A Comprehensive Study on Dental X-Ray Image Segmentation for Automated Dental Analysis

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ABSTRACT
The field of segmentation of dental x-rays has emerged as an essential area of analysis in medical imaging due to increased need for accurate tooth detection, automatic dental diagnosis and clinical assessment. This survey examines 20 scientific analysis published between 2024 and 2026 in the area of segmentation of dental x-rays, which use Machine Learning (ML), Deep Learning (DL), different variations of U-net, transformers, attention models, foundation models and hybrid segmentation models. Some of the methods used for the analysis of dental images that have been investigated include Convolutional Neural Networks (CNN), Transformers, semi-supervised methods, coordinate-based feature learning methods, boundary networks and attention-based networks. The existing literature proves the effectiveness of such methods in improving the quality of image segmentation, feature representation, boundary identification and automatic dental assessment. However, there are multiple problems that require attention regarding the absence of annotated datasets, the difficulty of the shapes of the teeth, overlapping of the teeth, high computational demands, domain adaptation and generalization. This survey presents an in-depth examination of the existing state-of-the-art techniques, datasets, metrics, results and shortcomings of dental X-ray image segmentation. This survey highlights the significance of lightweight, adaptive and strong segmentation methods, effective feature extraction, boundary detection and applications in the clinical environment. These developments used to design intelligent computer-based tools for dentistry to assist in the diagnosis and analysis of oral health care.

Keywords
Automated Dental Diagnosis, Dental Image Analysis, Dental Radiography, Dental Structure Extraction, Medical Image Processing, Radiographic Image Segmentation.

1. INTRODUCTION
The task of segmentation for dental radiographs aims at extracting tooth structures and pathologies from dental radiographic images to facilitate dental analysis. Modern Machine Learning (ML) and Deep Learning (DL) algorithms used in improving feature representation, segmentation and structure interpretation of panoramic and Cone Beam Computed Tomography (CBCT) dental images.

Dental X-ray Segmentation is still difficult to perform owing to complicated tooth structure, overlapping areas, lack of labeled data sets and image quality. Existing approaches demand significant computation power and fail to generalize to various dental imaging scenarios.

Tooth segmentation and orientation estimation were achieved using deep learning to analyze teeth and its position from panoramic radiographic images for better structural analysis results [1]. Semi-supervised Transformer architecture was used to decrease annotation dependence and increase tooth segmentation and detection accuracy using global feature extraction [2]. An automatic system for evaluating dental developmental stage was developed by combining the processes of tooth detection, segmentation and classification using panoramic X-rays [3]. A coordinate-based feature learning algorithm was introduced to enhance the localization and segmentation accuracy of dental anatomy using panoramic X-rays [4]. An advanced segmentation method using deep learning was introduced for oral screening through the identification of dental calculus, gingivitis and caries areas from intraoral images [5]. A new segmentation algorithm with attention was created to improve tooth segmentation and feature extraction in children's panoramic dental X-rays [6]. The application of U-Net based semantic segmentation approaches was analyzed in order to find out efficient methods of tooth segmentation at the pixel level for panoramic dental radiography [7]. Segmentation and agenesis detection method was implemented to detect agenesis and improve automatic dental diagnostics using panoramic radiographs [8]. To enhance the performance of tooth segmentation by incorporating the latest capabilities of vision feature learning, a strategy to adapt a foundation model with SAM2 has been considered [9]. ResU-Net with Coordinate Attention and Boundary-Aware Mechanisms has been developed to enhance the tooth boundary preservation and segmentation [10]..

2. BACKGROUND STUDY
Majanga et al. (2026) [11] developed ViTUNet which was a combination of Vision Transformer and U-Net to segment the lesions present on bitewing dental images. This model uses the benefits of transformer networks to learn global features along with U-Net's localization and gave high Dice, IoU 95.87% and accuracy. Nevertheless, it needs more computational power and hence, there is a scope in lightweight dental image segmentation.

Pan et al. (2025) [12] developed Multi-scale convolution-attention U-Net for medical image segmentation. Multi-scale convolution and attention modules were combined to maintain fine details and enhance boundary segmentation performance with DSC 89.77% and IoU 82.87%. The drawback of the analysis is that it used medical datasets for validation and dental X-rays were not considered.

Ma et al. (2025) [13] presented a two-channel dental panoramic X-ray image segmentation technique using transformer heterogeneous feature complementation approach. In its model, transformer heterogeneous features were used to fuse together complementary features and get high IoU 91.49% and Dice 94.54%. The complicated model structure led to high computational requirements.

Vanaja and Prakasam [14] (2025) came up with a U-Net architecture using convolutional block attention gates for segmentation in medical imaging. The authors applied attention gates with the U-Net model to enhance segmentation accuracy in small regions and boundaries, with an IoU score of 75.8%, Dice coefficient of 86.5% and a high AUC score. However, the experiment only focused on retinal images.

Hussain and Shouno (2024) [15] introduced MAGRes-UNet is a multi-attention gated residual U-Net for medical image segmentation. This algorithm utilizes residual learning with attention gates, which provides high accuracy and Dice score performance on the benchmark dataset. Yet, application of the approach to dental images is unexplored, dental image segmentation.

Table 1 Recent Advanced Approach for Dental X-Ray Segmentation and Analysis

Author, Year & Ref. No.	Concept	Method Used	Limitation	Results
Wang et al. (2024) [16]	Feature fusion for accurate segmentation	Multi-modality fusion gated U-Net	Requires dental adaptation	F1: 0.9191, 0.7410, 0.8421; 62% GFLOPs reduction
Hu et al. (2026) [17]	Dental X-ray structure segmentation	DCGC-UNet with directional convolution and gating	Higher complexity	Achieved High Accuracy, IoU 90.43%, Dice 94.96%
Wang and Li (2026) [18]	Early dental caries detection	Transformer-based detection model	Limited disease coverage	mAP 87.3%, Sensitivity 81.3–84.7%
Wang et al. (2026) [19]	3D tooth segmentation	ToothFormer Transformer network	Requires 3D CBCT data	Dice 94.66%, IoU 89.88%, ASSD 0.2906
Esmaeili et al. (2025) [20]	Dental structure segmentation	Hierarchical attention DNN	Lower IoU for complex regions	Achieved High Accuracy, IoU 78.76%, F1 84.54%

Table 1 shows information on new approaches for dental x-rays segmentation, which includes the concepts, methods, shortcomings and results of these approaches. Several types of approaches are described in this context, such as the U-Net approach, Transformer approach and attention models.

2.1 Research Gap

However, the techniques invented until now for segmenting dental X-rays have proven very impressive in its accuracy but, there are several limitations associated with computational cost, heterogeneity of data and generalization to different dental applications. In most of the existing algorithms, the problem lies in the detection of boundaries, segmentation of tiny lesions and representation of features. Thus, a robust method is essential.

3. DENTAL X-RAY ANALYSIS FOR PRECISE SEGMENTATION

Dental x-ray analysis via deep learning offers precise detection and segmentation of teeth as well as other structures within dental anatomy based on radiographic images. Analyze some of the sophisticated segmentation techniques that are used to better understand the structure and characteristics of dental images.

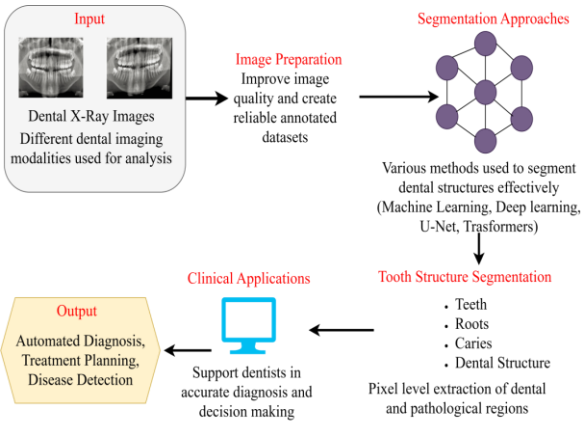


Figure 1: Dental X-Ray Image Segmentation Process for Clinical Analysis

Figure 1 depicts the different steps taken in the segmentation process of dental x-ray images that include image acquisition, image processing, segmentation methods, extraction of the tooth structure and clinical analysis. The segmented tooth structure is used in automated diagnosis and disease detection.

3.1 Dental X-Ray Image Analysis and Structural Understanding

The automatic teeth segmentation and orientation estimation algorithm using deep learning techniques is introduced in [1] by Deb et al. The approach recognizes tooth regions and estimates its orientation according to learning the features of dental structures from the X-ray image. The developed approach enhances the understanding of the tooth structure and makes possible automatic dental analysis.

Semi-supervised deep learning model based on transformers for tooth segmentation and recognition was implemented by Hao et al. [2]. Transformer model is capable of capturing the global context information from the dental images and semi-supervised learning technique assists in decreasing the requirement of large annotated datasets. This leads to improved tooth recognition and structural representation.

An automated deep learning technique for the assessment of dental development using panoramic radiographs was introduced by Ong et al. [3]. The system analyzes dental characteristics that contribute to development, which makes the process of assessment more accurate and reduces the efforts needed for this purpose.

The multi-features coordinate position learning algorithm was implemented by Ma et al. [4] to segment dental panoramic X-ray images. In this approach, the extraction process of visual features and coordinate information is considered together. It should be noted that the use of the discussed method increases the accuracy of detecting the image structures.

3.2 Tooth Structure Segmentation and Clinical Applications

Zannah et al. have introduced a panoramic dental image segmentation method based on U-Net architecture [7]. Such a method can serve as a strong baseline for the segmentation of teeth since it is capable of segmenting dental regions and analyzing panoramic images automatically.

An approach using the U-Net model method for tooth segmentation and agenesis was developed by Tunc et al. [8].This approach advances tooth segmentation into the clinical phase, enabling automatic detection of missing teeth and diagnosing the dentition problem.

The Adaptation of SAM2 Segmentation Model for Teeth Segmentation in Panoramic Dental Radiographs has been carried out by Li et al. [9]. This shows that it is effective to use advanced segmentation models to get teeth structure from complex images.

Xiong et al. have presented an innovative technique for segmentation of teeth in X-rays using ResU-Net with the use of coordinate attention and boundary-awareness methods [10].This technique facilitates better boundaries detection without compromising on the integrity of the structure.

Table 2: Application Areas of Dental X-Ray Segmentation Methods

Author, Year & Ref. No.	Application Area	Segmented Target	Contribution
Deb et al. (2025) [1]	Tooth structure analysis	Individual teeth and tooth orientation	Enables automated tooth localization and structural assessment from panoramic X-rays
Ong et al. (2024) [3]	Dental development evaluation	Developing tooth regions	Supports automated assessment of tooth growth and maturity stages
Liu et al. (2024) [5]	Oral disease screening	Dental calculus, gingivitis and caries regions	Enables segmentation-based identification of common oral conditions
Zhong et al. (2025) [6]	Pediatric tooth segmentation	Tooth structures in children's panoramic radiographs	Improves tooth structure extraction and boundary representation
Li et al. (2024) [9]	Automated tooth segmentation	Tooth regions in panoramic X-ray images	Applies foundation model adaptation for improved dental structure extraction
Hu et al. (2026) [17]	Dental X-ray image segmentation	Dental anatomical structures	Enhances feature selection and boundary detection for accurate segmentation
Wang et al. (2026) [19]	3D tooth segmentation	Tooth structures from CBCT images	Supports precise three-dimensional tooth structure analysis

Table 2 shows applications of dental X-ray segmentation using this approach and it include tooth detection, oral disease detection, dental development detection and 3D structure detection. This table shows how segmentation methods can be used in dental X-ray imaging.

3.3 Challenges in Dental X-Ray Image Segmentation

This approach has been developed by Pan et al. [12] through a multi-scale convolution-attention U-Net model, which is useful in overcoming the shortcomings of medical image segmentation such as fine structure detection and maintaining boundary information. It enhances the feature extraction process using multi-scale convolutions along with attention, thus used to retain the structure of images.

A two-stream dental panoramic X-ray image segmentation approach using transformers with heterogeneous feature complementation has been developed by Ma et al. [13]. This approach solves problems related to dental image segmentation, which include complicated dental structures, differences in the appearance of images and inadequate feature representation. The complementary characteristics in both streams make structure identification easier.

An approach based on a U-net structure for segmentation of dental x-ray images was introduced by Vanaja & Prakasam [14] where a convolutional block attention gate network is used. The authors highlight the importance of applying an attention mechanism when dealing with the issues related to small objects and precise boundary extraction.

MAGRes-UNet is an architectural design developed by Hussain et al. [15]. It represents a multi-attention gated residual U-Net design. The idea behind the approach is to achieve better results of segmentation of medical images. The technique intends to improve upon some limitations of existing segmentation techniques through residual learning and attention techniques.

3.4 Intelligent Dental Image Segmentation for Automated Diagnosis

DCGC-UNet is the abbreviation of Directional Convolution Gating Control U-Net which is used for the purpose of segmenting dental X-ray images and was developed by Hu et al. [17]. The DCGC-UNet uses the concept of directional convolutions and gating controls. The DCGC-UNet model improves upon the boundary detection and segmentation process.

An intelligent detection model based on the transformer is presented by Wang & Li [18] for the early diagnosis of dental caries in panoramic radiographs. This model is capable of detecting the early carious lesion in teeth by using transformer-based feature learning. The developed model can automatically detect early carious lesions.

Wang et al. [19] introduced ToothFormer, which is a region adaptive and axis-aware transformer-based neural network for effective 3D CBCT tooth segmentation. The architecture can learn the spatial features specific to a tooth and its orientation

to segment teeth effectively in 3D CBCT scans. This methodology enables effective analysis of the teeth for sophisticated dental applications using computers.

The analysis conducted by Esmaeili et al. [20] introduces a hierarchical attention model coupled with deep neural network models for the purpose of semantic segmentation of teeth in panoramic images. This process used in improving the representation of the features through attention to relevant hierarchical areas. This used in proper segmentation of dental structures.

4. SEGMENTATION OF DENTAL X-RAY IMAGE

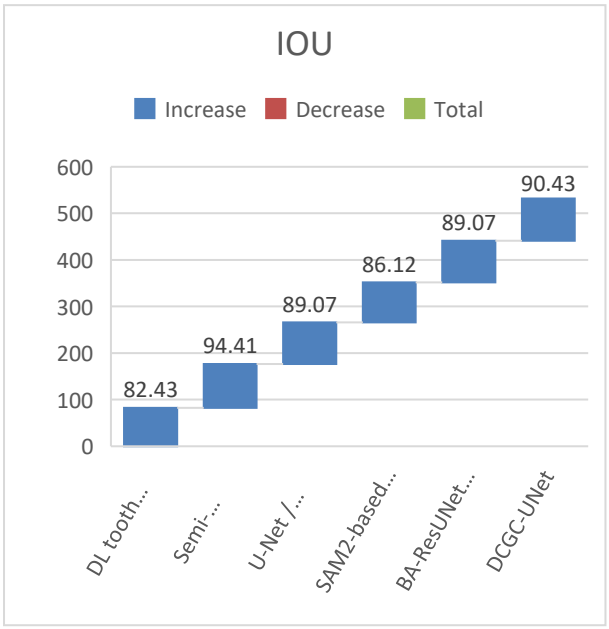
The advancements in learning algorithms in modern times have used to enhance the process of dental X-ray segmentation because of its ability to segment, detect and extract the tooth structure from the X-rays. Advanced learning algorithms utilized in the process of dental X-ray segmentation include complex algorithms like convolutional network, transformers, attention and hybrid neural networks.

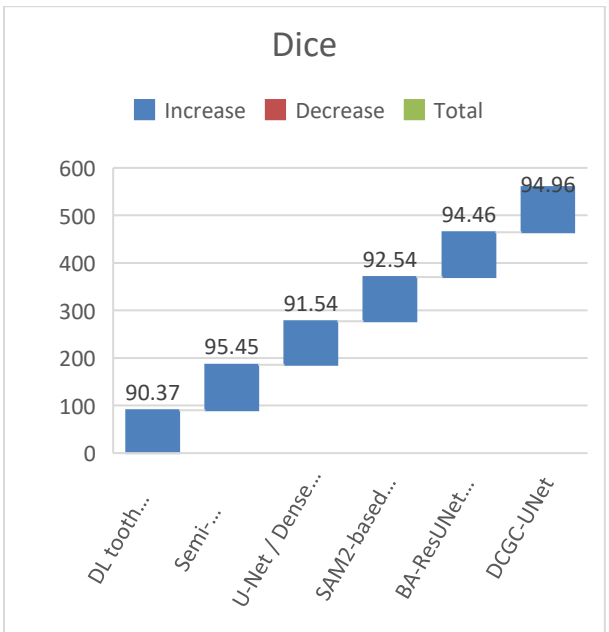
Table 3: Computational Methods for Dental X-Ray Image Segmentation

Author Name (Year) [Ref. No.]	Method / Model	Dataset	Process	Key Contribution	Results
Deb et al. (2025) [1]	DL tooth segmentation and orientation model	DNS dataset (543 panoramic X-rays)	Tooth instance segmentation and orientation estimation	Enables automatic tooth localization and structural analysis	IoU 82.43 %, Dice 90.37 %, RIoU 82.82 %
Hao et al. (2024) [2]	Semi-supervised Transformer (SemiTNet)	Panoramic radiographs	Transformer-based tooth segmentation and identification	Reduces annotation requirement and improves feature learning	IoU 94.41 %, Dice 95.45 %, F1 95.90 %
Zannah et al. (2024) [7]	U-Net / Dense U-Net	Panoramic dental X-rays	Pixel-level tooth segmentation	Provides baseline U-Net segmentation performance	Accuracy 95.94 %, IoU 89.07 % (Dense U-Net)
Li et al. (2024) [9]	SAM2-based segmentation model	Panoramic dental X-rays	Foundation model adaptation for tooth segmentation	Enhances complex dental structure extraction	IoU 86.12 %, Dice 92.54 %, F1 92.54 %
Xiong et al. (2026) [10]	BA-ResUNet with Attention	Tooth X-ray dataset	Boundary-aware tooth segmentation	Improves boundary preservation and accuracy	Dice 94.46 %, Achieved High IoU, HD 0.0238 mm
Hu et al. (2026) [17]	DCGC-UNet	Dental X-ray dataset	Directional convolution with gating control	Improves feature selection and boundary detection	Achieved High Accuracy, IoU 90.43 %, Dice 94.96 %

Table 3 shows some examples of recent techniques for segmenting dental X-ray images include U-net, transformer, attention mechanism and hybrid techniques. The table gives insight into the techniques used, the dataset used, image processing techniques used, the contributions of the authors and the results achieved.

Results





5. DENTAL X-RAY SEGMENTATION USING ADVANCED DEEP LEARNING TECHNIQUES

DL algorithms have improved the process of dental X-ray image segmentation through advancements in feature extraction, boundary detection and structural comprehension of the dentistry regions. Such models utilize convolutional networks, attention mechanisms, transformers and hybrid models for better segmentation results.

Table 4: Deep Learning Techniques for Segmentation of Structures in Dental X-Rays

Author Name (Year) [Ref. No.]	Method / Model	Dataset	Process	Key Contribution	Results
Ong et al. (2024) [3]	Fully automated DL method	Panoramic radiographs	Detects and segments developing teeth for dental assessment	Enables automated evaluation of dental growth and maturity	Achieved High Detection mAP, Segmentation accuracy
Ma et al. (2024) [4]	Multi-feature Coordinate Position Learning	Dental panoramic X-ray images	Combines feature extraction with coordinate-based localization	Improves spatial understanding and tooth structure segmentation	IoU 92.04%, Dice 95.64%, Achieved High Accuracy
Liu et al. (2024) [5]	DL segmentation method	Intraoral photographic images	Segments dental calculus, gingivitis and caries regions	Supports oral disease screening through image-based analysis	Segmentation accuracy 81–83%, Classification accuracy 85%
Zhong et al. (2025) [6]	Grouped Attention Network	Children's Dental Panoramic Radiographs	Applies attention-based feature learning for tooth segmentation	Enhances tooth boundary extraction and feature representation	Dice 93.38%, Sensitivity 94.26%, Achieved high Specificity
Ma et al. (2025) [13]	Dual-Stream Transformer Feature Complementation	Dental panoramic X-ray images	Extracts complementary features using dual transformer streams	Improves segmentation by combining heterogeneous features	IoU 91.49%, Dice 94.54%
Esmaeili et al. (2025) [20]	Hierarchical Attention Deep Neural Network	Panoramic dental radiographs	Uses hierarchical attention for dental structure separation	Enhances semantic segmentation of complex dental regions	Achieved High Accuracy, IoU 78.76%, F1-score 84.54%

Table 4 presents advanced DL algorithms used for segmentation of dental images such as attention based, transformer and feature fusion techniques. This table focuses on the datasets used, the process of segmentation, significant contributions and results obtained by different techniques.

6. CONCLUSION

In this survey, latest developments in the domain of dental X-ray images segmentation from the year 2024 to 2026 have been examined through various approaches including ML, DL, U-Net architecture, transformer, attention and hybrid approaches. The methods being discussed use convolutional neural networks, transformer-based architectures, semi-supervised learning techniques, feature fusion techniques, boundary-aware networks and attention-based models for obtaining precise tooth segmentation and lesion detection. The existing methods have shown better results in feature extraction, understanding of structure, boundary detection, efficiency and clinical decision support. However, existing approaches are hindered by several problems including limitations of available dental image databases, tooth structure complexity, overlapping anatomy, computational demands, domain adaptation and lack of generalizability. For future work, it is necessary to concentrate on building lightweight, adaptable and effective segmentation algorithms with better precision, understanding and real-time clinical usefulness. The use of self-supervised learning, efficient transformer architectures, different imaging techniques used in dentistry, uncertainty-aware modeling techniques and innovative attention mechanisms would enhance the segmentation task in complex dental images. Besides, there is also a need for extensive testing, cross-dataset testing and deployment on efficient platforms in the context of smart dental image analysis and computer-aided diagnostics.

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