such as dataset imbalance, limited sample size, and anatomical heterogeneity, all of which can significantly

affect model generalizability and robustness^{28,30}.

Future research should focus on expanding dataset size, ensuring balanced class distribution, and incorporating multi-center data to enhance model generalizability. In addition, external validation using multi-center datasets and prospective clinical studies will be crucial to establish the real-world applicability, reliability, and safety of these systems prior to their adoption in routine orthodontic and surgical practice. The integration of advanced techniques such as data augmentation, transfer learning, and hybrid modeling approaches may further improve segmentation performance. Furthermore, the development of multimodal AI frameworks that combine radiographic data with clinical and demographic parameters, as well as the incorporation of radiomics features and three-dimensional quantitative analysis, may enhance predictive performance, clinical relevance, and sensitivity in detecting subtle anatomical variations and pathological changes. With continued methodological improvements, deep learning-based systems are expected to play an increasingly important role in the diagnosis and management of impacted maxillary canines.

Conclusion

The findings of this study highlight that while deep learning models, particularly nnU-Net, offer a promising approach for automated CBCT analysis in dentomaxillofacial radiology, their clinical applicability remains constrained by dataset-related challenges. The discrepancy observed between high accuracy values and low segmentation performance further emphasizes the importance of using appropriate evaluation metrics, such as Dice coefficient and recall, in assessing model performance. Achieving reliable and consistent performance across all positional classes is essential before these systems can be implemented in routine clinical practice.

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