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Deep learning technologies in dental practice: Current applications and research trends

Diş hekimliğinde derin öğrenme teknolojileri: Güncel uygulamalar ve araştırma trendleri

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Deep Learning Technologies in Dental Practice: Current Applications and Research Trends

Highlights

- *This study systematically reviews over 100 studies on dental deep learning between 2020 and 2025.*
- *It compares segmentation and classification models like U-Net, YOLO, and Mask R-CNN.*
- *It provides performance insights across 2D and 3D dental imaging modalities.*
- *The review highlights the clinical applicability of AI-based systems in dentistry.*
- *Challenges such as data imbalance and model generalizability are discussed.*

Graphical Abstract

This review evaluates deep learning applications in dental image analysis, focusing on model performance in segmentation and classification tasks. It emphasizes the increasing clinical relevance of AI-assisted diagnostics in dentistry.

Figure. Flowchart of the literature search and study selection process.

Aim

This study aims to systematically analyze deep learning-based segmentation and classification approaches in dental radiographs published between 2020 and 2025, with an emphasis on clinical applicability.

Design & Methodology

A structured literature review was conducted using Scopus, PubMed, IEEE Xplore, and Google Scholar. Inclusion criteria involved peer-reviewed articles employing deep learning on dental radiographs, with a focus on model architecture, datasets, and performance metrics.

Originality

This study uniquely combines a task-based categorization of dental AI applications with performance comparisons of popular deep learning architectures, revealing current gaps and offering research directions.

Findings

U-Net and its variants dominated segmentation tasks, while YOLO and Mask R-CNN showed superiority in detection and multi-task frameworks. Most studies reported performance above %90, yet dataset limitations and clinical validation remain common concerns

Conclusion

Deep learning models have proven effective in automating dental image analysis. Multi-task architectures integrating segmentation and classification enhance clinical decision-making, though future work should focus on dataset standardization and real-world validation

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Deep Learning Technologies in Dental Practice: Current Applications and Research Trends

Derleme Makalesi / Review Article

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ABSTRACT

The use of deep learning technologies in dental practice has been steadily increasing in recent years, accompanied by significant progress in related research. This study provides a comprehensive review of deep learning-based image processing techniques within the field of dentistry, with a particular focus on the performance of models applied in dental segmentation and classification tasks. The analysis reveals that architectures such as U-Net, Mask R-CNN, and YOLO have demonstrated high accuracy in detecting teeth, diseases, and lesions in dental radiographs. By systematically examining studies conducted between 2020 and 2025, this review highlights the potential of deep learning methods to enhance clinical diagnosis and treatment processes, emphasizing the growing importance of automated dental image analysis. The discussion section offers a detailed evaluation of the frequent use and success of U-Net, Mask R-CNN, and YOLO architectures, concluding that deep learning-based approaches can be effectively integrated into clinical workflows. These technologies play a critical role in the early diagnosis of dental pathologies and the development of personalized treatment plans.

Keywords: Dental segmentation, Dental classification, Deep learning, Panoramic radiography, Dental artificial intelligence applications.

Diş Hekimliğinde Derin Öğrenme Teknolojileri: Güncel Uygulamalar ve Araştırma Trendleri

ÖZ

Son yıllarda diş hekimliği uygulamalarında derin öğrenme teknolojilerinin kullanımı giderek artmakta ve bu alandaki araştırmalarda önemli ilerlemeler kaydedilmektedir. Bu çalışma, diş hekimliği alanında derin öğrenmeye dayalı görüntü işleme tekniklerini kapsamlı bir şekilde inceleyerek özellikle diş segmentasyonu ve sınıflandırma görevlerinde uygulanan modellerin performansına odaklanmaktadır. Yapılan analizler, U-Net, Mask R-CNN ve YOLO gibi mimarilerin diş radyografilerinde dişlerin, hastalıkların ve lezyonların tespitinde yüksek doğruluk sağladığını göstermektedir. 2020 ile 2025 yılları arasında gerçekleştirilen çalışmaları sistematik olarak inceleyen bu derleme, derin öğrenme yöntemlerinin klinik tanı ve tedavi süreçlerini geliştirme potansiyelini vurgulamakta ve otomatik diş görüntü analizinin artan önemini ortaya koymaktadır. Tartışma bölümünde, U-Net, Mask R-CNN ve YOLO mimarilerinin sık kullanımı ve başarıları detaylı şekilde değerlendirilmekte ve derin öğrenmeye dayalı yaklaşımların klinik iş akışlarına etkin bir şekilde entegre edilebileceği sonucuna varılmaktadır. Bu teknolojiler, diş patolojilerinin erken tanısında ve kişiselleştirilmiş tedavi planlarının geliştirilmesinde kritik bir rol oynamaktadır.

Anahtar Kelimeler: Diş Segmentasyonu, Diş Sınıflandırması, Derin Öğrenme, Panoromik radyagrofi, Diş Hekimliğinde yapay zeka uygulamaları.

1. INTRODUCTION

Teeth are fundamental structures that initiate the first stage of digestion by mechanically breaking down food within the oral cavity. Therefore, oral and dental health is not merely a localized indicator of well-being but is also directly linked to an individual's overall systemic health [1]. Common dental pathologies—particularly dental caries and tooth loss—can disrupt nutritional intake and negatively affect digestive system functions [2]. Moreover, various epidemiological studies have demonstrated that conditions such as periodontitis, dental caries, and other oral diseases significantly increase the risk of severe systemic disorders, including coronary heart disease, myocardial infarction, stroke, and both ischemic and hemorrhagic cerebrovascular events [3].

In light of these systemic implications, global data reflecting the prevalence of oral and dental health conditions and their burden on public health clearly reveal that the issue extends beyond individual well-being and constitutes a broader societal concern. Indeed, according to the World Health Organization's Global Oral Health Report of 2019, approximately 3.5 billion people worldwide are affected by oral diseases [4].

The oral cavity is anatomically critical, as it serves as the entry point for both the respiratory and digestive systems. Disruption of the microbial balance in this region can lead not only to local pathologies but also to systemic complications [5,6].

Radiographic imaging is an indispensable tool in modern dentistry, enabling detailed examination of the

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morphological structures of teeth and surrounding tissues. It is widely regarded as one of the fundamental diagnostic modalities in clinical dental practice. However, the manual interpretation of these images is limited in reliability due to several factors, including time consumption, the requirement for high-level expertise, and inter-observer variability [7]. In this context, recent significant advances in artificial intelligence—particularly deep learning-based image processing techniques—have introduced a paradigm shift in the analysis of dental radiographs. Owing to their high accuracy in core tasks such as segmentation, classification, and detection, these models not only accelerate the diagnostic process but also enhance consistency, thereby making clinical decision-making more systematic and reliable. The integration of these technologies into clinical decision support systems markedly improves diagnostic accuracy and significantly reduces the cognitive and operational burden on dental professionals, ultimately contributing to the quality of patient care [8].

Deep learning, a subset of machine learning, builds high-level representations by learning complex patterns in data through multilayered artificial neural networks [9]. These architectures extract hierarchical features from data content, enabling them to perform tasks such as segmentation, classification, and detection with high levels of success. In recent years, deep learning-based artificial intelligence systems have been widely utilized in various clinical applications—such as lung nodule detection, brain lesion classification, and breast cancer screening—enabling the development of fast and reliable automated tools that support early diagnosis and achieve high levels of accuracy. [10,11].

Similarly, the growing application of artificial intelligence and deep learning technologies to dental imaging has introduced revolutionary advancements in the field of dentistry. These technologies also contribute significantly to the personalization of dental treatment processes. Particularly in panoramic and periapical radiographs, tasks such as tooth detection, segmentation, classification, and analysis have achieved high levels of accuracy [12]. These models not only alleviate the burden of manual interpretation but also enable the early diagnosis of caries, periodontitis, and other oral pathologies. Furthermore, the integration of AI-based systems with patients' historical clinical data facilitates the development of personalized treatment plans. These technologies enhance patient satisfaction [8], reduce diagnostic and procedural errors, and directly improve the reproducibility and efficiency of clinical services [13].

This study systematically reviews deep learning-based research articles published between 2020 and 2025 that focus on dental segmentation and/or classification. The primary aim is to comprehensively evaluate the current technological advancements in the field, the artificial intelligence approaches employed, and their implications for clinical applications. The methods used in the literature are compared in terms of architectural design, datasets, performance metrics, and intended use cases; and their technical capabilities and limitations are critically analyzed. In doing so, the review highlights the strengths of the current body of research, sheds light on existing gaps, and offers recommendations to guide future studies.

In this context, the study seeks to address the following core research questions:

- *Among the deep learning-based segmentation and classification models applied to dental images in studies published between 2020 and 2025, which architectures are most prominent?*
- *How does the performance of these architectures vary depending on the task type (e.g., segmentation, classification)?*
- *What are the main limitations regarding the clinical applicability of deep learning-based models, and how are these challenges addressed in the existing literature?*

2. MATERIAL and METHOD

This systematic review aims to comprehensively examine deep learning-based segmentation and classification applications in the field of dental imaging published between 2020 and 2025.

2.1. Literature Search Process

The literature search was conducted to include studies published between 2020 and 2025. The databases used for this process were Scopus, PubMed, IEEE Xplore, and Google Scholar. During the search, the following terms were applied to the title, abstract, and keyword fields: "*dental segmentation*", "*dental classification*", "tooth detection", "*teeth segmentation*", "*teeth classification*", *tooth numbering*", "*deep learning*", "*panoramic radiography*".

2.2. Inclusion and Exclusion Criteria

The following inclusion criteria were applied in the selection of studies:

- Peer-reviewed articles published between 2020 and 2025 with full-text availability,
- Studies conducted on dental radiographic images (such as panoramic, periapical, and CBCT, including both 2D and 3D images),
- Use of a deep learning-based architecture or method (e.g., U-Net, Mask R-CNN, YOLO),
- Clear reporting of technical details, including model structure, dataset characteristics, and performance metrics.

In this context, not only 2D panoramic and periapical images but also 3D dental radiographic data (such as CBCT) were included in the evaluation. This is because 3D images offer significant advantages, particularly in tasks requiring detailed analysis of complex anatomical structures and volumetric segmentation; moreover, certain tasks can only be performed using this type of data. Therefore, during the inclusion process, the focus was placed not on the dimensionality of the images, but rather on the task type, methodological approach, and technical adequacy of the studies.

The following types of studies were excluded from the review:

- Clinical case reports, conference abstracts, commentary articles, and non-systematic reviews,
- Studies that relied solely on traditional image processing techniques without the use of deep learning,
- Studies focused on non-dental structures (e.g., jawbone, sinus anatomy, etc.).

2.3. Classification and Analysis of the Included Studies

The included studies were categorized under three main groups based on the type of task addressed:

- **Segmentation-Focused Studies**: Models aiming to segment structures such as teeth, roots, lesions, or caries.
- **Detection, Numbering, and Classification**: Models focused on detecting, numbering, or categorizing teeth
- **Multi-Task Approaches**: Systems that handle multiple tasks—such as segmentation and classification—within a single model framework

Each study was analyzed based on the deep learning architecture employed (e.g., U-Net, Mask R-CNN, YOLO), the type and size of the dataset, and the reported performance metrics (e.g., IoU, Dice, Accuracy). Additionally, the strengths and limitations of the models were comparatively assessed, and the findings were structured to provide a comprehensive understanding of the potential of deep learning techniques in dental image analysis.

3. LITERATURE REVIEW

Deep learning-based approaches in dental image processing have gained prominence in recent years due to their high accuracy in clinical applications. In this section, commonly used deep learning architectures in the literature are examined in detail and analyzed within the scope of segmentation, classification, and multi-task applications. These architectures have been developed for the detection and analysis of dental structures, lesions, and other oral anomalies, and are widely integrated into clinical decision support systems. The methods employed in each study are comparatively evaluated using performance metrics such as accuracy, precision, F1 score and Dice coefficient. The performance of these architectures varies depending on both the task type and the type of data used, reflecting an ongoing effort to improve the accuracy and efficiency of dental imaging systems.

3.1. Segmentation

In recent years, dental image segmentation has undergone substantial advancement with the advent of deep learning, influencing applications in dentistry, forensic science, and orthodontics. The limited accuracy and labor-intensive nature of traditional techniques have led to an increasing demand for automated, precise, and reproducible solutions. In response, deep learning-based segmentation models have demonstrated high accuracy, particularly in imaging modalities such as panoramic radiography and cone-beam computed tomography [6,8,14–47].

In the majority of segmentation studies, the core architecture is based on the U-Net model, which is widely used in medical image processing [6,19,22,23,27-30,32,33,35,37,39,44-47]. It's encoder-decoder structure is particularly notable for its ability to perform effectively even in data-scarce environments. The literature also includes various enhanced U-Net variants incorporating attention mechanisms, residual connections, dense blocks, and squeeze-and-excitation (SE) modules. Architectures such as Teeth U-Net [6] and Attention U-Net [23], for instance, aim to enhance feature representation and improve segmentation accuracy in dental structures.

However, in segmentation tasks, pixel-level accuracy alone is not sufficient; classification sensitivity, boundary precision, and structural consistency are also critical. Therefore, recent studies have adopted more advanced architectures such as Mask R-CNN [14,38], Panoptic DeepLab [20] and MSLPNet [21]. These models offer more sophisticated analysis capabilities, particularly for multi-class differentiation, panoptic segmentation, and dental structures with ambiguous or complex boundaries.

An examination of dataset preferences reveals that panoramic dental X-ray images are predominantly used. This preference can be attributed to the low radiation dose, ease of application, broad anatomical coverage, and widespread use of panoramic images in clinical routines [8]. An illustrative example of a panoramic dental X-ray and its corresponding segmentation mask is provided in Figure 1, visually demonstrating how deep learning-based segmentation models delineate dental structures within this commonly used imaging modality. However, CBCT images are also utilized for the segmentation of more detailed anatomical structures. CBCT is particularly favored in segmentation tasks that require microscopic detail, such as root morphology, pulp cavity, or periodontal space[15,17,19,22,25,31,43].

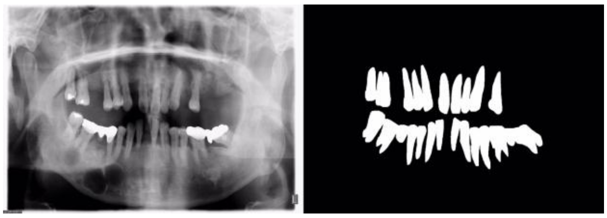

Figure 1. Panoramic dental X-ray (left) and its corresponding segmentation mask highlighting tooth structures (right)

The most commonly used performance metrics in the literature are the Dice Similarity Coefficient (DSC) and Intersection over Union (IoU), both of which evaluate the pixel-level overlap between the predicted output and the ground truth. Most segmentation studies report Dice scores exceeding 90%, highlighting the reliability and potential clinical applicability of these models (see Table 1). Additionally, complementary metrics such as accuracy and F1 score are frequently used for comparative evaluation. The use of diverse metrics prevents overly simplistic assessments and supports a more comprehensive evaluation of model performance.

The impact of segmentation technologies extends beyond clinica applications, playing a significant role in forensic tasks such as individual identification, age estimation, and post-mortem analysis [14]. Models developed in this context are thus gaining value not only in medical applications but also in legal and forensic investigations.

In conclusion, dental segmentation has exhibited multifaceted progress—driven by the diversification of deep learning architectures, improvements in dataset volume and quality, the integration of attention mechanisms, and the adoption of diverse evaluation metrics. Covering a broad spectrum of applications, from clinical decision support to forensic identification, these studies hold a pivotal role in both scientific advancement and the digital transformation of healthcare.

A detailed summary of the segmentation studies is provided in Table 1.

3.2. Detection, Numbering, and Classification

Over the past five years, detection, numbering, and classification tasks in dental radiographic imaging have been significantly transformed by deep learning-based approaches. Recent models not only address individual classification problems but also integrate multiple functions within a unified system—such as tooth detection, numbering, and classification according to clinical targets like caries, periodontitis, restorations, or osteoarthritis [50–85]. This multi-functional framework underscores the need to evaluate such studies not only in terms of classification accuracy but also in relation to localization performance and task-specific precision.

Within this framework, a significant portion of the reviewed studies reported separate performance metrics for each task, allowing for a more objective evaluation of model outputs. In particular, localization-based metrics such as mAP, IoU, and AP@50 were commonly used for detection tasks, while classification tasks employed metrics such as accuracy, F1 score, precision, recall, and area under the curve (AUC). The inclusion of these distinct metrics has enabled a systematic and comparative analysis across studies.

Commonly used architectures include advanced deep learning models such as Faster R-CNN [52,56,58,78–80], YOLO [63,65,73,76,79,80,84,85],ResNet

[54,55,57,62,64,68,69,71,74,77,78,82], Inception [52,53,54,57,58,62,68,74,81]. In several studies, these architectures were redesigned or adapted for specific tasks—for example, through the use of Multi-Input CNNs or task-oriented optimization. Additionally, Siamese and multitask CNN models have been employed in dental imaging to enhance task-specific performance. The choice of architecture often depends on factors such as the number of tasks involved, the desired level of accuracy, and the type of imaging modality used (e.g., panoramic, periapical, CBCT).

Since deep learning algorithms yield effective results X-rays [54]). While the majority of research is based on

panoramic images, specialized imaging modalities such as CBCT and periapical radiographs have also been employed to enhance classification quality. From a clinical standpoint, classification tasks extend beyond identifing the mere presence or absence of teeth. They also involve detailed labeling based on specific conditions such as restoration type, caries severity, osteoarthritis, or periodontitis. This level of complexity increases task difficulty and calls for more robust and specialized network architectures. For example, osteoarthritis classification using VGG-based models [51], early-stage caries detection with Inception models [54], and periodontitis diagnosis via EfficientNet-B0 [76] reflect targeted efforts addressing these multi-layered clinical distinctions.

In this domain, accuracy alone is often considered insufficient and is commonly complemented by metrics such as F1, AUC, and sensitivity–specificity pairs, which provide more balanced evaluation of model performance. This is particularly important in the presence of imbalanced datasets, where the combined use of these metrics offers a more reliable assessment. Indeed, the literature emphasizes that relying solely on accuracy can be misleading and highlights the importance of incorporating precision and recall as essential components of performance evaluation [49].

Table 2 presents a comprehensive summary of the studies focused on detection, numbering, and classification tasks.

Table 1. Dental Segmentation Studies

Ref.	Year	Dataset	Architecture	Performance Metrics
[14]	2020	30 panoramic X-ray	Mask R-CNN	IoU: 0.879, F1: 0.875
[15]	2020	175 CBCT	Modified 3D U-Net	F1: 0.96
[16]	2020	2602 panoramic X-ray	Efficient Encoder-Decoder Network	Dice: 0.9829, Acc: 0.9928
[17]	2020	25 CBCT	Multi-Task 3D FCN (V-net)	DSC: 0.936, IoU: 0.881
[18]	2020	1500 panoramic X-ray	TSASNet	Dice: %92.72, Acc: %96.94
[19]	2020	110 CBCT	Residual U-Net + DCRF	Dice: %91.66
[20]	2021	51 panoramic X-ray	Panoptic DeepLab	IoU: %85.4, PQ: %74.9, SQ: %83.2, RQ: %90
[21]	2021	1500 X-ray	MSLPNet	Dice: 93.01, PFOM: %76.56
[22]	2021	20 CBCT	U-Net	Dice:%95.7(Single root), Dice:%96.2 (Multi root)
[23]	2021	1500 X-ray	Attention U-Net	Dice: %94.7, F1: %88.9, Acc: % 92.8
[24]	2021	2000 tooth models	TSegNet	Dice.%98.0, F1: %94.2, Surface DSC: %98.6
[25]	2021	10 CBCT	CNN, Level Set	Dice: 0.9791, IoU: 0.9595, Acc: 0.9733
[26]	2021	120 tooth scans	Mask-MCNet	mIoU: 0.98, mAP: 0.98, mAR: 0.97
[27]	2022	153 dental X-ray	U-Net, Vision Transformer	Dice: 0.7487, Pixel Prec: 0.7443
[28]	2022	1500 X-ray	U-Net,DCU-Net, Nano-Net, DoubleU-Net	Dice:%92.88, Acc: %96.59 (DoubleU-Net)
[29]	2022	470 panoramic X-ray	U-Net-based CNN	Dice: 0.88, IoU: 0.79
[30]	2022	1781 panoramic X-ray	U-Net (ResNeXt-50 backbone)	IoU: 0.93, F1: 0.95
[31]	2022	4938 CBCT	V-Net-based Two-Stage Network	Dice: %92.54–94.1
[32]	2022	1000 panoramic X-ray	UNet, UNet++, PSPNet, DeepLabV3, DeepLabV3+, nnUNet, CE-Net	Dice: %92.46, IoU: %86.67 (UNet)
[33]	2022	250 panoramic X-ray	U-Net (ResNext50)	Pixel Acc: %99.81, Mean IoU: 0.767
[34]	2023	540 dental X-ray	M-Net, Swin Transformer, TAB	DSC: 0.9102, JI: 0.8501
[35]	2023	8138 OPG	U-Net	DSC: 0.85, Acc: 0.95 (Tooth)
[36]	2023	1321 panoramic dental X-ray	KCNet (Knowledge Consistency Network)	Dice:0.890±0.038%, IoU:0.804±0.058
[37]	2023	500 bitewing radiographs	U-Net	F1: 0.8818, Precision:0.9491 (Caries)
[38]	2023	Tufts DB	Mask R-CNN	Dice: 0.87, Acc: %98.4
[39]	2023	1366 panoramic X-ray	EfficientUnet	DSC: %85.7
[40]	2023	1159 panoramic X-ray	CariesNet	DSC: %93.64, Acc: %93.61
[6]	2023	1500 dental X-ray	Teeth U-Net	Dice:%94.28, Acc: %98.53
[8]	2024	103 panoramic X-ray	PSPNet + ResNet	Dice: %96.89, IoU: %85.34
[41]	2024	Tufts DB	CariSeg	Dice: %88.5, Acc: % 94.89 (Tooth)
[42]	2024	Teeth3DS, TeethIOS	DBGANet	DSC: %94.48 (Teeth3DS), %96.4 (TeethIOS)
[43]	2024	30 CBCT	MRCM-UCTransNet	Dice: 0.9061, mIoU: 0.8283
[44]	2024	389 panoramic X-ray	Vanilla U-Net, Dense U-Net, Attention U-Net, SE U-Net, Residual U-Net, R2 U-Net	Dice: %90.35, IoU: %88.87 (R2 U-Net)
[45]	2025	1,020 panoramic X-ray	nnU-Net + CVAE	Tooth: Dice = 0.92, Bone: Dice = 0.94
[46]	2025	407 panoramic X-ray	U-Net,PSPNet,LinkNet,FPN+ backbones	IoU:%85.29,F1:%92.02(U-Net+EfficientNetB7)
[47]	2025	UESB	GAN (U-Net + PatchGAN)	Dice. 0.9304, IoU: 0.8715

Table 2. Dental Detection, Numbering and Classification Studies

Ref.	Year	Dataset	Architecture	Performance Metrics
[50]	2020	550 panoramic X-rays	AlexNet, VGG-16, DetectNet	Acc: 0.96 (DetectNet)
[51]	2020	1000 panoramic radiograph	R-CNN, VGG16	Osteoarthritis Classification Acc: 0.84 (VGG16)
[52]	2021	421 panoramic X-ray	Faster R-CNN + Inception v2	Sens: 0.9804, Prec: 0.9571, F1: 0.9686
[53]	2021	21,398 implant images	Automated DCNN, VGGNet19, Inception – v3	Detection:AUC:0.984, Classification:AUC:0.869
[54]	2021	112 bitewing X-rays	Inception, ResNet	AUC: 0.861, Precision: 0.722, Recall: 0.866
[55]	2021	5008 panoramic X-rays	ResNet-34	Acc: 0.931, F1:0.933, AUC: 0.994
[56]	2021	2900 periapical X-rays	Faster R-CNN	IoU: 0.7159, Prec: 0.6193, Rec: 0.5439
[57]	2021	1100 panoramic X-rays	ResNet-101,SqueezeNet,ResNet-18, Inception-ResNet-V2	Acc: 0.927, F1: 0.928 (ResNet-101)
[58]	2021	1125 bitewing radiographs	Faster R-CNN (Inception v2)	F1: 0.9515, Prec: 0.9293, Sens: 0.9748
[59]	2021	476 periapical radiographs	CNN	Acc: %92.75, Sens: %94.87, Spec: %90
[60]	2021	1000 bitewing X-rays	YOLOv3	Acc: %94.59, Sens: %72.26, Spec: %98.19
[61]	2021	278 bitewing X-rays	AlexNet (Transfer Learning)	Acc:%90.3(Caries),%95.56 (Restoration)
[62]	2022	416 panoramic X-rays	DenseNet-121, VGG-16, Inception V3,ResNet50	Acc: 0.9259 (Inception V3)
[63]	2022	1200 panorami images	YOLOv3	mAP: %99.33, IoU: %84.56
[64]	2022	16,000 periapical X-rays	AlexNet, ResNet-18, ResNet-34, Optimized CNN	Acc: 0.852, F1: 0.850 (AlexNet)
[65]	2022	4097 panoramic images	U-Net, YOLOv5	Acc: 0.929, Prec: 0.724, Rec: 0.807
[66]	2022	116 panoramic images	NASNet, AlexNet, CNN	Acc: %96.51 (NASNet)
[67]	2022	1000 bitewing radiographs	Deep Gradient-Based LeNet	Acc: %98.74, Sens: %91.93, Spec: %98.92
[68]	2022	2468 bitewing radiographs	Inception-ResNet-v2, Inception-v3, ResNet-50	Acc:0.87, F1:0.87 (Inception-ResNet-v2)
[69]	2022	4129 periapical radiographs	Modified ResNet-18	F1: 0.8288, Sens: 0.8350, Spec: 0.82 (Caries Detection)
[70]	2022	108 panoramic X-rays	AlexNet, GoogleNet, SqueezeNet	Acc: %99.90 (SqueezeNet)
[71]	2022	1400 panoramic X-rays	AlexNet, GoogleNet, VGG19, ResNet50, ResNet101	Acc: %98.20 (GoogLeNet)
[72]	2022	1000 CBCT image pairs	Siamese Concatenated Network + DenseNet-121/VGG16	Acc:0.7000 (Siamese Concatenated Network + DenseNet-121)
[73]	2022	4518 panoramic X-rays	YOLOv4 (CSPDarknet53)	AP: %94.16, F1: %90
[74]	2023	188 dental X-ray	VGG-16,InceptionV3,ResNet-50, DenseNet-121	Acc: %99.5 (DenseNet-121)
[75]	2023	304 panoramic images	Tooth Type Enhanced Swin Transformer	Acc: 0.8557, F1: 0.8567, AUC: 0.9223
[76]	2023	2850 tooth images	EfficientNet-B0, YOLOv7	Acc: %95.44 (EfficientNet-B0)
[77]	2023	818 panoramic X-ray	Multitask CNN (ResNet-18)	Prec: 0.997, Rec: 0.972
[78]	2023	2800 single tooth images	Faster R-CNN (AlexNet, GoogleNet, VGG19, ResNet50, ResNet101)	Acc:%94.18 (Faster R-CNN + GoogLeNet)

Table 2 (Cont). Dental Detection, Numbering and Classification Studies

[79]	2024	1200 X-rays	YOLO-V4, Faster R-CNN	F1:%99.54, Prec: % 99.90 (YOLO-V4)
[80]	2024	1209 panoramic images	EfficientDet-D3, YOLO-v5, RetinaNet, Faster R-CNN, SSD	Acc:%94.4, mAP@50: %93.8 (EfficientDet-D3)
[81]	2024	1026 panoramic X-rays	PDCNET(CNN),EfficientNet,DenseNet, VGG, Inception, MobileNet	Acc: %98.39, F1: %98.31, AUC: %99.79
[82]	2025	270 panoramic X-ray	ResNet, DenseNet,DarkNet (Fusion)	Acc: %96.2
[83]	2025	1,568 images	MLP, VGG, GoogleNet, Vision Transformer	Acc: 0.92, AUC: 0.98 (ViT)
[84]	2025	1703 panoramic X-rays	YEM-SAFN (based on YOLOv8)	mAP@0.5: %86.7, F1: %82.1
[85]	2025	407 panoramic X-rays	YOLOv8+ RT-DETR + GFP-GAN+ WBF	mAP@0.5: %98.3, F1: %92.5

3.3. Multi – Task Studies

In recent years, deep learning-based approaches for dental image analysis have gained significant momentum, particularly through the adoption of multi-task architectures that enable segmentation and classification tasks to be performed within a unified model framework. This advancement has been further driven by the widespread clinical use of advanced imaging modalities such as panoramic radiography and CBCT. Integrating multiple tasks into a single system not only improves time efficiency but also enhances diagnostic accuracy.

These two tasks serve complementary functions in the field of dental imaging. Segmentation enables the accurate delineation of dental structures, while classification allows for a more detailed analysis based on the type, condition, and function of these structures. Segmentation plays a critical role in the detection of dental anomalies by dividing images into smaller, more homogeneous regions for detailed analysis. Classification, in turn, assigns the segmented data to appropriate categories, thereby distinguishing between different types of dental structures [86]. This integration leads to more precise detection of dental anomalies, caries, and cysts, contributing to more personalized treatment planning and improving clinical workflow efficiency by accelerating the diagnostic and treatment process.

The integrated execution of these tasks enhances not only the model's visual discrimination capabilities but also its ability to interpret the segmented regions meaningfully.

Widely used architectures such as U-Net, Mask R-CNN and YOLO have demonstrated high performance in both segmentation and classification tasks, showcasing the strength of this approach. Numerous studies have reported that these models achieved accuracy, sensitivity, and F1 scores exceeding %90, confirming their clinical applicability. An illustrative example demonstrating how deep learning models segment and classify individual teeth within panoramic radiographs is presented in Figure 2.

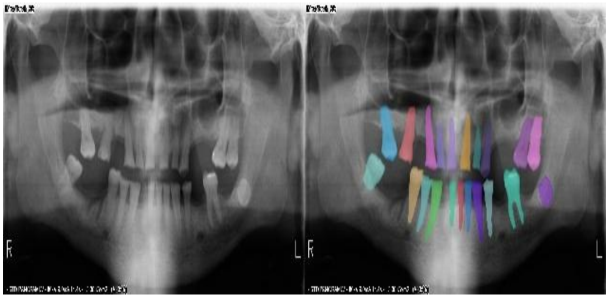

Figure 2. Panoramic dental radiograph and segmentation mask with labeled teeth for segmentation and type classification

The performance of multi-task systems largely depends on the depth of the employed architectures and the size and quality of the datasets. Notably, three-dimensional CBCT data have been shown to significantly improve segmentation and classification accuracy by capturing spatial relationships among dental structures with high precision.

Additionally, datasets enriched with high-resolution images and detailed annotations are widely acknowledged in the literature for enhancing the learning capacity and overall performance of these models.

Table 3 highlights representative multi-task studies conducted in the field of dental image analysis. The concurrent use of segmentation alongside classification, numbering, detection, and labeling has been shown to improve the overall performance of multi-task models.

Specifically:

- **Segmentation + Classification:** [88, 90, 91, 100, 101, 106, 110, 112]
- **Segmentation + Numbering:** [7, 96, 97, 107, 108, 109]
- **Segmentation + Detection:** [92, 99, 102, 104, 105, 111, 113, 115, 117,119, 120, 121].

Table 3. Multi – Task Studies

Ref.	Year	Dataset	Architecture	Performance Metrics
[87]	2020	303 panoramic X-ray	Faster R-CNN + heuristic algorithm	Detection: mAP@0.5: % 96.7 Numbering: Accuracy: % 84.5
[88]	2021	1160 panoramic X-ray	nnU-Net, DenseNet121	Segmentation: Dice: 0.663, IoU: 0.785(nnU-net) Classification:Acc: %95.7(DenseNet121)
[89]	2021	100 panoramic X-ray	DetectNet, ResNet-50	Detection: Sensitivity: %96.4 (DetectNet) Classification: Accuracy: %93.2 (ResNet-50)
[90]	2021	186 CBCT scan	3D U-Net	Segmentation: Dice: 0.90, IoU: 0.82 Classification: Accuracy: %96.6
[91]	2021	1171 panoramic X-ray	Morphological Segmentation, Modified LeNet	Segmentation: DSC: %98.04, IoU: %97.6 Classification:Accuracy:%99.63(ModifiedLeNet)
[92]	2021	153 panoramic X-ray	FCN, Deeplabv3 (ResNet-101)	Tooth Det.: Prec: %99.6, Sens: %98.9 (FCN) Segmentation:IoU:%95.3,F1:%97.5(DeepLabv3)
[93]	2021	160 panoramic X-ray	Faster R-CNN (GoogLeNet)	Detection: Detection Rate: % 98.9 Classification and Numbering: Acc: % 91.7
[94]	2022	1686 periapical radiogra	Faster R-CNN (GoogLeNet)	Detection and Numbering: F1: 0.8720, Pre: 0.7812, Sens: 0.9867
[95]	2022	591 panoramic X-ray	U-Net, Faster R-CNN, VGG-16	Tooth Detection: Rec: 0.992, Prec: 0.994 (Faster R-CNN) Tooth Numbering: Acc: 0.9986 (VGG-16)
[96]	2022	1000 bitewing radiographs	Mask R-CNN (ResNet-101)	Segmentation: mAP: %97.49 Numbering: Prec: % 94.35
[97]	2022	1500 panoramic X-ray	Mask R-CNN, U-Net, Faster R-CNN, YOLO-v5	Segmentation: Acc: %98.77 (Mask R-CNN) Numbering: Acc:%98.44 (Faster R-CNN)
[98]	2022	1250 periapical X-ray	Relation-based Faster R-CNN	F1:0.953, Prec: 0.951, Rec: .0.955
[99]	2022	455 panoramic X-ray	Mask R-CNN, Faster R-CNN (ResNet-101)	Segmentation: mAP: %92.14 (Mask R-CNN) Missing Tooth Det: mAP: %59.09 (Faster R-CNN)
[7]	2022	2702 panoromic X-ray	Mask R-CNN + heuristic algorithm	Segmentation and Numbering: mAP@IoU: %92.49
[100]	2022	470 panoramic X-ray	PaXNet(CheXNet, InceptionNet, Encoder)	Segmentation:Acc: %95.23 (Jaw Segmentation) Classification:Acc: %86.05 (Caries Detection)
[101]	2022	534 periapical X-ray	Mask R-CNN (MobileNet-v2)	Segmentation: mAP: %85, IoU: %71 Classification: Acc: %93
[102]	2022	200 panoramic X-ray	YOLOv8	Segmentation: mAP@50: % 96.6 Detection:mAP@50: % 97.5
[103]	2022	994 bitewing X-ray	YOLOv3 (Darknet-53)	Detection + Classification: mAP@50: 0.73
[104]	2022	280 panoramic X-ray	Mask R-CNN (ResNet-101)	Tooth Segmentation: F1: %96.5 Missing Tooth Detection Acc: %95.41
[105]	2022	8000 periapical radiographs	U-Net, YOLOv5, VGG-16	Segmentation: IoU: %86.3 (U-Net) Tooth Position Detection Acc: %88.8 (YOLOv5)
[106]	2023	215 CBCT scans	Multiple U-Net	Segmentation: IoU: %99, Dice: %99 Classification Acc: %100
[107]	2023	6046 panoromic X-rays	U-Net, HTC (ResNet-50)	Segmentation: mIoU:0.9250 Numbering: Prec: 0.9783, Rec: 0.9773
[108]	2024	250 panoramic X-ray	U-Net, Faster R-CNN	Segmentation: Dice: 90.1%, IoU: 82.1% (U-net) Numbering: Acc: 93.9% (Faster R-CNN)
[109]	2024	DNS, UFBA	DenUnet	Numbering: mAP: %74.22 (DNS) Segmentation: %71.32 (DNS)
[110]	2024	666 panoromic X-rays	VGG-16, U-Net, YOLO	Segmentation and Classification: Acc: %85, F1: 84% (U-Net + VGG-16)
[111]	2024	107 panoramic X-ray	Mask R-CNN (ResNet-101)	Segmentation and Detection: mAP: %90, F1: %63
[112]	2024	562 lesion images	U-Net, Lightweight CNN	Segmentation and Classification: Acc: %95.74, F1: %95.5
[113]	2024	6000 panoramic X-ray	Mask R-CNN, Cascade R-CNN	Segmentation: Acc: 0.977 (Mask R CNN) Bone Loss Det: Acc: 0.98 (Cascade R-CNN)
[114]	2024	272 panoramic X-ray	U-Net, Mask R-CNN	Segmentation: mAP: >%79 Average Classification Acc: %88
[115]	2024	1008 panoramic X-ray	Improved Mask R-CNN	Segmentation and Detection: AP: 0.795
[116]	2024	3000 bitewing X-ray	YOLOv8s	Detection: mAP: 0.99 Numbering: mAP: 0.963

Table 3 (Cont). Multi – Task Studies

[117]	2024	3854 panoromic X-ray	YOLOv5x	Detection: F1: 0.99 Segmentation: F1: 0.98
[118]	2025	O2PR, CDD	YOLOv8 backbone + UCL-Net	Segmentation: AP50 = %99.5, AP75 = %96.7 Classification: Acc = %67.1 (CDD)
[119]	2025	2720 panoramic X-ray	YOLO – DentSeg (YOLOv8n based)	Segmentation: mAP50 = %85.5, Detection: mAP50 = %87.2
[120]	2025	32585 panoramic X-ray	YOLOv8	Segmentation: F1 = %93.1, Detection: F1 = 0.917 to 0.966
[121]	2025	5569 periapical X-rays	YOLOX, FCN-8s	Segmentation: Dice = 0.843, IoU = 0.7286 (FCN-8s) Detection: mAP@0.5 = 0.7789, F1 = 0.6576

4. DISCUSSION

This systematic review provides a comprehensive analysis of deep learning-based segmentation and classification approaches that have been rapidly adopted in dental image analysis in recent years. It also evaluates the methodological diversity and model performance of multi-task studies through a comparative lens based on task type. The findings reveal meaningful distinctions not only in terms of performance metrics such as accuracy, sensitivity, and F1, but also with respect to architectural choices, task compatibility, clinical applicability, and data dependency.

Among the models focused specifically on segmentation tasks, **U-Net and its variants** (e.g., nnU-Net, Dense U-Net, Attention U-Net) have been widely adopted for both 2D panoramic and 3D CBCT data and have become a reliable reference architecture in the literature. U-Net's encoder-decoder structure and symmetric skip connection mechanism allow for the preservation of small and intricate structures in dental images, enabling the precise delineation of anatomical regions such as apical lesions, pulp chambers, and tooth roots. An illustrative schematic of this architecture is presented in Figure 3. In the study [22], U-Net was employed for the segmentation of single- and multi-rooted teeth as well as dental pulp using CBCT data, achieving Dice scores of %95.7 and %96.2 for tooth segmentation, and %88.6 and %87.6 for pulp segmentation, respectively.

Moreover, through the use of multi-view imaging strategies and specialized loss functions designed to reduce edge roughness, high precision was achieved even with a limited number of annotations.

One of the key advantages of the U-Net architecture lies in its modular and extensible structure, which allows for easy customization across different tasks and data types. This flexibility is particularly beneficial in domains such as dental segmentation, where the precise delineation of small anatomical structures is essential. A notable example is Teeth U-Net [6], a customized variant optimized for panoramic dental images. By integrating detail-preserving blocks and attention mechanisms into the architecture, the model effectively combines multi-scale information, leading to improved segmentation performance. Teeth U-Net has demonstrated strong results among U-Net-based customized models, achieving %94.28 Dice and %98.53 accuracy on panoramic X-ray images.

The success of these architectures is largely attributed to their ability to achieve high performance even with limited data. U-Net, in particular, has gained attention in clinical settings for offering a low-cost and fast training process, and it can be optimized for real-time systems.

However, since U-Net does not inherently provide classification capabilities, many studies require a separate classifier following segmentation, which introduces additional complexity to the system architecture and can limit its suitability for real-time applications. In multi-task frameworks, such limitations have led to an increased interest in alternative architectures such as Mask R-CNN.

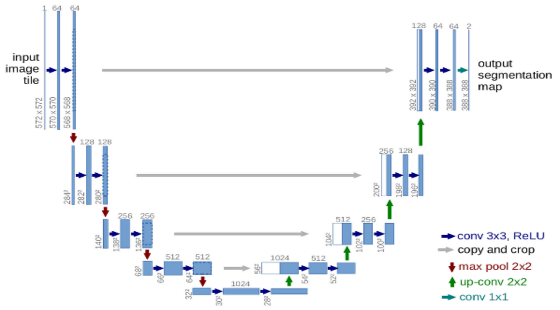

Figure 3. Schematic representation of the U-Net architecture

Moreover, more sophisticated approaches that go beyond segmentation and also perform object detection simultaneously have gained prominence, particularly in the analysis of complex dental structures. In this context, the **Mask R-CNN** architecture has established a significant presence in the literature due to its integrated design, which supports multi-task dental imaging applications. This architecture enables the simultaneous execution of various tasks such as tooth detection, numbering, missing tooth identification, and lesion classification, thereby enhancing system functionality. Its instance segmentation capability offers advantages such as separating overlapping dental structures and providing both positional and class information for each segment.

In a study utilizing the Mask R-CNN architecture, both tooth segmentation and numbering according to the FDI system were successfully performed on bitewing images. The model achieved strong performance metrics, with %97.49 mAP and % 100 precision for segmentation, and

%91.51 mAP and %94.35 precision for numbering [96]. These high levels of accuracy demonstrate the model's applicability not only in theory but also in clinical practice, offering a significant advantage in practical implementation through its compatibility with FDI-compliant labeling.

The success of Mask R-CNN is largely attributed to its integration with powerful backbone networks, such as ResNet-50 enhanced with attention mechanisms like the Convolutional Block Attention Module (CBAM), which improve both accuracy and generalization in the analysis of complex dental structures. For instance, an improved Mask R-CNN incorporating attention modules achieved superior performance in detecting non-normal teeth on dental X-ray images, outperforming the standard Mask R-CNN with an average precision (AP) of 0.795 compared to 0.750, and a high sensitivity of %95.65 for detecting secondary caries [115]. This approach demonstrated rapid and accurate segmentation of abnormal teeth, highlighting the adaptability and effectiveness of Mask R-CNN when combined with modern attention-based enhancements. Similarly, the Mask R-CNN model achieved an F1-score of %96.5 for tooth segmentation, and an accuracy of %95.41 in identifying missing teeth, demonstrating strong performance in clinically relevant tasks [104]. These findings indicate that Mask R-CNN is not only a flexible architecture well-suited for multi-task frameworks but also a highly accurate and reliable tool for clinical applications when combined with robust backbone networks.

However, the high accuracy levels offered by Mask R-CNN are often constrained by its dependency on large, balanced, and meticulously annotated datasets. In scenarios with limited samples—particularly in tasks involving the detection of small anatomical structures or where fine-grained class distinctions are critical—the model has shown reduced sensitivity and weakened generalization performance in the presence of class imbalance.

Originally introduced by Redmon et al. in 2015 [122], **YOLO** architectures have become indispensable tools for time-critical tasks such as tooth detection and numbering in dental image analysis, owing to their exceptional speed and efficiency in real-time object detection. Their single-stage detection structure, low computational load and hardware independence provide significant advantages, particularly in clinical scenarios where rapid decision-support systems are essential. In [73], a YOLOv4-based model developed for detecting permanent tooth germs in pediatric panoramic radiographs achieved an average precision (AP) of %94.16 and an inference time of 90 ms, enabling the processing of approximately 11 images per second. These results demonstrate a notable superiority in both accuracy and speed compared to conventional CNN-based object detection approaches. Similarly, in [116], a YOLOv8s -based system designed for posterior tooth detection and labeling achieved %99 mAP accuracy and an inference time of just 9.1 ms, underlining not only its high detection accuracy but also its strong potential for integration into real-time clinical applications. An illustrative example of the model's output compared to the ground truth is shown in Figure 4.

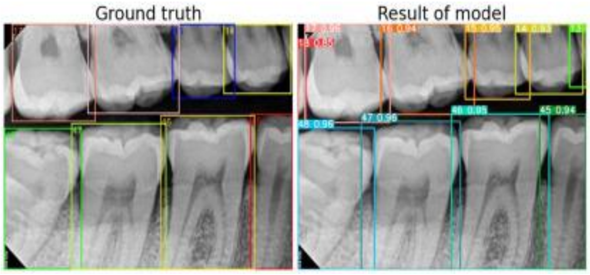

Figure 4. Visual comparison of ground truth and model output for posterior tooth detection and labeling using a YOLO-based architecture. **Adapted from [116].**

Moreover, these models enable high-speed inference even on systems with limited hardware resources, offering significant advantages for mobile health solutions and in-clinic screening applications. However, YOLO architectures can be limited in tasks that require detailed segmentation—particularly when compared to architectures such as Mask R-CNN and U-Net.

This limitation becomes especially evident in dental images, where the accurate delineation of small and overlapping anatomical structures is often critical.

In light of these findings, U-Net stands out for its segmentation accuracy and architectural simplicity; Mask R-CNN offers a more comprehensive framework through its integrated design for multi-task systems; and YOLO provides exceptional speed and computational efficiency for real-time detection tasks. The advantages of each architecture vary depending on the clinical context and task requirements of the target application. Therefore, when selecting a model, task priority, data characteristics, and operational constraints should be considered holistically.

Additionally, a significant portion of the reviewed studies revealed that model performance is highly dependent on dataset characteristics. Factors such as dataset size, class distribution, annotation quality, and demographic diversity are among the primary determinants of model effectiveness. Future research is recommended to be supported by larger and more balanced datasets collected from diverse geographic regions and populations, and to be tested under real-time clinical usage scenarios. This approach would enable the developed systems to achieve not only academic success but also true clinical validity.

Table 4 provides a comparative summary of the advantages and disadvantages of widely adopted deep learning architectures such as U-Net, Mask R-CNN, and YOLO. This evaluation is based not only on the findings of the studies reviewed in this systematic analysis but also on the prevailing trends observed across a broad spectrum of academic literature on these architectures.

Table 4. Advantages and disadvantages of widely used deep learning archtitectures in dental imaging

Architectures	Advantages	Disadvantages
U-Net	• Achieves high accuracy in the segmentation of small and detailed anatomical structures. • The encoder-decoder architecture with skip connections helps minimize information loss. • Can produce effective results even with a limited number of annotated images, making it ideal for medical fields with scarce data.	• May be slow for real-time applications. • Training on large datasets can be time-consuming. • Integration into complex multi-task models may be limited.
Mask RCNN	• Capable of performing object detection and pixel-level segmentation simultaneously. • Offers high accuracy in analyzing complex anatomical structures. • Sensitive to regional details, enabling precise boundary delineation.	• Computationally intensive and requires high-performance hardware. • Not fast enough for real-time applications. • Training process is complex and requires careful hyperparameter tuning.
YOLO	• Provides high speed and efficiency for real time image processing task • Its single-pass architecture enables low hardware cost and fast inference • Effective and practical for tasks such astooth detection and numbering	• Performance may decrease for small object detection and fine-grained structures. • Not well-suited for pixel-level tasks like segmentation. • Error rates may increase in highly complex, multi-class environments

5. CONCLUSİON

This systematic review has comprehensively examined the current state of deep learning-based segmentation and classification approaches in dental image analysis, offering an extensive framework regarding the methodological choices, performance metrics, and clinical applicability of multi-task architectures. Deep learning models provide significant advantages not only in terms of high accuracy but also in processing speed and operational efficiency, particularly in the analysis of complex anatomical structures in dental radiographs such as panoramic and CBCT images.

In this context, the Mask R-CNN architecture directly addresses the requirements of multi-task frameworks by integrating both segmentation and object detection tasks, demonstrating superior performance in concurrent applications such as tooth detection, numbering, and lesion classification. Its ability to separate overlapping dental structures, provide both positional and class information for each segment, and perform instance segmentation makes it a particularly powerful architecture in clinical settings. On the other hand, U-Net and its variants (e.g., nnU-Net, Dense U-Net) continue to serve as benchmark architectures for dental segmentation tasks in the literature, especially due to their ability to deliver high accuracy with limited data and to effectively distinguish small anatomical structures. U-Net's computational efficiency, architectural simplicity, and compatibility with clinical use make it attractive for both academic research and practical applications. In scenarios where real-time detection is a priority, YOLO architectures offer significant advantages through their single-stage detection mechanisms, delivering high speed and low computational cost. These architectures stand out for tasks such as tooth detection, implant localization, or identification of radiolucent lesions, providing a solid foundation for the development of real-time decision support systems.

Despite these advancements, the analyses indicate that model performance remains heavily dependent on dataset size, diversity, and annotation quality. In the field of dental imaging, accessing open-source, balanced, and comprehensively annotated datasets continues to be a significant challenge. Many of the datasets used in the literature are limited in sample size, demographic representation, and imaging protocols, which often raises concerns regarding the generalizability and clinical validity of the developed models. This underscores the growing importance of data augmentation techniques, transfer learning, and architectures enriched with anatomical prior knowledge. It also clearly highlights the need for the development of larger and more universally representative data resources.

From a clinical perspective, the speed, accuracy, and automation potential offered by the models evaluated in this review provide strong support for dental practitioners by reducing manual workload and enhancing decision-making processes. However, for the widespread integration of these models into real-time systems, further efforts are needed to optimize processing times, develop transparent and interpretable solutions, and expand testing across different devices, patient populations, and imaging conditions.

In conclusion, this study demonstrates that dee learning-based models possess significant potential not only at the level of academic research but also in clinical applications for dental image analysis. The integrated handling of tasks such as segmentation and classification through multi-task architectures accelerates diagnostic workflows and leads to more accurate outcomes. Future research should focus on the development of large-scale, diverse, and open-access datasets, the advancement of architectures enriched with anatomical knowledge, and the validation of models in real-world clinical settings. These efforts are critical for the broader adoption of dental AI applications and their tangible contributions to patient care.

ABBREVIATONS

- **DSC:** Dice Similarity Coefficent
- **IoU:** Intersection over Union
- **AUC:** Area under Curve
- **Acc**: Accuracy
- **Prec**: Precision
- **Rec**: Recall
- **Sens**: Sensitivity
- **Spec**: Specificity

DECLARATION OF ETHICAL STANDARDS

This article do not require ethical commitee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Murat Can ŞENER: Contributed to defining the selection criteria for the literature review, systematically organizing the relevant studies, and preparing the manuscript for publication.

Hacer KARACAN: Contributed to defining the selection criteria for the literature review, systematically organizing the relevant studies, and preparing the manuscript for publication.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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