Journal of Robotics and Control (JRC)
Volume 5, Issue 6, 2024
ISSN: 2715-5072, DOI: 10.18196/jrc.v5i6.23056

A Comprehensive Review of AI and Deep Learning Applications in Dentistry: From Image Segmentation to Treatment Planning

Rajashree Nambiar [1*], Raghu Nanjundegowda [2]
[1] Research Scholar, Faculty of Engineering and Technology, JAIN (Deemed to be University), Bengaluru, India
[1] Assistant Professor, Department of Robotics and AI Engineering, NMAM Institute of Technology, NITTE (Deemed to be University), Nitte, India
[2] Associate Professor, Department of Electrical and Electronics Engineering, JAIN (Deemed to be University), Bengaluru, India
Email: [1] raji24oct@gmail.com, [1] rajashree.n@nitte.edu.in, [2] raghu1987n@gmail.com
*Corresponding Author

Abstract—**Deep learning leverages multi-layered neural networks to analyze intricate data patterns, offering advancements beyond traditional methods. This review paper explores the significant impact of deep learning on diagnostic and treatment processes across various dental specialties. In restorative dentistry, deep learning algorithms enhance the detection of dental caries and optimize the design of restorations. Orthodontics benefits from automated cephalometric analysis and personalized treatment planning. Periodontics utilizes deep learning for accurate diagnosis and classification of periodontal diseases, as well as monitoring disease progression. In endodontics, these technologies improve root canal detection and treatment outcome predictions. Prosthodontics and oral surgery leverage deep learning for precise prosthesis design and surgical planning, enhancing patient-specific care. Despite the promising advancements, challenges such as data quality, model interpretability, and regulatory issues persist. To solve these problems and get the most out of deep learning in dentistry, the review stresses the need for ongoing research and collaboration between different fields. In our review, we discuss significant deep learning models such as Convolutional Neural Networks (CNNs) and their applications in dentistry, including tooth segmentation, lesion detection, and orthodontic treatment planning. We also examine the use of Generative Adversarial Networks (GANs) for generating synthetic data to enhance training datasets. This paper reviews recent research to provide a comprehensive overview of how deep learning is transforming dentistry, leading to improved patient outcomes, diagnostic accuracy, and treatment efficiency. The advancements in AI and 3D imaging herald a future of automated, high-quality dental diagnostics and treatments.**

Keywords—Artificial Intelligence; Deep Learning; Dental Imaging; Generative Adversarial Networks; Neural Network; Segmentation.

I. Introduction

This In recent years, Artificial Intelligence (AI) and Deep Learning (DL) have made significant progress, finding applications in a variety of fields, including healthcare [1][2]. AI involves creating machines that mimic human intelligence, allowing them to execute tasks that usually need human cognitive abilities. Deep learning, uses multi-layered neural networks to recognize intricate data patterns. These advancements are revolutionizing healthcare by boosting diagnostic precision, optimizing treatment strategies, and enhancing patient care. In dentistry, integration of AI and DL is proving to be particularly transformative. From aiding in the detection of dental caries to assisting in complex orthodontic treatment planning [3][4], these technologies offer the potential to significantly improve clinical practice. For instance, deep learning algorithms can analyze dental radiographs with remarkable accuracy [5], identifying pathologies that might be missed by the human eye.

The relevance of AI in dentistry extends across its various specialties, each benefiting uniquely from these technological advancements. In restorative dentistry, AI aids in the precise detection of caries and the design of dental restorations. Orthodontics leverages AI for automated cephalometric analysis and personalized treatment planning [6]. Periodontics and endodontics utilize deep learning for disease detection and monitoring, while prosthodontics and oral surgery benefit from AI-enhanced prosthesis design and surgical planning [7]. Despite significant advancements, incorporating AI in dentistry faces several challenges. Problems with data quality, understanding model decisions, and meeting regulatory standards are major obstacles. Ensuring high-quality and accessible dental data for AI training is a significant issue [8]. Furthermore, the opaque nature of deep learning models complicates the interpretation of their decisions, which is vital for clinical trust. Additionally, ethical and regulatory issues, including patient privacy and data security, must be resolved to enable the broader use of AI in dentistry. AI has transformed dentistry through its various applications, including diagnostic imaging, predictive analytics, and personalized treatment plans. Grasping the types of neural networks and techniques employed is essential to understanding these advancements. Convolutional Neural Networks (CNNs) are especially potent for image-related tasks, making them indispensable in dental imaging applications. CNNs feature layers that automatically identify elements from raw images, such as edges, textures, and complex patterns, facilitating precise analysis of dental radiographs and intraoral images [9]. Recurrent Neural Networks (RNNs), such as Long Short-

Term Memory (LSTM) networks, excel in handling sequential data, making them valuable for predictive modeling and analyzing time-series data like patient treatment progress [10]. Transfer learning techniques enable these neural networks to use pre-trained models, minimizing the need for extensive dental-specific datasets [11].

Generative adversarial networks (GANs), including 3D Convolutional GANs (3DCGANs), are being investigated for generating synthetic dental images to supplement training data, which is particularly beneficial for 3D imaging in dental applications [12]. UNet, an architecture renowned for biomedical image segmentation, is extensively used for segmenting dental structures in radiographs and CBCT scans, improving the precision of diagnostic tools [13]. Additionally, VGG16, a deep convolutional network for large-scale image recognition, is employed for feature extraction and classification in dental image analysis due to its deep architecture and reliable performance [14]. These sophisticated neural network architectures and techniques are central to the technological progress in AI-driven dentistry, enhancing diagnostic accuracy and treatment outcomes.

However, ongoing research and interdisciplinary collaboration continue to push the boundaries of what AI can achieve in dental care. Emerging technologies hold the promise of further advancements, and collaboration between dental professionals, AI researchers, and other stakeholders is essential to overcome the existing challenges and fully realize the potential of AI in dentistry. This paper investigates the use of DL in various dental fields as in Fig. 1, emphasizing major developments, challenges, and future prospects. Through a review of existing literature, we aim to offer a thorough understanding of the impact deep learning is having on the future of dental practice. An electronic search was performed in the databases PubMed, Google Scholar, Scopus, and arXiv up until April 2024. The search was restricted to publications from 2018 onwards, considering that the use of deep learning for image analysis has gained significant traction in recent years.

II. COMPARATIVE ANALYSIS OF DEEP LEARNING'S INFLUENCE ON DENTAL PRACTICE

Advanced learning algorithms known as Artificial Neural Networks (ANNs) are modelled after neural network structures that are found in the human brain. These networks are extremely versatile for a range of learning tasks, including supervised, unsupervised, and reinforcement learning, because they can process intricate patterns and learn from data. Their versatility has enabled ANNs to address a broad spectrum of problems across different domains.

In the context of dentistry, the application of deep learning (DL) techniques stands out as one of the most promising areas of research. These advanced methods hold the potential to revolutionize decision-making support systems by enabling the precise identification of patterns from extensive databases of images. This capability is particularly useful for diagnostic and treatment planning purposes. The versatility of DL algorithms extends far beyond imaging; they can process a wide variety of biomedical signals from a variety of sources, making them powerful resources for dentistry [15].

The integration of DL in dentistry facilitates the development of robust, high-performance systems that can assist clinicians in making more accurate and efficient decisions. For example, DL models can analyze radiographs to detect dental caries, periodontal disease, and other oral pathologies with a high degree of accuracy, often surpassing human performance. Additionally, these technologies can be used to predict the outcomes of various dental treatments, customize patient care, and even automate routine tasks, thereby enhancing the overall efficiency of dental practices [16]. Furthermore, the continuous advancements in DL algorithms and computational power are expected to drive further innovations in dentistry. As these systems become more sophisticated, they will likely provide even greater insights and support, ultimately leading to improved patient outcomes and advancing the field of dental medicine. The ongoing research and development in this area underscore the transformative potential of DL in dentistry, paving the way for new diagnostic tools, treatment modalities, and personalized patient care solutions.

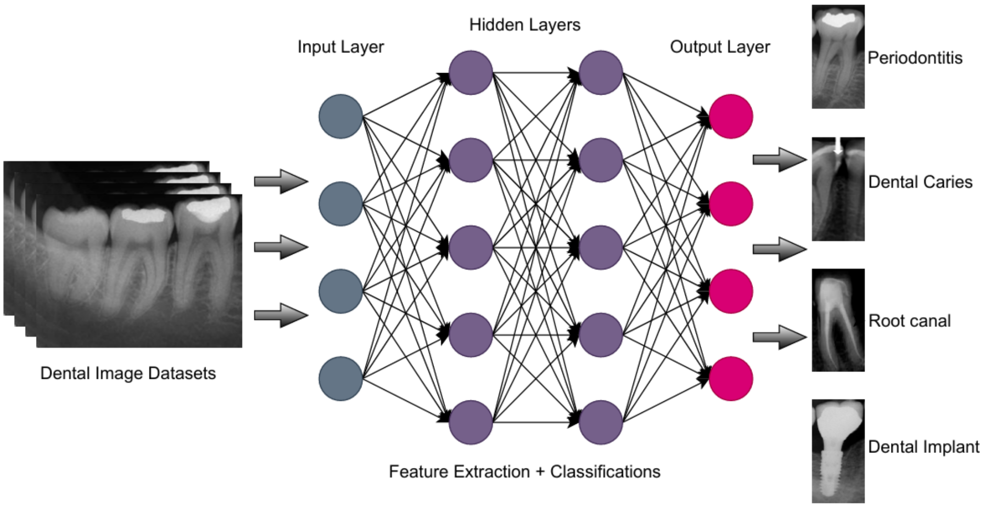

Fig. 1. Applications of deep learning (DL) in various areas of dentistry, including diagnostic imaging, disease detection, treatment planning, and personalized care, showcasing how DL enhances precision, efficiency, and outcomes in dental practice

A. Neural Networks for Periodontics

Billion individuals around the world suffer with periodontitis, making it one of the best-known diseases. Treatment is necessary to prevent tooth movement and, eventually, tooth loss [17]. Prevention of severe periodontitis requires prompt diagnosis and treatment. Gingival recession and pocket probing depths are the standard clinical tools for diagnosing periodontal disease. For clinical attachment loss, the Periodontal Screening Index (PSI) is a common tool to utilize. However, this clinical evaluation can be unreliable as it depends significantly on the dentist's expertise, potentially leading to overlooked localized periodontal tissue loss [18].

Artificial Intelligence has been applied to the field of periodontics to diagnose and classify various forms of periodontal disease [19]. Convolutional neural networks (CNNs), for instance, were used by [18] to detect Periodontal Bone Loss (PBL) in panoramic radiographs. An example of a CNN model is shown in Fig. 2. A suggested CNN algorithm's potential efficacy and accuracy for automatically identifying teeth with damaged periodontal tissue were assessed by authors of [20]. Reference [21] demonstrated that a CNN algorithm created by their research team and integrating systemic health-related data may be used to evaluate periodontal diseases. Table I shows a detailed comparison of different researches in periodontal dentistry.

TABLE I. COMPARISON OF PREVIOUS WORKS ON PERIODONTAL DENTISTRY

Ref.	Image Types	Algorithms	Dataset sizes	Accuracy
[18]	Periodontal bone loss detection	CNN	1809	0.81
[20]	Periodontally compromised teeth detection	CNN	1740	0.734-0.828
[21]	Periodontal condition examination	CNN	284	0.897

B. Neural Networks for Orthodontics

In general, the planning of orthodontic treatment is contingent upon the preferences and expertise of orthodontists. Unique perspectives are brought by each patient and orthodontist, resulting in a collaborative process for treatment decisions. Traditionally, diagnosing malocclusion requires significant effort from orthodontists, as numerous variables must be considered in cephalometric analysis.

AI is well-suited to address orthodontic challenges [22]. Table II shows a detailed comparison of different researches in orthodontal dentistry. A deep learning approach that can correctly recognize cephalometric landmarks on radiographs was proven by authors of [23], [24] and [25] also created algorithms that could recognize these landmarks as accurately as human examiners. To automatically categorize skeletons from lateral cephalometric radiographs, [26] put up a technique.

Using lateral cephalometric radiographs, [27] suggested an AI model to ascertain the need for surgery. Most artificial intelligence (AI) applications for orthodontics aim to automate the orthodontist's time-consuming and laborious work in landmark recognition and treatment planning. Segmenting and classifying the teeth is an important step in orthodontic treatment planning. These tasks have also made use of AI on a variety of sources, including radiography and full-arch 3D digital optical scans [28]. Using 3D intraoral scanner and CBCT data to create digital teeth models, [29] suggested multiple AI algorithms for automatic tooth segmentation. Their effectiveness was 500 times higher than that of radiologists, and they were able to segment alveolar bone in addition to teeth. Their approach proved effective even in the most difficult cases with a wide range of dental problems.

TABLE II. COMPARISON OF PREVIOUS WORKS ON ORTHODONTIC DENTISTRY

Ref.	Image Types	Algorithms	Dataset sizes	Accuracy
[24]	Cephalometric landmarks locating	CNN	1311	0.804-0.962
[25]	Tooth landmark/axis detection	NN	3084	0.934
[26]	Skeletal classification	CNN	5890	0.8951-0.964
[28]	Tooth segmentation	CNN	2000	0.980-0.986
[29]	Tooth and alveolar bone segmentation	CNN	4331	Tooth: 0.915 Alveolar bone: 0.93

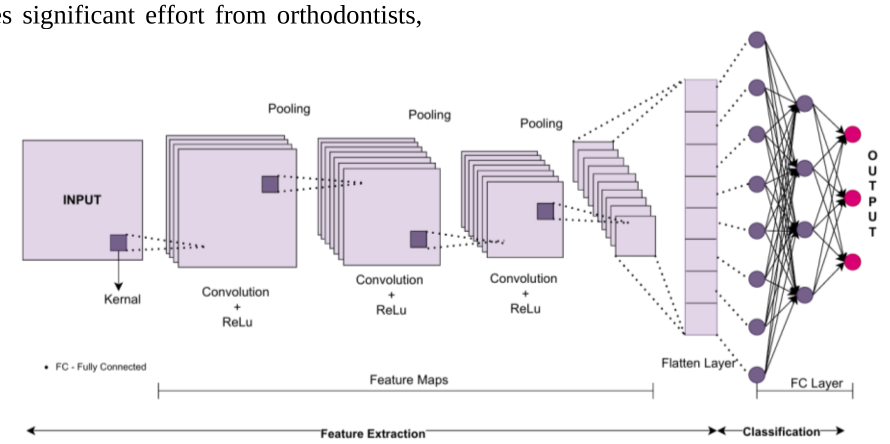

Fig. 2. Example of a Convolutional Neural Network (CNN) model, illustrating the architecture and layers involved in processing images for tasks such as segmentation, diagnosis, and treatment planning

C. Neural Networks for Prosthodontics

A dental crown is often prepared in prosthodontics using a multi-step process that includes tooth planning, impressions, cast trimming, fabrication, restoration design, try-in, and cementation. Computer-aided design and manufacturing (CAD/CAM) systems, found in commercial products like CEREC, Sirona, and 3Shape, have digitized the design process. While these systems have enhanced the efficiency of crown design by using a tooth library, they still lack the capability to produce custom-made designs tailored for individual patients [30].

Recent advancements in AI have led to innovative methods for crown design. By using 2D-GAN models as in Fig. 3, author of [31] have created crowns by using technician designs as a source of knowledge. 2D depth maps created from 3D tooth models served as the training set for these models. Furthermore, [32] generated crowns using a 3D-DCGAN network that directly utilized 3D data, producing crown morphologies that resembled real teeth. The workflow can be made more efficient and effective by combining AI with CAD/CAM or 3D/4D printing technologies [33]. AI has also been applied to shade matching and CAD/CAM restorative debonding prediction [34].

Currently, ML algorithms primarily aid in the creation of removable dentures by doing tasks like categorizing dental arches [35] and making predictions about how edentulous patients' faces would look [36].

The design process for removable prosthodontics is more complex due to the involvement of more factors and variables. Currently, no machine learning (ML) algorithms are available for creating custom removable dentures, although several expert systems were developed [37]. Table III. Shows a detailed comparison of different researches in prosthodontic dentistry.

TABLE III. COMPARISON OF PREVIOUS WORKS ON PROSTHODONTIC DENTISTRY

Ref.	Image Types	Algorithms	Dataset sizes	Accuracy
[30]	Crown generation	GAN	3313	0.92
[31]	Crown generation	GAN	780	0.936
[32]	Crown generation	3D-DCGAN	612	0.965
[33]	Crown debonding prediction	CNN	8640	0.985
[34]	Dental arch classification	CNN	1184	0.997

D. Neural Networks for maxillofacial and oral pathologies

The field of Oral and Maxillofacial Pathology (OMFP) is dedicated to the diagnosis and study of pathological problems that affect the oral and maxillofacial areas. Oral cancer represents the most critical form of OMFP. As reported by the World Health Organization (WHO), over 657,000 new cases of oral cancer are identified each year [38]. In OMFP, AI research has predominantly targeted the detection of tumors and cancers through radiographic, microscopic, and ultrasonographic images. AI is also employed to identify irregularities in radiographs [39].

It is crucial to diagnose and identify different mucosal lesions as soon as possible to determine whether they are benign or malignant; surgical excision is required for malignant lesions. However, other lesions have a similar appearance and need to be diagnosed with radiographs and biopsy slides. Using a microscope to examine the morphology of stained specimens on glass slides, pathologists can identify illnesses [40]. This painstaking task requires considerable effort from pathologists. Of the biopsies examined, only around 20% are malignant. Thus, AI can serve as an invaluable tool to aid pathologists in this process. Table IV. shows a detailed comparison of different researches in oral and maxillofacial pathology.

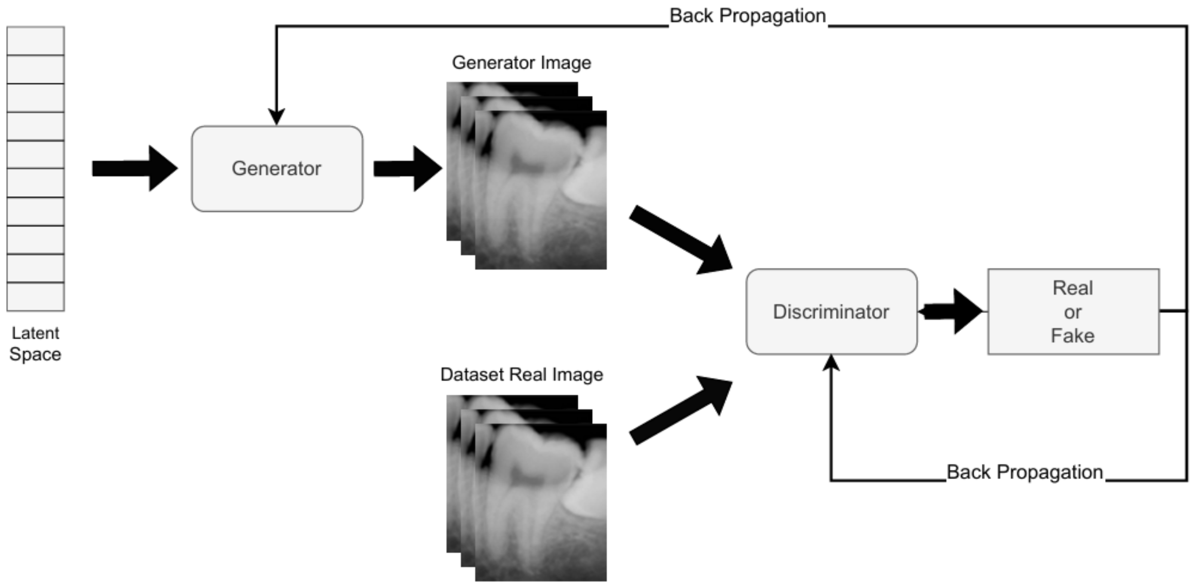

Fig. 3. General workflow of a Generative Adversarial Network (GAN), depicting the interaction between the generator and discriminator to create and refine synthetic dental images for enhanced data augmentation and analysis

On intraoral optical images, [41] used a CNN method to identify oral squamous cell carcinoma (OSCC) and oral potentially malignant disorders (OPMDs). The use of optical coherence tomography (OCT) has also allowed for the differentiation of oral mucosal lesions into benign and malignant varieties. To demonstrate the efficacy of the CNN algorithm for early SCC diagnosis, [42] automated the diagnosis of oral Squamous Cell Carcinoma (SCC) using confocal laser endomicroscopy pictures. Additionally, a CNN algorithm was employed by [43] to distinguish between ameloblastoma and Keratocystic Odontogenic Tumors (KCOT), two oral tumors that share radiographic characteristics.

With the help of ANN and SVM models, authors of [44] were able to distinguish between dysplastic and malignant oral lesions. When put side-by-side with biopsy data, the CNN algorithm obtained 83% accuracy and a diagnostic time of 38 seconds, which are in line with what oral and maxillofacial professionals achieve. Using AlexNet, a convolutional neural network (CNN), [45] were able to distinguish between healthy and unhealthy mucosa in the head and neck.

TABLE IV. COMPARISON OF PREVIOUS WORKS ON ORAL AND MAXILLOFACIAL PATHOLOGY

Ref.	Image Types	Algorithms	Dataset sizes	Accuracy
[39]	Mandibular molar and inferior nerve relation detection	CNN (ResNet - 50)	571	0.7232
[41]	OSCC diagnosis CT	CNN	116 (video sequences)	0.883
[43]	CBCT	CNN	500	0.83
[45]	CBCT	CNN	21 Sets	0.82

E. Neural Networks for Oral Implantology

Dental implants [46][47] involve placing implants in the alveolar bone without the need for grinding or harming adjacent teeth, which is a significant advantage. They are more aesthetically pleasing and durable but also more expensive [48]. Reference [49] initially identified ten different dental diseases using a deep neural network model, but found it to be more effective at identifying implants and crowns rather than roots and caries.

Also [50] utilized Faster R-CNN to identify implants and detect alveolar bone loss at the implant edges. Later [51] optimized VGG16 to develop TVGG16, which reduces computational effort and improves the accuracy of recognizing implant manufacturers. Table V. shows a detailed comparison of different researches in oral implantology.

TABLE V. COMPARISON OF PREVIOUS WORKS ON ORAL IMPLANTOLOGY

Ref.	Image Types	Algorithms	Dataset Size	Accuracy
[50]	X-ray	Faster R CNN	1670 radiographic images	0.83
[51]	Panoramic radiographs	TVGG16 by optimizing VGG16	1781 panoramic images	-

F. Neural Networks for Restorative Dentistry

Treating missing teeth and providing post-dental procedure care are the main areas of focus for restorative dentistry [52][53]. Using mouth images, [54] fine-tuned ResNet-18 to execute a multi-classification job, quickly identifying one of 10 anomalies in teeth. In their investigation, the use of these oral pictures in place of conventional medical imaging produced noteworthy and encouraging outcomes. In order to anticipate root locations following orthodontic treatment, [55] generated a 3D model of the tooth using convolutional neural networks (CNNs) trained using cone beam computed tomography (CBCT) scans taken before orthodontic treatment [56]. By identifying 11 different types of dental restorative materials, Takahashi's deep learning algorithm [50] helps physicians better understand how leftover teeth are restored.

Orthodontics utilizes CNNs and multi-stage CNNs for automated cephalometric analysis and treatment planning, while Faster R-CNN and GoogleNet Inception v2 enhance the accuracy of landmark detection. Periodontics employs CNNs and modified ANFIS for diagnosing and monitoring periodontal diseases. In prosthodontics and oral surgery, CNNs and Generative Adversarial Networks (GANs) assist in prosthesis design and surgical planning, with ResNet and AlexNet improving the classification of dental prostheses. Additionally, transfer learning techniques enhance neural network performance, reducing the need for extensive dental-specific datasets. These advancements highlight the transformative impact of DL on dental diagnostics and patient care.

III. COMPARISON OF DEEP LEARNING SEGMENTATION ALGORITHMS FOR DENTISTRY

Dentistry research must prioritize early identification of decay and other reasons for tooth loss [57][58]. Traditionally, doctors judge the location and size of tooth defects through visual observation and experience. However, medical imaging technology enables more accurate identification of tooth lesions. Different conditions require specific types of dental films. Panoramic radiographs [59] capture images of all teeth and both jaws, while bitewing radiographs are less common but provide valuable information. Regardless of the type, dental films aim to assist dentists in delivering more precise and effective treatment. The block diagram representation of dental segmentation and numbering is shown in Fig. 4.

A. Tooth Image Segmentation and Labeling

Accurately marking three-dimensional tooth surfaces is still a challenge in computer-aided treatment [60]. As the first stage of computer-aided diagnosis, tooth image segmentation is essential to medical image processing. The techniques for segmenting and annotating dental images are reviewed in this section and are included in Table VI.

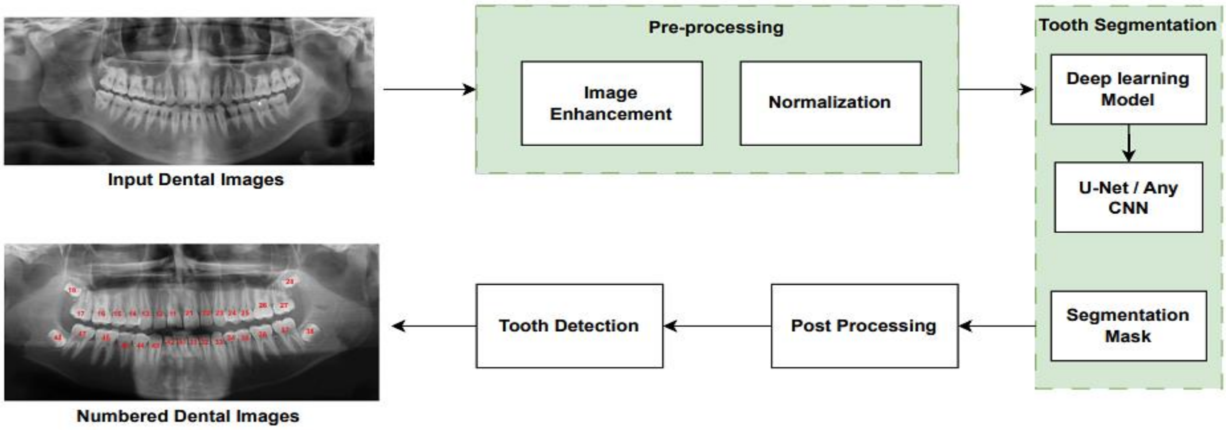

Fig. 4. Pipeline for tooth segmentation, detection, and numbering, illustrating the sequential steps from image preprocessing, segmentation using deep learning models, to the final detection and numbering of individual teeth for clinical analysis

TABLE VI. COMPARISON OF PREVIOUS STUDIES ON VARIOUS DEEP LEARNING SEGMENTATION ALGORITHMS FOR DENTISTRY

Ref	Image Types	Algorithms	Characteristics	Performance
[55]	PR's	SWin – U-Net	U-shaped encoders and decoders with skip-connections	F1: 0.64 Mean: 0.47 Accuracy: 0.88
[56]	OPG Images	Automatic segmentation	genetic algorithm to segment individual tooth images and detect gap valleys.	F1:0.80 Mean:0.75 IoU:0.80 Accuracy: 0.73
[57]	CT Images	Grey-scale morphological and filtering	Enhanced segmentation and counting using morphological operations.	F1:0.96 Mean: 0.98 Acc:0.93 IoU:0.94
[58]	Panoramic Radiographs	Training on smaller images	Cropping reduces information loss, improving CNN-based segmentation.	F1: 0.95 IoU: 0.93 Sensitivity: 0.95
[59]	CBCT Scans	Mixed-scale dense CNN	Segments jaws, teeth, and background for orthodontic treatment planning.	Jaw: 0.93 0.90 -Teeth: 0.199mm 0.20
[60]	X-ray Images	NASNet multi-classification	Classifies cavities, fillings, implants with high accuracy without data enhancement.	Accuracy: 0.93 IoU: 0.96
[61]	CT Images	U-Net with attention mechanism	Adds attention mechanism for better tooth contour definition.	MPA: 0.86 IoU: 0.84 Accuracy: 0.84
[62]	X-ray Images	CNN and RCNN	Multi-class segmentation including implant devices for interpretable results.	Sensitivity: 0.75 Precision: .084 Acc: 0.77
[63]	CBCT	3D U-Net	Segments teeth individually using 3D U-Net, with framework for image size specification.	Acc: 0.96 IoU: 0.82 Precision: 0.98
[65]	X-ray Images	Local ternary encoder-decoder NN	Improves LBCDNN for better tooth contour extraction.	Acc: 0.94 Dice: 0.92
[66]	X-ray Images	CNN	Introduced three additional detailed classification labels for tooth segmentation.	-

An encoder-decoder constructed using a transformer and including skip-connections is used by Swin-Unet, which was presented by [61], to precisely segment teeth on panoramic radiographs. Reference [52] proposed an automatic segmentation system for OPG images, employing a line removal technique and genetic algorithm to detect tooth boundaries and gap valleys. Also [63] enhanced segmentation and counting using grey-scale morphological operations. Before using CNN, [64] recommended practicing with smaller, equidistant visuals to minimize information loss. Reference [65] used a mixed-scale dense CNN for segmenting jaws, teeth, and background in orthodontic treatment planning. Authors of [66] achieved high accuracy with NASNet for multi-classification, without data enhancement during pre-processing. Reference [67] enhanced U-Net with an attention mechanism for improved segmentation efficiency.

The reference [68] incorporated implant devices into multi-class segmentation by utilizing CNN and RCNN, and the findings were interpretable. Three-dimensional U-Net, which treats each tooth as if it were a class, was proposed by [69] as a method for multi-class segmentation. DL network combinations were investigated in [70], with a particular emphasis on VGG and ResNet models. The extraction of dental contours was also improved by [71] by the utilization of a local ternary encoder-decoder neural network. After that,

[72] presented a brand-new teeth classification system that included descriptive labelling.

To use dental and medical data for machine learning (ML) training, it is crucial to handle its complexity, sensitivity, and limited validation methods with care [73]. Electronic medical records often have low data integrity, lacking systematic allocation and randomness; for example, hospital data may overrepresent severe cases, while wearable device data may reflect overly healthy individuals. Additionally, disparities in healthcare systems across different regions can result in data that may be precise but not broadly accurate, leading to biases in AI applications [74]. Studies have explored ways to mitigate the impact of such long-tailed data in ML [75]. Furthermore, the results of AI models are often not directly applicable to clinical settings, as the single outputs from most current medical AI applications only partially address the complex decision-making needs in clinical practice.

In conclusion, the SWin-Unet, U-Net with attention mechanism, 3D U-Net, NASNet, and LTPEDN models are notably effective for dental segmentation tasks. These deep learning methods have shown outstanding performance in terms of accuracy, precision, and efficiency in various dental imaging applications.

IV. Conclusion and Future Work

The integration of AI and DL in dentistry has shown transformative potential by significantly enhancing diagnostic precision, treatment planning, and patient care. AI technologies, particularly deep learning algorithms, excel in analyzing dental radiographs, detecting pathologies, and aiding complex orthodontic and prosthodontic procedures. In periodontics, AI effectively diagnoses and categorizes periodontal diseases, improving early detection and treatment outcomes. Orthodontics has benefited from automated cephalometric analysis and personalized treatment planning, reducing labor-intensive tasks and increasing accuracy. In prosthodontics, AI has revolutionized the design process for dental restorations, especially crowns, through advanced CAD/CAM systems and generative adversarial networks, improving workflow efficiency and customization. Despite these advancements, challenges such as data quality, interpretability of AI models, and regulatory compliance remain. Ensuring high-quality, accessible dental data and addressing ethical and privacy concerns are essential for broader AI adoption in dentistry. AI can assist in everything from material research and diagnostic tools to treatment planning and post-treatment monitoring, enhancing overall patient care and operational efficiency.

Future research should aim to overcome existing challenges to fully leverage AI in dentistry by developing robust data management systems that ensure high-quality dental datasets for training AI models and enhancing the interpretability of AI algorithms to make their decision-making processes more transparent to clinicians. Establishing comprehensive regulatory frameworks addressing ethical, legal, and privacy concerns is essential for the safe and effective integration of AI into dental practice, requiring collaboration among AI researchers, dental professionals, and regulatory bodies [76][77]. Further exploration of AI applications in underdeveloped areas of dentistry, such as designing removable dentures and planning dental implants, could lead to significant advancements. Investigating AI's potential in personalized patient care, predictive analytics, and real-time diagnostic support is also crucial. By addressing these future directions, the dental field can continue to innovate and improve patient outcomes, ultimately advancing the standard of care in dental medicine. As dental data collection increases, integrating DL with such data will likely enhance results further. Given DL's requirement for extensive data, initiatives to collect more data are crucial. Storing this data locally is impractical as it grows, so cloud services are becoming a preferred solution due to their scalability and processing power. Cloud services also enable the integration of various data sources, such as X-ray images and clinical records, leading to more robust predictions [78]-[80]. This integration supports precision medicine, allowing for more personalized treatments and improved patient outcomes.

References

[1] M. Yamada, "Development of a real-time endoscopic image diagnosis support system using deep learning technology in colonoscopy," *Scientific Reports*, vol. 9, no. 1, 2019, doi: 10.1038/s41598-019-50567-5.

[2] S. Kalra, "Pan-cancer diagnostic consensus through searching archival histopathology images using artificial intelligence," *npj Digital Medicine*, vol. 3, no. 1, 2020, doi: 10.1038/s41746-020-0238-2.

[3] S. R. Motamedian, "Machine learning and orthodontics, current trends and the future opportunities: A scoping review," *American Journal of Orthodontics and Dentofacial Orthopedics*, vol. 160, no. 2, pp. 170-192.e4, 2021, doi: 10.1016/j.ajodo.2021.02.013.

[4] J. Gomez, "Detection and diagnosis of the early caries lesion," *BMC Oral Health*, vol. 15, 2015, doi: 10.1186/1472-6831-15-s1-s3.

[5] F. Schwendicke, K. Elhennawy, S. Paris, P. Friebertshäuser, and J. Krois, "Deep learning for caries lesion detection in near-infrared light transillumination images: A pilot study," *Journal of Dentistry*, vol. 92, p. 103260, 2020, doi: 10.1016/j.jdent.2019.103260.

[6] M.-J. Kim, Y. Liu, S. H. Oh, H.-W. Ahn, S.-H. Kim, and G. Nelson, "Automatic Cephalometric Landmark Identification System Based on the Multi-Stage Convolutional Neural Networks with CBCT Combination Images," *Sensors*, vol. 21, no. 2, p. 505, 2021, doi: 10.3390/s21020505.

[7] S. B. Khanagar, "Developments, application, and performance of artificial intelligence in dentistry – A systematic review," *Journal of Dental Sciences*, vol. 16, no. 1, pp. 508-522, 2021, doi: 10.1016/j.jds.2020.06.019.

[8] H. W. Loh, "Application of Deep Learning Models for Automated Identification of Parkinson's Disease: A Review (2011–2021)," *Sensors*, vol. 21, no. 21, p. 7034, 2021, doi: 10.3390/s21217034.

[9] E. Y. Park, H. Cho, S. Kang, S. Jeong, and E.-K. Kim, "Caries detection with tooth surface segmentation on intraoral photographic images using deep learning," *BMC Oral Health*, vol. 22, no. 1, 2022, doi: 10.1186/s12903-022-02589-1.

[10] P. Singh and P. Sehgal, "G.V Black dental caries classification and preparation technique using optimal CNN-LSTM classifier," *Multimedia Tools and Applications*, vol. 80, no. 4, pp. 5255-5272, 2020, doi: 10.1007/s11042-020-09891-6.

[11] M. A. Morid, A. Borjali, and G. Del Fiol, "A scoping review of transfer learning research on medical image analysis using ImageNet," *Computers in Biology and Medicine*, vol. 128, p. 104115, 2021, doi: 10.1016/j.compbiomed.2020.104115.

[12] Z. Cui, "TSegNet: An efficient and accurate tooth segmentation network on 3D dental model," *Medical Image Analysis*, vol. 69, p. 101949, 2021, doi: 10.1016/j.media.2020.101949.

[13] R. Jain, A. Sutradhar, A. K. Dash, and S. Das, "Automatic Multi-organ Segmentation on Abdominal CT scans using Deep U-Net Model," *2021 19th OITS International Conference on Information Technology (OCIT)*, pp. 48-53, 2021, doi: 10.1109/ocit53463.2021.00021.

[14] S. Ramya, S. Sanjika, V. G. Sruthi, S. Swathi, and S. Sweetha, "MRI Image Based Diagnosis Model for Alzheimer's Disease Using VGG16," *Recent Trends in Data Science and its Applications*, pp. 1044-1049, 2023, doi: 10.13052/rp-9788770040723.201.

[15] I. H. Sarker, "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions," *SN Computer Science*, vol. 2, no. 6, 2021, doi: 10.1007/s42979-021-00815-1.

[16] A. Katsumata, "Deep learning and artificial intelligence in dental diagnostic imaging," *Japanese Dental Science Review*, vol. 59, pp. 329-333, 2023, doi: 10.1016/j.jdsr.2023.09.004.

[17] M. S. Tonetti, S. Jepsen, L. Jin, and J. Otomo-Corgel, "Impact of the global burden of periodontal diseases on health, nutrition and wellbeing of mankind: A call for global action," *Journal of Clinical Periodontology*, vol. 44, no. 5, pp. 456-462, 2017, doi: 10.1111/jcpe.12732.

[18] J. Krois, "Deep Learning for the Radiographic Detection of Periodontal Bone Loss," *Scientific Reports*, vol. 9, no. 1, 2019, doi: 10.1038/s41598-019-44839-3.

[19] E.-H. Kim, "Prediction of Chronic Periodontitis Severity Using Machine Learning Models Based On Salivary Bacterial Copy Number," *Frontiers in Cellular and Infection Microbiology*, vol. 10, 2020, doi: 10.3389/fcimb.2020.571515.

[20] J.-H. Lee, D.- hyung Kim, S.-N. Jeong, and S.-H. Choi, "Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm," *Journal of Periodontal & Implant Science*, vol. 48, no. 2, p. 114, 2018, doi: 10.5051/jpis.2018.48.2.114.

[21] G. Yauney, A. Rana, L. C. Wong, P. Javia, A. Muftu, and P. Shah, "Automated Process Incorporating Machine Learning Segmentation and Correlation of Oral Diseases with Systemic Health," *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 3387-3393, 2019, doi: 10.1109/embc.2019.8857965.

[22] W. R. Proffita, "The evolution of orthodontics to a data-based specialty," *American Journal of Orthodontics and Dentofacial Orthopedics*, vol. 117, no. 5, pp. 545-547, 2000, doi: 10.1016/s0889-5406(00)70194-6.

[23] J.-H. Park, "Automated identification of cephalometric landmarks: Part 1—Comparisons between the latest deep-learning methods YOLOV3 and SSD," *The Angle Orthodontist*, vol. 89, no. 6, pp. 903-909, 2019, doi: 10.2319/022019-127.1.

[24] G. Bulatova, B. Kusnoto, V. Grace, T. P. Tsay, D. M. Avenetti, and F. J. C. Sanchez, "Assessment of automatic cephalometric landmark identification using artificial intelligence," *Orthodontics & Craniofacial Research*, vol. 24, pp. 37-42, 2021, doi: 10.1111/ocr.12542.

[25] F. Kunz, A. Stellzig-Eisenhauer, F. Zeman, and J. Boldt, "Artificial intelligence in orthodontics," *Journal of Orofacial Orthopedics / Fortschritte der Kieferorthopädie*, vol. 81, no. 1, pp. 52-68, 2019, doi: 10.1007/s00056-019-00203-8.

[26] H. Yu, S. Cho, M. Kim, W. Kim, J. Kim, and J. Choi, "Automated Skeletal Classification with Lateral Cephalometry Based on Artificial Intelligence," *Journal of Dental Research*, vol. 99, no. 3, pp. 249-256, 2020, doi: 10.1177/0022034520901715.

[27] H.-I. Choi, "Artificial Intelligent Model With Neural Network Machine Learning for the Diagnosis of Orthognathic Surgery," *Journal of Craniofacial Surgery*, vol. 30, no. 7, pp. 1986-1989, 2019, doi: 10.1097/scs.0000000000005650.

[28] Z. Cui, "TSegNet: An efficient and accurate tooth segmentation network on 3D dental model," *Medical Image Analysis*, vol. 69, p. 101949, 2021, doi: 10.1016/j.media.2020.101949.

[29] Z. Cui, "A fully automatic AI system for tooth and alveolar bone segmentation from cone-beam CT images," *Nature Communications*, vol. 13, no. 1, 2022, doi: 10.1038/s41467-022-29637-2

[30] Y. Chen, J. K. Y. Lee, G. Kwong, E. H. N. Pow, and J. K. H. Tsoi, "Morphology and fracture behavior of lithium disilicate dental crowns designed by human and knowledge-based AI," *Journal of the Mechanical Behavior of Biomedical Materials*, vol. 131, p. 105256, 2022, doi: 10.1016/j.jmbbm.2022.105256.

[31] S. Tian, "DCPR-GAN: Dental Crown Prosthesis Restoration Using Two-Stage Generative Adversarial Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 1, pp. 151-160, 2022, doi: 10.1109/jbhi.2021.3119394.

[32] H. Ding, "Morphology and mechanical performance of dental crown designed by 3D-DCGAN," *Dental Materials*, vol. 39, no. 3, pp. 320-332, 2023, doi: 10.1016/j.dental.2023.02.001.

[33] D. Rokaya, "3D-Printed Biomaterials in Biomedical Application," *Functional Biomaterials*, pp. 319-339, 2022, doi: 10.1007/978-981-16-7152-4_12.

[34] J. Wei, M. Peng, Q. Li, and Y. Wang, "Evaluation of a Novel Computer Color Matching System Based on the Improved Back-Propagation Neural Network Model," *Journal of Prosthodontics*, vol. 27, no. 8, pp. 775-783, 2016, doi: 10.1111/jopr.12561.

[35] T. Takahashi, K. Nozaki, T. Gonda, and K. Ikebe, "A system for designing removable partial dentures using artificial intelligence. Part 1. Classification of partially edentulous arches using a convolutional neural network," *Journal of Prosthodontic Research*, vol. 65, no. 1, pp. 115-118, 2021, doi: 10.2186/jpr.jpor_2019_354.

[36] C. Cheng, X. Cheng, N. Dai, X. Jiang, Y. Sun, and W. Li, "Prediction of facial deformation after complete denture prosthesis using BP neural network," *Computers in Biology and Medicine*, vol. 66, pp. 103-112, 2015, doi: 10.1016/j.compbiomed.2015.08.018.

[37] J. Sporring and K. Hommelhoff Jensen, "Bayes Reconstruction of Missing Teeth," *Journal of Mathematical Imaging and Vision*, vol. 31, no. 2, pp. 245-254, 2008, doi: 10.1007/s10851-008-0081-6.

[38] National Cancer Institute. *World Health Organization*. Qeios, 2020, doi:10.32388/XO5AWV.

[39] E. Choi, "Artificial intelligence in positioning between mandibular third molar and inferior alveolar nerve on panoramic radiography," *Scientific Reports*, vol. 12, no. 1, 2022, doi: 10.1038/s41598-022-06483-2.

[40] J. Ferracane, "Models of Caries Formation around Dental Composite Restorations," *Journal of Dental Research*, vol. 96, no. 4, pp. 364-371, 2016, doi: 10.1177/0022034516683395.

[41] K. Warin, W. Limprasert, S. Suebnukarn, S. Jinaporntham, P. Jantana, and S. Vicharueang, "AI-based Analysis of Oral Lesions Using Novel Deep Convolutional Neural Networks for Early Detection of Oral Cancer," *Plos one*, vol. 17, no. 8, 2022, doi: 10.21203/rs.3.rs-1049349/v1.

[42] M. Aubreville, "Automatic Classification of Cancerous Tissue in Laser Endomicroscopy Images of the Oral Cavity using Deep Learning," *Scientific Reports*, vol. 7, no. 1, 2017, doi: 10.1038/s41598-017-12320-8.

[43] W. Poedjiastoeti and S. Suebnukarn, "Application of Convolutional Neural Network in the Diagnosis of Jaw Tumors," *Healthcare Informatics Research*, vol. 24, no. 3, p. 236, 2018, doi: 10.4258/hir.2018.24.3.236.

[44] B. L. James, "Validation of a Point-of-Care Optical Coherence Tomography Device with Machine Learning Algorithm for Detection of Oral Potentially Malignant and Malignant Lesions," *Cancers*, vol. 13, no. 14, p. 3583, 2021, doi: 10.3390/cancers13143583.

[45] A. E. Heidari, "The use of optical coherence tomography and convolutional neural networks to distinguish normal and abnormal oral mucosa," *Journal of Biophotonics*, vol. 13, no. 3, 2020, doi: 10.1002/jbio.201900221.

[46] H.-J. Kong, S.-H. Eom, J.-Y. Yoo, and J.-H. Lee, "Identification of 130 Dental Implant Types Using Ensemble Deep Learning," *International Journal of Oral and Maxillofacial Implants*, vol. 38, no. 1, pp. 150-156, 2023, doi: 10.11607/jomi.9818.

[47] V. Kwok, J. G. Caton, I. D. Hart, and T. Kim, "Dental implant prognostication: A commentary," *Journal of Periodontology*, vol. 94, no. 6, pp. 713-721, 2023, doi: 10.1002/jper.22-0196.

[48] C. Xu, "Calcium Phosphate Ceramics and Synergistic Bioactive Agents for Osteogenesis in Implant Dentistry," *Tissue Engineering Part C: Methods*, vol. 29, no. 5, pp. 197-215, 2023, doi: 10.1089/ten.tec.2023.0042.

[49] T. Takahashi, K. Nozaki, T. Gonda, T. Mameno, and K. Ikebe, "Deep learning-based detection of dental prostheses and restorations," *Scientific Reports*, vol. 11, no. 1, 2021, doi: 10.1038/s41598-021-81202-x.

[50] M. Liu, S. Wang, H. Chen, and Y. Liu, "A pilot study of a deep learning approach to detect marginal bone loss around implants," *BMC Oral Health*, vol. 22, no. 1, 2022, doi: 10.1186/s12903-021-02035-8.

[51] G. Nijaguna, J. A. Babu, B. Parameshachari, R. P. De Prado, and J. Frnda, "Quantum Fruit Fly algorithm and ResNet50-VGG16 for medical diagnosis," *Applied Soft Computing*, vol. 136, p. 110055, 2023, doi: 10.1016/j.asoc.2023.110055.

[52] S. Nagarkar, A. D. Loguercio, and J. Perdigão, "Evidence-based fact checking for selective procedures in restorative dentistry," *Clinical Oral Investigations*, vol. 27, no. 2, pp. 475-488, 2023, doi: 10.1007/s00784-022-04832-z.

[53] A. K. Swanson, I. S. Duqum, L. H. Heimisdóttir, and J. T. Wright, "Digital restorative workflows for developmental dental defects in young patients," *The Journal of the American Dental Association*, vol. 154, no. 4, pp. 340-348, 2023, doi: 10.1016/j.adaj.2022.11.014.

[54] K. M. Sunnetci, E. Kaba, F. Beyazal Çeliker, and A. Alkan, "Comparative parotid gland segmentation by using ResNet-18 and MobileNetV2 based DeepLab v3+ architectures from magnetic resonance images," *Concurrency and Computation: Practice and Experience*, vol. 35, no. 1, 2022, doi: 10.1002/cpe.7405.

[55] M. Madi, I. Almindil, M. Alrassasi, D. Alramadan, O. Zakaria, and A. S. Alagl, "Cone-Beam Computed Tomography and Histological Findings for Socket Preservation Techniques Using Different Grafting Materials: A Systematic Review," *Journal of Functional Biomaterials*, vol. 14, no. 5, p. 282, 2023, doi: 10.3390/jfb14050282.

[56] H. Choi, J. P. Yun, A. Lee, S.-S. Han, S. W. Kim, and C. Lee, "Deep learning synthesis of cone-beam computed tomography from zero echo time magnetic resonance imaging," *Scientific Reports*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-33288-8.

[57] L. Jiang, "Analysis of epidemiological trends of and associated factors for tooth loss among 35- to 44-year-old adults in Guangdong, Southern China, 1995–2015: a population-based cross-sectional survey," *BMC Oral Health*, vol. 23, no. 1, 2023, doi: 10.1186/s12903-023-02776-8.

[58] B. Jabeen, Z. Afshan, K. Aslam, M. Iftikhar, S. Rasool, and H. Ahsan, "Association of Smoked and Smokeless Tobacco with Tooth Loss," *Pakistan Journal of Medical and Health Sciences*, vol. 17, no. 5, pp. 136-137, 2023, doi: 10.53350/pjmhs2023175136.

[59] A. M. Scott, W. M. Reed, S. Ajwani, and T. R. Parmenter, "Panoramic radiographs and dental patients with Down syndrome: A scoping review," *Special Care in Dentistry*, vol. 43, no. 2, pp. 199-220, 2022, doi: 10.1111/scd.12762.

[60] A. Kang, F. A. Firth, J. Antoun, L. Mei, A. Ali, and M. Farella, "Three-dimensional digital assessment of typodont activations," *Orthodontics & Craniofacial Research*, vol. 26, no. 2, pp. 285-296, 2022, doi: 10.1111/ocr.12611.

[61] C. Sheng, "Transformer-Based Deep Learning Network for Tooth Segmentation on Panoramic Radiographs," *Journal of Systems Science and Complexity*, vol. 36, no. 1, pp. 257-272, 2022, doi: 10.1007/s11424-022-2057-9.

[62] A. Haghanifar, M. M. Majdabadi, and S.-B. Ko, "Automated Teeth Extraction from Dental Panoramic X-Ray Images using Genetic Algorithm," *2020 IEEE International Symposium on Circuits and Systems (ISCAS)*, 2020, doi: 10.1109/iscas45731.2020.9180937.

[63] S. Helli and A. Hamamci, "Tooth Instance Segmentation on Panoramic Dental Radiographs Using U-Nets and Morphological Processing," *Düzce Üniversitesi Bilim ve Teknoloji Dergisi*, vol. 10, no. 1, pp. 39-50, 2022, doi: 10.29130/dubited.950568.

[64] C. Rohrer, J. Krois, J. Patel, H. Meyer-Lueckel, J. A. Rodrigues, and F. Schwendicke, "Segmentation of Dental Restorations on Panoramic Radiographs Using Deep Learning," *Diagnostics*, vol. 12, no. 6, p. 1316, 2022, doi: 10.3390/diagnostics12061316.

[65] H. Wang, J. Minnema, K. Batenburg, T. Forouzanfar, F. Hu, and G. Wu, "Multiclass CBCT Image Segmentation for Orthodontics with Deep Learning," *Journal of Dental Research*, vol. 100, no. 9, pp. 943-949, 2021, doi: 10.1177/00220345211005338.

[66] A. S. A.-M. AL-Ghamdi, M. Ragab, S. A. AlGhamdi, A. H. Asseri, R. F. Mansour, and D. Koundal, "Detection of Dental Diseases through X-Ray Images Using Neural Search Architecture Network," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1-7, 2022, doi: 10.1155/2022/3500552.

[67] S. Tao and Z. Wang, "Tooth CT Image Segmentation Method Based on the U-Net Network and Attention Module," *Computational and Mathematical Methods in Medicine*, vol. 2022, pp. 1-8, 2022, doi: 10.1155/2022/3289663.

[68] C. Kim, D. Kim, H. Jeong, S.-J. Yoon, and S. Youm, "Automatic Tooth Detection and Numbering Using a Combination of a CNN and Heuristic Algorithm," *Applied Sciences*, vol. 10, no. 16, p. 5624, 2020, doi: 10.3390/app10165624.

[69] E. Shaheen, "A novel deep learning system for multi-class tooth segmentation and classification on cone beam computed tomography. A validation study," *Journal of Dentistry*, vol. 115, p. 103865, 2021, doi: 10.1016/j.jdent.2021.103865.

[70] L. Schneider, "Benchmarking Deep Learning Models for Tooth Structure Segmentation," *Journal of Dental Research*, vol. 101, no. 11, pp. 1343-1349, 2022, doi: 10.1177/00220345221100169.

[71] O. Salih and K. J. Duffy, "The local ternary pattern encoder–decoder neural network for dental image segmentation," *IET Image Processing*, vol. 16, no. 6, pp. 1520-1530, 2022, doi: 10.1049/ipr2.12416.

[72] K. Zhang, H. Chen, P. Lyu, and J. Wu, "A relation-based framework for effective teeth recognition on dental periapical X-rays," *Computerized Medical Imaging and Graphics*, vol. 95, p. 102022, 2022, doi: 10.1016/j.compmedimag.2021.102022.

[73] J. R. Vest and L. D. Gamm, "Health information exchange: persistent challenges and new strategies," *J Am Med Inform Assoc.*, vol. 17, no. 3, pp. 288–294, 2010, doi: 10.1136/jamia.2010.003673.

[74] F. Schwendicke, W. Samek, and J. Krois, "Artificial intelligence in dentistry: chances and challenges," *J Dent Res.*, vol. 99, no. 7, pp. 769–74, 2020, doi: 10.1177/0022034520915714

[75] K. Li, Y. Li, J. Zhang, X. Liu, and Z. Ma, "Federated deep long-tailed learning: A survey," *Neurocomputing*, vol. 595, p. 127906, 2024, doi: 10.1016/j.neucom.2024.127906.

[76] R. Rischke, L. Schneider, K. Müller, W. Samek, F. Schwendicke, and J. Krois, "Federated Learning in Dentistry: Chances and Challenges," *Journal of Dental Research*, vol. 101, no. 11, pp. 1269-1273, 2022, doi: 10.1177/00220345221108953.

[77] F. Schwendicke *et al*., "Artificial intelligence for oral and dental healthcare: core education curriculum," *Journal of Dentistry*, vol. 128, p. 104363, 2023.

[78] T. Ma and A. Zhang, "Integrate multi-omics data with biological interaction networks using Multi-view Factorization AutoEncoder (MAE)," *BMC Genomics*, vol. 20, 2019, doi: 10.1186/s12864-019-6285-x.

[79] A. Cheerla and O. Gevaert, "Deep learning with multimodal representation for pancancer prognosis prediction," *Bioinformatics*, vol. 35, no. 14, 2019, doi: 10.1093/bioinformatics/btz342.

[80] N. Haghjoo, A. Moeini, and A. Masoudi-Nejad, "Introducing a panel for early detection of lung adenocarcinoma by using data integration of genomics, epigenomics, transcriptomics and proteomics," *Experimental and Molecular Pathology*, vol. 112, p. 104360, 2020, doi: 10.1016/j.yexmp.2019.104360.