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Deep Learning for Automated Segmentation of the Edentulous Region on Cone Beam Computed Tomography for Dental Implant Planning: A Narrative Review

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ABSTRACT

Background: Edentulism remains a considerable concern in dental practice, and dental implant is favored among rehabilitation options for its stability and long-term survival. The outcome of implant therapy depends heavily on pre-surgical planning, which requires precise identification of the edentulous area, the residual alveolar bone, and adjacent vital structures on Cone Beam Computed Tomography (CBCT). Conventional manual segmentation of these structures is time-consuming, requires substantial operator expertise, and is prone to inter-operator variability. Deep learning-based automated segmentation has therefore been increasingly explored as a solution to these limitations. ***Purpose:*** This narrative review discusses the current application, performance, and limitations of deep learning for automated segmentation of the edentulous area on CBCT in supporting dental implant planning. ***Review:*** A literature search was conducted through PubMed, Scopus, ScienceDirect, IEEE Xplore, and Google Scholar for articles published between 2015 and 2026 using combinations of keywords related to artificial intelligence, deep learning, CBCT, segmentation, and dental implant. Convolutional neural network-based architectures, particularly U-Net and YOLO-derived models, have been applied to automatically delineate the edentulous alveolar ridge together with the mandibular canal and maxillary sinus, achieving accuracy that approaches manual segmentation performed by experienced clinicians while considerably shortening analysis time. Dataset limitations, cross-institutional variability, and the continued need for clinician oversight remain the main challenges. ***Conclusion:*** Deep learning offers meaningful potential to improve the efficiency and consistency of CBCT-based edentulous area segmentation, although its clinical use should remain supervised by trained clinicians.

Keywords: *artificial intelligence; cone beam computed tomography; deep learning; dental implant; image segmentation*

INTRODUCTION

Edentulism, the condition of tooth loss, continues to affect a substantial proportion of the population despite a global decline in its prevalence [1]. In Indonesia, national data indicate that tooth loss affects approximately 19% of the population, with the figure rising to 30.6% among individuals aged 65 years and above [2], while a more recent report estimated that around one in five Indonesian adults has lost at least one tooth [3]. Edentulism also remains a public health concern in low- and middle-income countries, where its prevalence ranges from 2.9% to 15.3% [4]. Given this burden, an effective rehabilitation approach is required to restore masticatory function, phonetics, and esthetics.

Dental implants have become one of the preferred rehabilitation options for tooth loss because of its favorable long-term survival and its ability to preserve the surrounding alveolar bone without requiring preparation of adjacent teeth [5]. Long-term follow-up studies have reported implant survival rates that remain excellent even after 20 to 22 years of function [6,7], and implant therapy has also been shown to significantly improve oral health-related quality of life [8].

However, the long-term success of implant treatment is not determined solely by the surgical procedure itself but is largely influenced by the accuracy of pre-surgical planning [9].

This planning requires careful identification of the edentulous region, measurement of the available alveolar bone, and evaluation of vital anatomical structures, since errors at this stage may result in nerve injury, failure of osseointegration, or other surgical complications [10]. Errors in the identification of the edentulous region and the surrounding anatomy during pre-surgical planning are not merely a theoretical concern. A radiographic analysis by Alaqeely et al. [4] found that malpositioned implants were frequently associated with inadequate pre-operative assessment of the available bone and its proximity to vital structures, which in turn increased the risk of complications such as nerve paresthesia, sinus perforation, and compromised prosthetic outcomes. This finding reinforces the clinical importance of obtaining an accurate and reproducible assessment of the edentulous region before implant surgery is performed.

Cone Beam Computed Tomography (CBCT) has become the imaging modality of choice for implant planning because it provides three-dimensional visualization of the maxillofacial structures with a relatively low radiation dose and sub-millimeter spatial resolution [11,12].

Nevertheless, extracting clinically useful information from CBCT still commonly relies on manual segmentation performed by a trained operator, a process that is time-consuming, requires considerable expertise, and is susceptible to variability between operators, particularly when the anatomy surrounding the edentulous area is complex [13]. Compared with two-dimensional radiographic modalities such as periapical radiography and orthopantomography, CBCT offers the advantage of eliminating superimposition and geometric distortion, thereby allowing more reliable linear and volumetric measurement of the alveolar bone in the edentulous region. Carneiro et al. [9] emphasized that low-dose CBCT protocols can provide measurement accuracy for implant planning that is comparable to standard-dose protocols, supporting the feasibility of incorporating CBCT more routinely into implant planning workflows without exposing patients to unnecessarily high radiation doses. These limitations have encouraged the development of automated segmentation approaches based on artificial intelligence (AI), particularly deep learning. Deep learning is a subfield of machine learning that employs multilayer neural networks capable of learning representative image features directly from data without relying on manually engineered features [14].

In dentomaxillofacial radiology, deep learning-based systems have been increasingly investigated to assist diagnosis and treatment planning by automating tasks such as tooth detection, bone segmentation, and identification of vital anatomical structures [15,16]. When applied to CBCT images, deep learning is expected to enable faster, more objective, and more standardized delineation of the edentulous alveolar ridge and its surrounding structures compared with conventional manual methods. Although an increasing number of studies have investigated deep learning for automated segmentation of the edentulous area on CBCT, the available evidence remains scattered across different network architectures, datasets, and evaluation metrics.

This narrative review was therefore conducted to summarize the current application, performance, and limitations of deep learning-based automated segmentation of the edentulous area on CBCT in supporting dental implant planning, based on a literature search performed through PubMed, Scopus, ScienceDirect, IEEE Xplore, and Google Scholar for articles published between 2015 and 2026, using combinations of the keywords “artificial intelligence”, “deep learning”, “convolutional neural network”, “cone beam computed tomography”, “segmentation”, and “dental implant”.

DISCUSSION

Artificial intelligence (AI) broadly refers to computational systems designed to perform tasks that typically require human cognitive ability, such as pattern recognition and decision-making [14]. Machine learning represents a subfield of AI in which systems learn patterns directly from data rather than following explicitly programmed rules, while deep learning is a further specialization of machine learning that relies on multilayer artificial neural networks to automatically extract hierarchical features from raw data, including medical images [14]. Among the various deep learning architectures, convolutional neural networks (CNNs) have become the dominant approach for medical image segmentation because their convolutional layers are able to capture spatial patterns such as edges, textures, and shapes that are relevant for distinguishing anatomical structures [27]. Encoder-decoder architectures such as U-Net were specifically designed for biomedical image segmentation and have become a common backbone for CBCT-based segmentation tasks, while object detection architectures such as YOLO have been adapted to simultaneously localize and delineate multiple anatomical structures within a single image [28]. The recent expansion of deep learning applications in dentistry has been driven in part by the growing availability of digital CBCT datasets together with increased computing capacity, both of which are required to train multilayer neural networks on large volumes of three-dimensional imaging data [16]. As more institutions adopt CBCT as a routine part of implant planning, the resulting accumulation of digital imaging data has created an opportunity to train and refine deep learning models specifically for tasks relevant to implant dentistry, including the segmentation of the edentulous alveolar ridge and its surrounding anatomy.

Several deep learning architectures have been developed to automatically segment the edentulous alveolar ridge on CBCT prior to implant placement. Moufti et al. [5] developed a fully automated segmentation system based on a U-Net architecture to delineate the edentulous mandibular bone and reported an overall segmentation accuracy of 96% for the mandible, demonstrating that the model closely approximated the boundaries produced by manual segmentation while markedly reducing the required analysis time. A comparable approach was taken by Al-Asali et al. [17], who developed a three-dimensional deep learning model capable not only of segmenting the alveolar bone but also of predicting the contour of the missing tooth region, which is intended to directly support virtual implant planning.

Comparable efforts have also been reported by researchers affiliated with the Faculty of Dental Medicine, Universitas Airlangga. Widiasri et al. [18] introduced Dental-YOLO, a modified YOLOv4-based model developed to simultaneously detect the alveolar bone and the mandibular canal on two-dimensional CBCT slices for posterior mandibular implant planning, showing that the model could automatically estimate the available bone height and width with performance approaching that of manual measurement by a radiologist. This model was later extended by Naufal et al. [19] using a YOLOv8-based architecture combined with three-dimensional reconstruction, allowing the alveolar bone and mandibular canal to be visualized more comprehensively across the CBCT volume rather than being limited to a single cross-sectional slice.

The importance of validating deep learning models on large and diverse datasets was demonstrated by Cui et al. [29], who developed a fully automatic AI system for simultaneous tooth and alveolar bone segmentation on CBCT and evaluated it on 4,938 scans collected from 4,215 patients across 15 different centers. The system achieved average Dice similarity coefficients of 91.5% for tooth segmentation and 93.0% for alveolar bone segmentation, values comparable to those obtained by experienced radiologists, while completing the segmentation approximately 500 times faster than manual delineation. Although this study was not limited specifically to the edentulous region, its multi-center validation strategy illustrates an approach that could be adapted to strengthen the generalizability of models developed for edentulous area segmentation.

Segmentation of the edentulous area for implant planning cannot be separated from the evaluation of adjacent vital structures, particularly the mandibular canal in the posterior mandible and the maxillary sinus in the posterior maxilla, since both determine the safe height of bone available for implant placement [9]. Bayrakdar et al. [20] evaluated a deep convolutional neural network for automated implant planning on CBCT and found that the system detected the mandibular canal, maxillary sinus, and edentulous region with a level of agreement comparable to manual assessment across the anterior, premolar, and molar regions. Ding et al. [21] further noted that deep learning-based detection of structures such as the mandibular canal and maxillary sinus has been shown to reduce inter-operator variability while accelerating the interpretation of increasingly complex three-dimensional CBCT datasets.

The clinical relevance of accurately assessing structures around the edentulous area is further supported by recent evidence published in the Dental Journal (Majalah Kedokteran Gigi). Guler and Gulsun [22] used CBCT to evaluate the prevalence and location of maxillary sinus septa prior to sinus surgery and found that this anatomical variation was present in approximately one-third of the population studied, underlining the importance of thorough three-dimensional assessment of the maxillary sinus before implant-related surgery is performed in this region. In line with this, Singhai et al. [23] reported that linear and volumetric measurement of the maxillary sinus using CBCT provides more detailed anatomical information than two-dimensional imaging, which is particularly relevant when planning implant placement in the posterior maxilla. Meanwhile, Alhamdani et al. [24] demonstrated that a bone-preserving implant preparation protocol was associated with favorable bone augmentation outcomes over a five-year follow-up period, reflecting how precise pre-surgical evaluation of the available alveolar bone, the kind of information that automated CBCT segmentation is intended to provide, may directly support long-term implant success.

Accurate delineation of these adjacent structures is directly relevant to patient safety, since inadequate assessment of their position relative to the edentulous ridge has been associated with a higher risk of implant malposition and related surgical complications [4]. Automated segmentation consistently identifies the mandibular canal and maxillary sinus alongside the edentulous region may therefore contribute not only to more efficient planning, but also to a more standardized safety margin during virtual implant placement.

The performance of deep learning-based segmentation models is commonly reported using a combination of overlap-based and distance-based metrics. The Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) measure the degree of spatial overlap between the automated segmentation and a manually annotated ground truth, with values closer to 1 indicating better agreement, while the Hausdorff Distance quantifies the maximum boundary discrepancy between the two segmentations and is therefore particularly sensitive to localized segmentation errors [27,28]. Accuracy, sensitivity, and specificity are also frequently reported to describe how reliably a model distinguishes the target structure from surrounding tissue at the pixel or voxel level. Table 1 summarizes the architecture, segmentation target, and key reported outcome of representative deep learning studies discussed in this review. Taken together, these studies illustrate that although the specific metrics used vary between studies, which complicates direct comparison, the overall pattern consistently favors deep learning-based segmentation approaching the performance of experienced clinicians across different anatomical targets relevant to implant planning.

TABLE 1: Summary of representative deep learning studies for CBCT-based segmentation relevant to dental implant planning.

Study	Architecture	Segmentation Target	Key Reported Outcome
Moufti et al. [5] (2023)	U-Net (CNN)	Edentulous mandibular alveolar bone	Overall accuracy 96% (mandible); 83% (maxilla)
Al-Asali et al. [17] (2024)	3D deep learning model	Alveolar bone & missing tooth region	Predicted missing tooth contour to support virtual implant planning
Widiasri et al. [18] (2022) – Dental-YOLO	Modified YOLOv4	Alveolar bone & mandibular canal (2D slice)	Automated bone height/width estimation approaching manual measurement
Naufal et al. [19] (2024)	YOLOv8 + 3D reconstruction	Alveolar bone & mandibular canal (3D volume)	Volumetric visualization across the CBCT volume
Bayrakdar et al. [20] (2021)	Deep CNN (Diagnocat)	Edentulous region, mandibular canal, maxillary sinus	75 CBCT images, 508 implant regions; agreement comparable to manual assessment
Cui et al. [29] (2022)	Two-stage CNN (ROI + segmentation network)	Individual teeth & alveolar bone	DSC 91.5% (teeth), 93.0% (bone); ~500× faster; 4,938 scans, 15 centers

Across the studies discussed above, deep learning-based segmentation has consistently been reported to reduce the time required for CBCT analysis compared with manual segmentation, while achieving accuracy that approaches expert performance. A systematic review and meta-analysis by Alqutaibi et al. [10] concluded that artificial intelligence-based systems for implant planning generally demonstrate high accuracy in identifying the edentulous region and vital anatomical structures, and that these systems have the potential to shorten planning time in clinical practice. Comparable findings have also been reported in the context of tooth detection, since Putra et al. [25], also affiliated with Universitas Airlangga, developed a deep learning model for automated tooth detection and numbering on panoramic radiographs that achieved detection accuracy close to that of experienced examiners, supporting the broader premise that deep learning-based automation can be applied consistently across different types of dental radiographic analysis, including CBCT-based segmentation for implant planning.

Nevertheless, the reported accuracy of automated segmentation is not always uniform across anatomical regions. Moufti et al. [5] observed that segmentation accuracy was noticeably lower in the maxilla (83%) compared with the mandible (96%), a difference attributed to the more complex trabecular pattern and thinner cortical structure typically found in the maxilla. This finding indicates that although deep learning models can perform well overall, their performance may still vary depending on the anatomical complexity of the region being segmented.

This efficiency gain is consistent with the finding by Cui et al. [29], whose system completed segmentation roughly 500 times faster than manual analysis. This indicates that the time savings offered by deep learning-based segmentation are not limited to a single architecture or anatomical target, but appear to be a general characteristic of automated approaches applied to CBCT.

Despite its promising performance, the clinical application of deep learning for edentulous area segmentation still faces several limitations. Palani et al. [13] emphasized that the performance of deep learning models remains highly dependent on the size and quality of the training dataset, and that not all CBCT data can be used for model development because of ethical considerations and patient data protection requirements. Variation in CBCT acquisition protocols and scanner types between institutions can also produce differences in image characteristics, so that a model trained using data from one institution may not necessarily perform equally well when applied to data obtained from a different institution or device [26].

Putra et al. [15] similarly noted that although artificial intelligence applications in digital dental radiography continue to develop rapidly, their implementation in clinical practice should still be regarded as a decision-support tool rather than a replacement for clinical judgment, since the final treatment decision requires comprehensive consideration of each patient's individual condition. This view is consistent with the broader consensus that outputs generated by automated segmentation systems require validation by an experienced clinician before being used as the basis for implant planning [10].

Emerging architectures may help address some of these limitations. Yang et al. [30] proposed ImplantFormer, a vision transformer-based model that predicts implant position directly from CBCT data by capturing long-range spatial relationships across the image, an approach that may complement the more locally focused feature extraction of CNN-based models such as U-Net and YOLO. Continued exploration of such hybrid or transformer-based approaches, combined with the multi-center validation strategy demonstrated by Cui et al. [29], may help improve both the accuracy and generalizability of deep learning models for edentulous area segmentation in future studies.

From a clinical workflow perspective, the integration of automated segmentation into implant planning software may allow clinicians to obtain an initial delineation of the edentulous ridge and surrounding vital structures within seconds rather than the considerable time typically required for manual segmentation, potentially freeing clinician time for treatment planning and patient communication rather than repetitive image annotation [10,15]. This is particularly relevant in institutions with a high volume of implant cases or limited access to a dedicated oral radiologist.

Nonetheless, the evidence discussed in this review consistently indicates that automated segmentation performs best when positioned as a decision-support tool integrated within a clinician-supervised workflow, rather than as a fully autonomous replacement for clinical judgment [10,15]. Before such systems can be more widely adopted in routine implant planning, clinicians are encouraged to critically evaluate the training data, validation methodology, and reported performance metrics of a given system, particularly regarding its performance on the specific anatomical region and patient population relevant to their practice.

It is also worth situating these findings within the broader workflow that clinicians currently follow. In conventional practice, an operator typically scrolls through dozens of axial, coronal, and sagittal CBCT slices to manually trace the contour of the edentulous ridge and the surrounding vital structures before any virtual implant can be positioned, a process that becomes increasingly laborious as the number of implant sites or the anatomical complexity of a case increases [13]. The studies discussed in this review suggest that deep learning-based segmentation can compress this multi-step manual process into a near-instantaneous automated output, which the clinician can then review, adjust if necessary, and use as the basis for virtual implant placement [5,20].

This shift in workflow does not eliminate the clinician's role but rather changes its emphasis, from performing repetitive tracing tasks toward verifying and refining an automatically generated segmentation. Such a shift is consistent with how AI-based tools have generally been positioned across other areas of dental radiology, where the technology is intended to augment rather than replace the clinician's diagnostic and planning responsibilities [15,16].

CONCLUSIONS

Deep learning-based automated segmentation, particularly using U-Net and YOLO-derived architectures, has shown promising performance in delineating the edentulous alveolar ridge together with adjacent vital structures such as the mandibular canal and maxillary sinus on CBCT, with accuracy that approaches manual segmentation while substantially reducing analysis time. However, variation in performance across anatomical regions, dependence on the quality and diversity of training datasets, and differences in CBCT acquisition protocols between institutions remain challenges that limit its generalizability. Automated segmentation should therefore currently be regarded as a decision-support tool that still requires validation by an experienced clinician rather than a fully autonomous replacement for clinical judgment in dental implant planning. Continued development of larger, multi-institutional datasets and exploration of emerging architectures such as vision transformers may further improve the accuracy and generalizability of these systems, supporting their responsible integration into everyday implant planning workflows.

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