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Dental Diagnostic Imaging in AI-based System: A Systematic Mapping Study

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***Abstract*—The analysis of human dental images is a complex and time-consuming task for a dentist, owing to the irregular and inconsistent various teeth's stuctures. Such analysis is required to detect tooth-related issues, anomalies, or alterations in tooth structure. Therefore, automation is crucial for dental image segmentation and inspection to guarantee accurate diagnosis and improved treatment planning. This article presents a thorough examination and analysis of dental image segmentation. It explores around 62 research works done between 2019 and 2023, utilizing several dental imaging modalities. The survey provides comprehensive information on the latest techniques, encompassing several imaging modalities, performance metrics, datasets employed, and the study's objectives.**

***Keywords*—dental image, teeth, systematic mapping study, artificial intelligence, deep learning**

I. Introduction

Artificial Intelligence (AI) has currently changed various fields including dental diagnostic imaging. This convergence of technology and healthcare is reshaping the diagnostic capabilities in dentistry. The integration of AI in dental practice is being extensively studied. It is crucial to systematically examine its applications and consequences in diagnostic imaging, as it greatly assists in detecting problems in tooth structures [1]. Dental imagery is crucial for dentists as it greatly aids in the assessment of images for a comprehensive clinical diagnosis and preventative exams of dental structures [2]. Nevertheless, the process of manually reviewing a vast assortment of dental photos can be laborious due to the poor accuracy of visual inspection and tooth structure analysis [3].

The utilization of computerized tools that employ dental imaging modalities can greatly enhance the investigative procedure in most instances [4]. Dental imaging techniques provide valuable information on tooth development, bone architecture, soft tissues, tooth loss, and decay [5]. The classification of dental imaging techniques primarily consists of intra-oral x-rays (periapical, bitewing, panoramic) and the x-rays of extra-oral (CBCT) [6]. The images are commonly utilized in dentistry and their efficiency enhances the accuracy of medical diagnoses [7]. The process of examining dental images includes several stages such as improving the quality of the image, dividing it into different parts, extracting important characteristics, and identifying specific areas. These steps are important for detecting various dental conditions.

Currently, there is a significant surge in the application of deep learning (DL) and machine learning (ML) methods in dentistry diagnostic imaging. ML was a subset of AI and DL was a subset of ML that used a deep neural network [6]. DL frameworks, often referred to as convolutional neural networks (CNNs), are common for analyzing extensive and intricate picture datasets due to their ability to extract various characteristics from hidden layers [8].

Researchers have put forth a multitude of ML methods to enhance the efficiency and the analysis of dental image segmentation [9]. The use of DL and AI techniques has proven to be highly effective in solving complex segmentation problems in different studies [10] & [11]. This suggests that in the future, we can expect a surge of innovative approaches and significant advancements in dental diagnostic imaging, specifically in ML models for semiotic segmentation.

Previous studies have examined different techniques and procedures used in dental diagnostic imaging. The paper by Katsumata [12] categorizes segmentation techniques into two divisions: edge-based and region-based. Nevertheless, there is a lack of discourse regarding the methods employed to improve the quality of dental diagnostic imaging, the specific image databases utilized, and the many modalities employed in this field. In the following study conducted by Rahimi et al. [13], an examination of dental image diagnosis is offered. The study specifically focuses on the use of a CNN and its ability to accurately diagnose dental conditions. The evaluation primarily compares the CNN's performance against a reference test utilizing ordinary image data. The past surveys have lacked a comprehensive examination of classical image processing, ML, and DL methods.

In this research, we have introduced two novel contributions that were not addressed in the prior surveys: Initially, we conducted a range of research from 2019 to 2023. This represents a significant increase compared to the earlier surveys conducted by Katsumata [12] and Rahimi et al. [13], which had a smaller sample size. Furthermore, approaches based on distinct imaging modalities, such as periapical, panoramic, CBCT, and bitewing are classified. This paper offers a methodical mapping research with the goal of completing a thorough categorization of AI applications in dentistry diagnostic imaging.

II. Materials and Methods

A. Data Sources

The current systematic mapping study was performed in accordance with the principles in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension (PRISMA) [14]. The search was limited to articles published between 2019 and 2023 and focused on terms related to AI in dentistry, DL, dental diagnostic imaging, and computer-aided diagnostics. The search was performed utilizing the PICO (problem, intervention, comparison, and outcome) framework, as depicted in Table 1. Eldawlatly et al. [15] said the fundamental rule in the PICO format is that the title refers to the research question; otherwise, the abstract should be followed by the content. Then, the question should then be formulated in such a way that it is easier to find a specific answer. To attain these goals, the questions are focused and well-articulated in all four components of its "anatomy," the PICO.

TABLE I. Description of The Problem, Intervention, Comparison, and Outcome (PICO) Elements

Research Question	Is AI can significantly support the image analysis in dentistry purposes?
Problem	The patient's diagnostic images include Periapical, Bitewing, Panoramic, CBCT, and color tooth images.
Intervention	AI-based models for detecting various dental conditions such as teeth detection, dental disease identification, and dental treatment prediction.
Comparison	Opinions from the experts and standards from references.
Outcome	Accuracy, sensitivity, specificity, and f1-score as a measurable or predictive outcome.

B. Resources selection

Complete articles were obtained. Both manual and computer methods were utilized to thoroughly examine the journals. At this initial identification stage, the computer method used is Zotero software, but it is still rechecked manually. The data necessary for this evaluation was chosen with two-stage process. During the initial phase, the papers were chosen based on the relevance of abstracts and their titles to our study subject. The initial search yielded 483 articles that were sufficiently relevant to address the objective of the study. A total of 102 items were eliminated as a result of duplication. Therefore, we obtained 381 articles for the second phase of selection. Subsequently, the subsequent criterion was employed.

C. Consideration studies' criteria

1) Criteria for inclusion

- The paper must have a specific focus on AI and should be relevant to the field of dentistry.
- It is necessary to have specific predicted or quantitative results that can be quantified.

2) Criteria for exclusion

- The articles pertaining to non-AI domains.
- The articles comprised solely of abstracts, lacking the whole content.

These criteria reduced the number of papers to 62 research publications that have undergone screening and article selection (Fig. 1). The entirety of the articles was thoroughly read. The years of articles were considered to analyze the advancement of AI trends that have been produced and evolved in the field of dentistry over time.

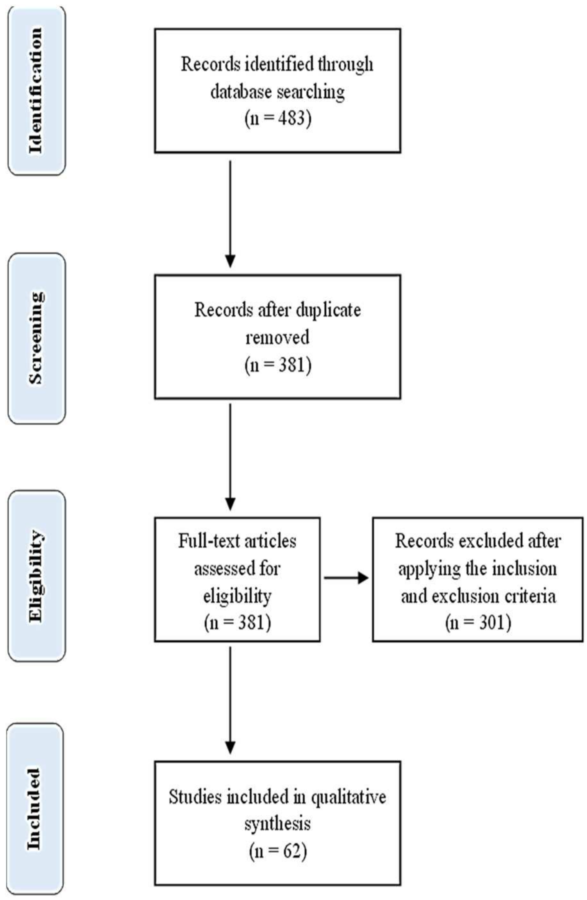

Fig. 1. The preferred reporting items for systematic reviews and meta-analyses extension (PRISMA) procedure was applied in this research.

III. Results

The research examined in this systematic review has demonstrated the extensive utilization of AI across many dental disciplines. The majority of the research has employed DL techniques utilizing CNNs such as U-Net, VGG16, InceptionV3, ResNet, YOLO, and others. Several research utilized the geodesic active contour methodology, SVM algorithm, and Fuzzy C-means. Moreover, operations are categorized based on imaging modalities, such as Periapical, Bitewing, CBCT, Panoramic, and color tooth (Fig. 2).

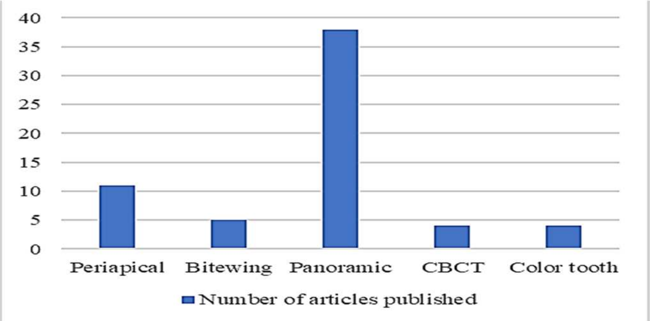

Fig. 2. Articles published based on imaging modalities.

In this research, AI has been employed in 26 studies on teeth detection, 24 studies in dental disease identification, and 12 studies in dental treatment prediction. The dental disease detection comprises 14 studies focused on identifying and diagnosing dental caries, 5 studies aimed at detecting periodontal bone loss, 3 studies dedicated to identifying dental anomalies, 1 study focused on classifying canine impaction, and 1 study focused on detecting apical lesions. The dental predictive treatment includes 5 studies for detecting the mandibular third molar, 2 studies for assessing dental restorations, 1 study for evaluating dental implants, 1 study for identifying dental root canals, 1 study for detecting the dental mental foramen, 1 study for maxillofacial segmentation, and 1 study for classifying dental radiographs. The information may be found in Table 2.

TABLE II. Specifics On The Research That Have Employed AI Models In Several Branches Of Dentistry

Authors (Year)	**Algorithm Architecture**	**Modality**	**Performances**
AI for Teeth Detection			
Ali et al. (2023) [16]	YOLOv7	3138 Panoramic	F1 score 0.987
Almalki & Latecki (2023) [17]	SD-SimMIM	543 Panoramic	AP^{box} 92.7%; AP^{mask} 90.8%
Datta et al. (2023) [7]	Fuzzy C-Means	236 Panoramic	Accuracy 93.20%
Hou et al. (2023) [18]	U-Net	1350 Panoramic	Accuracy 98.53%
Yilmaz et al. (2023) [19]	R-CNN and YOLO-V4	1200 Panoramic	R-CNN: Precision 93.67% YOLO-V4: Precision 99.90%,
Zhao et al. (2023) [20]	Mask RCNN	280 Panoramic	Precision 96.59 %,
Chandrashekar et al. (2022) [21]	Faster R–CNN	1500 Panoramic	Accuracy 98.77%
Im et al. (2022) [22]	DGCNN	516 CBCT	ICCs 0.987–0.997
Karaoglu et al. (2022) [23]	Mask R-CNN	2702 Panoramic	Precision 96.08%,
Nader et al. (2022) [24]	U-Net	543 Panoramic	Average of Dice coefficient 94%
Tekin et al. (2022) [25]	Mask R-CNN	1200 Bitewing	Precision 100%, mAP 97.49%
Wu et al. (2022) [26]	Two-Stage Mesh DL	136 CBCT	DSC 0.964 ± 0.054
Bilgir et al. (2021) [27]	Faster R-CNN, Inceptionv2	2482 Panoramic	Sensitivity 0.9559
Cui et al. (2021) [28]	TSegNet	2000 CBCT	F1 score 3.0%
Estai et al. (2021) [29]	CNNs	591 Panoramic	Recall 0.99; Precision 0.99
Kaya et al. (2021) [30]	CNN (YOLO V4)	4545 Panoramic	F1 score 0.91
Lin & Chang (2021) [31]	CNN	895 Panoramic	Accuracy 90.93%
Privado et al. (2021) [32]	Matterport Mask RCNN	8000 Panoramic	Accuracy 99.24%
Kim et al. (2020) [33]	RCNN	303 Panoramic	mAP(@IOU = 0.5) 96.7%
Mahdi et al. (2020) [34]	RCNN	1000 Panoramic	Average F1 score >0.970
Muresan et al. (2020) [35]	CNN	1000 Panoramic	Accuracy 89%
Silva et al. (2020) [36]	RCNN, PANet, HTC, ResNeSt	778 Panoramic	mAP of 74.0%
Zhao et al. (2020) [11]	TSASNet	1500 Panoramic	Accuracy 96.94%
Chen et al. (2019) [37]	Faster-RCNN	1250 Periapical	Recall and precision: above 90%.
Koch et al. (2019) [10]	U-Net	1500 Panoramic	Dice score 0.934
Tuzoff et al. (2019) [38]	CNN (VGG-16)	1352 Panoramic	Precision 0.9945
AI for Dental Disease Identification			
Chen et al. (2023) [39]	YOLOv5, VGG16 and U-Net	8000 Periapical, Bitewing	Accuracy 92.61
Frutos et al. (2023) [40]	ResNet50, YOLOv5, EfficientDet	13887 Bitewing	Mean average accuracy of 0.647
Qayyum et al. (2023) [41]	Resnet101	229 Periapical	Average accuracy 98.38%
Zhang et al. (2023) [3]	R2 U-Net	2692 Panoramic	Accuracy 97.19%
Aljabri et al. (2022) [42]	CNNs	416 Panoramic	Accuracy 0.9259
Almalki et al. (2022) [43]	YOLOv3	1200 Panoramic	Accuracy 99.33%
Lee, C., et al. (2022) [44]	CNN	693 Periapical	DSC 0.91
Lee, S., et al. (2022) [45]	R-CNN	23000 Panoramic	High sensitivity: 0.99
Zhu et al. (2022) [46]	Faster-RCNN	800 Periapical	AP 7.28%; F1 score 0.68

Duong et al. (2021) [47]	VNC+NSC	Color tooth	Accuracy 92.37%
Krois et al. (2021) [48]	CNNs (U-Net)	1300 Panoramic	The F1-score 46.1 ± 0.9%.
Lee et al. (2021) [49]	CNN (U-Net)	354 Bitewing	F1 score 64.14%
Lian et al., (2021) [50]	CNN (nnU-Net)	1160 Panoramic	Accuracy 98.6%
Moran et al. (2021) [51]	Inception & ResNet	112 Bitewing	Accuracy 73.3%
Vinayahalingam et al. (2021) [52]	CNN MobileNet V2	400 Panoramic	Accuracy 87%
Haghanifar et al. (2020) [1]	PaXNet	710 Panoramic	Accuracy 86.05%
Moran et al. (2020) [2]	Inception	2622 Periapical	Accuracy 0.817,
Singh & Sehgal (2020) [53]	CNN	1500 Periapical	Accuracy 96%
Wang et al. (2020) [54]	CNNs	7200 Color tooth	Accuracy 95.3%
Bouchahma et al. (2019) [55]	CNN	200 X-Ray	Overall accuracy 87%
Datta et al. (2019) [56]	Geodesic active contour	120 Periapical	Overall accuracy 94%
Kim et al. (2019) [57]	DeNTnet	12179 Panoramic	F1 score 0.75
Krois et al. (2019) [58]	CNN	2001 Panoramic	Accuracy 0.81
Moutselos et al. (2019) [59]	Mask R-CNN	88 Color tooth	The highest severity: 0.889
AI for Dental Treatment Prediction			
Park et al. (2023) [60]	Neuro-T version 3.0.1	156965 Panoramic, Periapical	Accuracy 88.53%
Takebe et al. (2023) [61]	YOLOv3	579 Panoramic	Accuracy 0.927
Lee et al. (2022) [62]	ROI	4903 Panoramic	mAP 99%
Xu et al. (2022) [5]	SIFT-SVM, CNN	920 Periapical	Accuracies > 95%
Cejudo et al. (2021) [6]	CNN, ResNet, CapsNet	90388 Panoramic, Periapical, Bitewing	The accuracy > 98%.
Takahashi et al. (2021) [63]	YOLOv3	1904 Color tooth	An AP > 0.80
Zhu et al. (2021) [64]	YOLOv4	915 Panoramic	The highest AP 88.06%
Aslan et al. (2020) [4]	Cubic Support Vector	738 Panoramic	Overall accuracy 93.6%
Kong et al. (2020) [65]	EED-Net	2602 Panoramic	Accuracy 0.9928
Kwak et al. (2020) [8]	2D SegNet, 2D, 3D U-Nets	49094 CBCT	Accuracy for: The 2D SegNet: 0.96 The 3D U-Net: 0.99
Dasanayaka et al. (2019) [9]	DCNN (U-Net)	1000 Panoramic	High mean DSC 0.987
Vinayahalingam et al. (2019) [66]	CNN (U-Net)	81 Panoramic	The mean dice-coefficients M3s 0.947±0.033

IV. Discussion

AI is revolutionizing the conventional elements of dentistry. AI technologies are frequently employed to develop automated software that optimize the diagnostic and management of data in dentistry [40]. Primarily, they are clinical decision support tools that aid and direct professionals in making more informed judgments. These methods have been employed to improve the accuracy of diagnosis, aid in treatment planning, and forecast the prognosis [43] & [55]. The need for these systems is rapidly increasing due to their efficacy in delivering explanations and logical reasoning [39]. Clinical decision support systems utilizing AI primarily aim to offer expert assistance to healthcare practitioners [38]. Even though AI helps experts, AI also has the challenge of having to consider the practical implications of doctors' decisions, and AI in the world of health, especially dentistry, only helps dentists to take the initial steps in diagnosing, not as the one who takes the final decision to take action. This systematic study examines the application of AI in dentistry, assessing its efficacy in teeth detection, dental disease identification, and dental treatment prediction.

A. *Application of AI in the Domain of Teeth Detection*

Kim et al. [33] utilized AI-based combined CNN to assess the accuracy of teeth identification. The model had a mAP rate of 96.7%, indicating a high level of accuracy, but the data used is still lacking. Tuzoff et al. [38], demonstrated highly comparable outcomes by employing an AI-powered CNN model for tooth recognition, thereafter organizing the findings in a numerical format. The computer-aided diagnostic approach demonstrated an average sensitivity of 0.941 and a precision of 0.9945. The output closely resembled that of an expert but can be further enhanced by augmentation data.

Chen et al. [37], utilized CNN to determine the number of teeth in periapical images and then identify the tooth. The model exhibited exceptional accuracy namely 90% of precision. However, this study did not detect the entire tooth because it used periapical images. The findings demonstrated that AI technologies enhance the convenience of physicians in doing their duties. There is no requirement for them to input the details manually. Dentists can enhance their productivity by inputting their dental charts digitally using automated technologies.

B. *Application of AI in the Domain of Dental Disease Identification*

Lee et al. [45] showed that the use of AI, namely R-CNN algorithms, for detecting 17 specific and detailed dental abnormalities on panoramic radiographs yielded good results. The research approach demonstrated a high sensitivity of 0.99. The application exhibited a significantly high level of performance. But model needs to detect anomalies that might be in the early or asymptomatic stages. Lian et al. [50], utilized a DL model specifically created for detecting and locating dental lesions in panoramic images. This study yielded encouraging outcomes that were consistent with previous findings. But changes in pixel intensity due to overlapping skeletal structures, pose significant challenges. Datta et al. [56] utilized periapical images to diagnose dental caries and demonstrated that the AI-based models performed satisfactorily namely an overall accuracy of 94%, but the proposed method unable to find multiple caries lesions in a single tooth from an x-ray dental image.

Lee, C et al. [44] conducted a study in which they utilized a computer-aided diagnosis system that relied on a sophisticated CNN algorithm. The purpose of this system was to accurately identify and forecast the teeth that were affected by periodontal health issues. The results were satisfactory, with the mean dice similarity coefficient for segmentation exceeding 0.91, but the study image was of poor quality due to overlapping teeth and could not identify vertical defect depth. Moran et al. [2], employed an AI system utilizing CNN to establish a correlation between inadequate periodontal health and systemic health outcomes namely an accuracy of 81.7%, but this study was not able to evaluate the severity of the lesion. Their findings indicate that AI has the potential to facilitate automated diagnosis and serve as a valuable tool for conducting screens for various diseases. Krois et al. [58], employed CNN to identify periodontal bone loss (PBL) based on panoramic dental radiographs and achieved 0.81 accuracy, but it just focused on detecting apical lesions. This device can nonetheless assist in minimizing the dentist's diagnostic endeavors.

C. *Application of AI in the Domain of Dental Treatment Prediction*

Precise identification and strategic treatment detection are the important elements for achieving successful dental intervention. AI has been utilized to determine the necessity of extractions before commencing dental therapy. Vinayahalingam et al. [66] conducted research where they utilized a CNN model to determine the necessity of identifying and isolating the third molar and inferior alveolar nerve from panoramic radiographs. The outcomes exhibited high promise but the data used was very little. Lee et al. [62] demonstrated a mAP 99% accuracy rate by employing an AI expert system for just identifying mandibular third molars in panoramic radiography images, not maxillary third molars, and possible complications. The findings from both tests indicate that the AI models were successful and accurate in forecasting the necessity for third molar detection. These models serve as a valuable instrument for making informed decisions in clinical practice.

Xu et al. [5] showed a high level of accuracy that proposed an AI model utilizing a SIFT-SVM and CNN for detecting root canal treatment through the analysis of periapical radiographs. The efficacy of root canal therapy mostly hinges on the precision of working length determination. The treatment's prognosis can only be guaranteed when the instrumentation stops at the apical constriction. The findings were comparable to the research conducted by Dasanayaka et al. [9], in which they employed the CNN system to identify the mental foramen, achieving a high DSC rate of 0.987 which can be improved using hyperparameter tuning and an ensemble model.

V. Conclusion

In recent years, AI applications in dentistry diagnostic imaging have expanded rapidly namely teeth detection [17], dental disease identification [41], and dental treatment prediction [60]. This systematic mapping study offers a thorough examination of this environment. By conducting a thorough examination of the current literature, we have identified significant patterns and prospective changes that define the merging of AI with dentistry practice. The current trend is that AI research in dentistry still uses panoramic images [16], but in the future, CBCT images [8] and color tooth images [54] will be the datasets used in research. In addition, DL models are a method that is increasingly in demand in managing large datasets like CNNs [6].

Research indicates that these AI-driven automated systems shown exceptional performance across a range of different settings. While these results may not surpass those of dentists, they do demonstrate that AI can be deemed suitable for clinical use. These technologies provide significant benefits by strengthening diagnostic accuracy, improving clinical decision-making, and anticipating treatment options, thus enabling physicians to deliver high-quality care to their patients [40]. This feature is invaluable as it enables experts to detect instances in the initial stages of tooth diseases [45]. While AI is extensively utilized in several areas of dentistry, certain specializations like pedodontics and oral pathology have yet to fully embrace and implement AI technology. In the future, it can use a DL-based Graphical User Interface (GUI) application that dentists can use without the requirement for programming knowledge [12] and ensure regulatory compliance. Besides that, there are potential drawbacks of AI applications in dentistry, such as the need for large datasets [6] & [60], images of poor quality due to overlapping teeth [44], the risk of algorithmic bias, and the need for human monitoring.

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References

[1] A. Haghanifar, M. M. Majdabadi, and S. B. Ko, "PaXNet: dental caries detection in panoramic x-ray using ensemble transfer learning and capsule classifier," in International Symposium on Circuits and Systems (ISCAS), Spain, 2020.

[2] M. B. H. Moran, M. Faria, G. Giraldi, L. Bastos, B. d. S. Inacio, and A. Conci, "On using convolutional neural networks to classify periodontal bone destruction in periapical radiographs," in International Conference on Bioinformatics and Biomedicine (BIBM), 2020.

[3] Y. Zhang, F. Ye, L. Chen, F. Xu, X. Chen, H. Wu, M. Cao, Y. Li, Y. Wang, and X. Huang, "Children's dental panoramic radiographs

dataset for caries segmentation and dental disease detection," Scientific Data, vol. 10, no. 380, pp. 1-11, 2023.

[4] R. A. Aslan, T. Yeshua, D. Kabla, I. Leichter, and C. Nadler, "An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography," Oral And Maxillofacial Radiology, vol. 130, no. 5, pp. 593-602, 2020.

[5] T. Xu, Y. Zhu, L. Peng, Y. Cao, X. Zhao, F. Meng, J. Ding, and S. Liang, "Artificial intelligence assisted identification of therapy history from," Displays, vol. 71, pp. 1-11, 2022.

[6] J. E. Cejudo, A. Chaurasia, B. Feldberg, J. Krois, and F. Schwendicke, "Classification of dental radiographs using deep learning," Journal of Clinical Medicine, vol. 10, no. 1496, pp. 1-9, 2021.

[7] S. Datta, N. Chaki and B. Modak, "A novel technique for dental radiographic image segmentation based on neutrosophic logic," Decision Analytics Journal, vol. 7, pp. 1-13, 2023.

[8] G. H. Kwak, E. J. Kwak, J. M. Song, H. R. Park, Y. H. Jung, B. H. Cho, P. Hui, and J. J. Hwang, "Automatic mandibular canal detection using a deep convolutional neural network," Scientific Reports, vol. 10, no. 5711, pp. 1-8, 2020.

[9] C. Dasanayaka, B. Dharmasena, W. R. Bandara, M. B. Dissanayake, and R. Jayasinghe, "Segmentation of mental foramen in dental panoramic tomography using deep learning," in International Conference on Industrial and Information Systems (ICIIS), Sri Lanka, 2019.

[10] T. L. Koch, M. Perslev, C. Igel, and S. S. Brandt, "Accurate segmentation of dental panoramic radiographs with u-nets," in International Symposium on Biomedical Imaging (ISBI), Italy, 2019.

[11] Y. Zhao, P. Li, C. Gao, Y. Liu, Q. Chen, F. Yang, and D. Meng, "TSASNet: tooth segmentation on dental panoramic x-ray images by two-stage attention segmentation network," Knowledge-Based Systems, vol. 206, pp. 1-10, 2020.

[12] A. Katsumata, "Deep learning and artificial intelligence in dental diagnostic imaging," Japanese Dental Science Review, vol. 59, pp. 329-333, 2023.

[13] H. M. Rahimi, S. R. Motamedian, M. H. Rohban, J. Krois, S. E. Uribe, E. Mahmoudinia, R. Rokhshad, M. Nadimi, and F. Schwendicke, "Deep learning for caries detection: a systematic review," Journal of Dentistry, vol. 122, pp. 1-16, 2022.

[14] T. A. McGrath, M. Alabousi, B. Skidmore, D. A. Korevaar, P. M. M. Bossuyt, D. Moher, B. Thombs, and M. D. F. McInnes, "Recommendations for reporting of systematic reviews and meta-analyses of diagnostic test accuracy: a systematic review," System Review, vol. 6, p. 194, 2017.

[15] A. Eldawlatly, H. Alshehri, A. Alqahtani, A. Ahmad, F. Al Dammas, and A. Marzouk, "Appearance of population, intervention, comparison, and outcome as research question in the title of articles of three different anesthesia journals: a pilot study," Saudi Journal of Anesthesia, vol. 12, no. 2, pp. 283-286, 2018.

[16] M. A. Ali, D. Fujita and S. Kobashi, "Teeth and prostheses detection in dental panoramic x rays using cnn based object detector and a priori knowledge based algorithm," Scientific Reports, vol. 13, no. 16542, pp. 1-15, 2023.

[17] A. Almalki and L. J. Latecki, "Enhanced masked image modeling for analysis of dental panoramic radiographs," in International Symposium on Biomedical Imaging (ISBI), 2023.

[18] S. Hou, T. Zhou, Y. Liu, P. Dang, H. Lu, and H. Shi, "Teeth U-Net A segmentation model of dental panoramic x-ray images for context semantics and contrast enhancement," Computers in Biology and Medicine, vol. 152, pp. 1-14, 2023.

[19] S. Yilmaz, M. Tasyurek, M. Amuk, M. Celik, and E. M. Canger, "Developing deep learning methods for classification of teeth in dental panoramic radiography," Oral And Maxillofacial Radiology, pp. 1-10, 2023.

[20] X. Zhao, T. Xu, L. Peng, S. Li, Y. Zhao, H. Liu, J. He, and S. Liang, "Recognition and segmentation of teeth and mandibular nerve canals in," Displays, vol. 78, pp. 1-10, 2023.

[21] G. Chandrashekar, S. A. Qarni, E. E. Bumann, and Y. Lee, "Collaborative deep learning model for tooth segmentation and identification using panoramic radiographs," Computers in Biology and Medicine, vol. 148, pp. 1-18, 2022.

[22] J. Im, J. Y. Kim, H. S. Yu, K. J. Lee, S. H. Choi, J. H. Kim, H. K. Ahn, and J. Y. Cha, "Accuracy and efficiency of automatic tooth segmentation in digital dental models using deep learning," Scientific Reports, vol. 12, no. 9429, pp. 1-11, 2022.

[23] A. Karaoglu, C. Ozcan, A. Pekince, and Y. Yasa, "Numbering teeth in panoramic images: a novel method based on deep learning and heuristic algorithm," Engineering Science and Technology an International Journal, vol. 37, pp. 1-8, 2022.

[24] R. Nader, A. Smorodin, N. D. L. Fourniere, Y. Amouriq, and F. Autrusseau, "Automatic teeth segmentation on panoramic x-rays using deep neural networks," in International Conference on Pattern Recognition (ICPR), Canada, 2022.

[25] B. Y. Tekin, C. Ozcan, A. Pekince, and Y. Yasa, "An enhanced tooth segmentation and numbering according to fdi notation," Computers in Biology and Medicine, vol. 146, pp. 1-10, 2022.

[26] T. H. Wu, C. Lian, S. Lee, M. Pastewait, C. Piers, J. Liu, F. Wang, L. Wang, C. Y. Chiu, W. Wang, C. Jackson, W. L. Chao, D. Shen, and C. C. Ko, "Two-stage mesh deep learning for automated tooth segmentation and landmark localization on 3d intraoral scans," Transactions on Medical Imaging, vol. 41, no. 11, pp. 3158-3166, 2022.

[27] E. Bilgir, . İ. Ş. Bayrakdar, Ö. Çelik, K. Orhan, F. Akkoca, H. Sağlam, A. Odabaş, A. F. Aslan, C. Ozcetin, M. Kıllı, and I. R. Kalinowska, "An artificial ıntelligence approach to automatic tooth detection and numbering in panoramic radiographs," BMC Medical Imaging, vol. 21, no. 124, pp. 1-9, 2021.

[28] Z. Cui, C. Li, N. Chen, G. Wei, R. Chen, Y. Zhou, D. Shen, and W. Wang, "TSegNet: an efficient and accurate tooth segmentation network on 3d dental model," Medical Image Analysis, vol. 69, pp. 1-12, 2021.

[29] M. Estai, M. Tennant, D. Gebauer, A. Brostek, J. Vignarajan, M. Mehdizadeh, and S. Saha, "Deep learning for automated detection and numbering of permanent teeth on panoramic images," Dentomaxillofac Radiol, vol. 51, pp. 1-8, 2021.

[30] E. Kaya, H. G. Gunec, S. S. Gokyay, S. Kutal, S. Gulum, and H. F. Ates, "Proposing a cnn method for primary and permanent tooth detection and enumeration on pediatric dental radiographs," The Journal of Clinical Pediatric Dentistry, vol. 46, no. 4, pp. 293-298, 2021.

[31] S. Y. Lin and H. Y. Chang, "Tooth numbering and condition recognition on dental panoramic radiograph images using cnns," IEEEAccess, vol. 9, pp. 1-19, 2021.

[32] M. P. Privado, J. G. Villalon, A. B. Torres, C. H. M. Martinez, and C. Ivorra, "A convolutional neural network for automatic tooth numbering in panoramic images," BioMed Research International, pp. 1-7, 2021.

[33] C. Kim, D. Kim, H. G. 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. 5624, pp. 1-12, 2020.

[34] F. P. Mahdi, K. Motoki, and S. Kobashi, "Optimization technique combined with deep learning method for teeth recognition in dental panoramic radiographs," Scientific Reports, vol. 10, pp. 1-12, 2020.

[35] M. P. Muresan, A. R. Barbura, and S. Nedevschi, "Teeth detection and dental problem classification in panoramic x-ray images using deep learning and image processing techniques," IEEE, pp. 457-463, 2020.

[36] B. Silva, L. Pinheiro, L. Oliveira, and M. Pithon, "A study on tooth segmentation and numbering using end-to-end deep neural

networks," in Conference on Graphics, Patterns and Images (SIBGRAPI), 2020.

[37] H. Chen, K. Zhang, P. Lyu, H. Li, L. Zhang, J. Wu, and C. H. Lee, "A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films," Scientific Reports, vol. 9, no. 3840, pp. 1-11, 2019.

[38] D. V. Tuzoff, L. N. Tuzova, M. M. Bornstein, A. S. Krasnov, M. A. Kharchenko, S. I. Nikolenko, M. M. Sveshnikov, and G. B. Bednenko, "Tooth detection and numbering in panoramic radiographs using convolutional neural networks," Dentomaxillofacial Radiology, vol. 48, pp. 1-10, 2019.

[39] C. C. Chen, Y. F. Wu, L. M. Aung, J. C. Y. Lin, S. T. Ngo, J. N. Su, Y. M. Lin, and W. J. Chang, "Automatic recognition of teeth and periodontal bone loss measurement in digital radiographs using deep-learning artificial intelligence," Journal of Dental Sciences, vol. 18, pp. 1301-1309, 2023.

[40] J. P. d. Frutos, R. H. Helland, S. Desai, L. C. Nymoen, T. Langø, T. Remman, and S. Abhijit, "AI-dentify: deep learning for proximal caries detection on bitewing x-ray - hunt4 oral health study," arXiv, pp. 1-22, 2023.

[41] A. Qayyum, A. Tahir, M. A. Butt, A. Luke, H. T. Abbas, J. Qadir, K. Arshad, K. Assaleh, M. A. Imran, and Q. H. Abbasi, "Dental caries detection using a semi-supervised learning approach," Scientific Reports, vol. 13, no. 749, pp. 1-11, 2023.

[42] M. Aljabri, S. S. Aljameel, N. M. Allah, J. Alhuthayfi, L. Alghamdi, N. Alduhailan, R. Alfehaid, R. Alqarawi, M. Alhareky, S. Y. Shahin, and W. A. Turki, "Canine impaction classification from panoramic dental radiographic images using deep learning models," Informatics in Medicine Unlocked, vol. 30, pp. 1-10, 2022.

[43] Y. E. Almalki, A. I. Din, M. Ramzan, M. Irfan, K. M. Aamir, A. Almalki, S. Alotaibi, G. Alaglan, H. A. Alshamrani, and S. Rahman, "Deep learning models for classification of dental diseases using orthopantomography x-ray opg images," Sensors, vol. 22, no. 7370, pp. 1-16, 2022.

[44] C. T. Lee, T. Kabir, J. Nelson, S. Sheng, H. W. Meng, T. E. V. Dyke, M. F. Walji, X. Jiang, and S. Shams, "Use of the deep learning approach to measure alveolar bone level," J Clin Periodontol, vol. 3, no. 49, pp. 260-269, 2022.

[45] S. Lee, D. Kim and H. G. Jeong, "Detecting 17 fne-grained dental anomalies from panoramic dental radiography using artifcial intelligence," Scientific Reports, vol. 12, no. 5172, pp. 1-8, 2022.

[46] Y. Zhu, T. Xu, L. Peng, Y. Cao, X. Zhao, S. Li, Y. Zhao, F. Meng, J. Ding, and S. Liang, "Faster-rcnn based intelligent detection and localization of dental caries," Displays, vol. 74, pp. 1-8, 2022.

[47] D. L. Duong, M. H. Kabir, and R. F. Kuo, "Automated caries detection with smartphone color photography using machine learning," Health Informatics Journal, pp. 1-17, 2021.

[48] J. Krois, A. G. Cantu, A. Chaurasia, R. Patil, P. K. Chaudhari, R. Gaudin, S. Gehrung, and F. Schwendicke, "Generalizability of deep learning models for dental image analysis," Scientific Reports, vol. 11, no. 6102, pp. 1-7, 2021.

[49] S. Lee, S. I. Oh, S. Kang, Y. Shin, and J. W. Park, "Deep learning for early dental caries detection in bitewing radiographs," Scientific Reports, vol. 11, pp. 1-8, 2021.

[50] L. Lian, T. Zhu, F. Zhu, and H. Zhu, "Deep learning for caries detection and classification," Diagnostics, vol. 11, no. 1672, pp. 1-11, 2021.

[51] M. Moran, M. Faria, G. Giraldi, L. Bastos, L. Oliveira, and A. Conci, "Classification of approximal caries in bitewing radiographs using convolutional neural networks," Sensors, vol. 21, no. 5192, pp. 1-12, 2021.

[52] S. Vinayahalingam, S. Kempers, L. Limon, D. Deibel, T. Maal, M. Hanisch, S. Berge, and T. Xi, "Classification of caries in third molars on panoramic radiographs using deep learning," Scientific Reports, vol. 11, pp. 1-7, 2021.

[53] 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, p. 5255–5272, 2020.

[54] C. Wang, H. Qin, G. Lai, G. Zheng, H. Xiang, J. Wang, and D. Zhang, "Automated classification of dual channel dental imaging of auto-uorescence and white lightby convolutional neural networks," Journal of Innovative Optical Health Sciences, vol. 13, no. 4, pp. 1-8, 2020.

[55] M. Bouchahma, S. B. Hammouda, S. Kouki, M. Alshemaili, and K. Samara, "An automatic dental decay treatment prediction using a deep convolutional neural network on x-ray images," in International Conference on Computer Systems and Applications (AICCSA), 2019.

[56] S. Datta, N. Chaki and B. Modak, "A novel technique to detect caries lesion using isophote concepts," IRBM, vol. 40, pp. 174-182, 2019.

[57] J. Kim, H. S. Lee, I. S. Song, and K. H. Jung, "DeNTNet: deep neural transfer network for the detection of periodontal bone loss using panoramic dental radiographs," Scientific Reports, vol. 9, pp. 1-9, 2019.

[58] J. Krois, T. Ekert, L. Meinhold, T. Golla, B. Kharbot, A. Wittemeier, C. Dörfer, and F. Schwendicke, "Deep learning for the radiographic," Scientific Reports, vol. 9, no. 8495, pp. 1-6, 2019.

[59] K. Moutselos, E. Berdouses, C. Oulis. and I. Maglogiannis, "Recognizing occlusal caries in dental intraoral images using deep learning," in Engineering in Medicine and Biology Society (EMBC), 2019.

[60] W. Park, J. K. Huh, and J. H. Lee, "Automated deep learning for classification of dental implant radiographs using a large multi-center dataset," Scientific Reports, vol. 13, no. 4862, pp. 1-8, 2023.

[61] K. Takebe, T. Imai, S. Kubota, A. Nishimoto, S. Amekawa, and N. Uzawa, "Deep learning model for the automated evaluation of contact between the lower third molar and inferior alveolar nerve on panoramic radiography," Journal of Dental Sciences, vol. 18, pp. 991-996, 2023.

[62] J. Lee, J. Park, S. Y. Moon, and K. Lee, "Automated prediction of extraction difficulty and inferior alveolar nerve injury for mandibular third molar using a deep neural network," Applied Sciences, vol. 12, no. 475, pp. 1-12, 2022.

[63] 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. 1960, pp. 1-7, 2021.

[64] T. Zhu, D. Chen, F. Wu, F. Zhu, and H. Zhu, "Artificial intelligence model to detect real contact relationship between mandibular third molars and inferior alveolar nerve based on panoramic radiographs," Diagnostics, vol. 11, no. 1664, pp. 1-9, 2021.

[65] Z. Kong, F. Xiong, C. Zhang, Z. Fu, M. Zhang, J. Weng, and M. Fan, "Automated maxillofacial segmentation in panoramic dental x-ray images using an efficient encoder-decoder network," IEEEAccess, vol. 8, pp. 207822-207833, 2020.

[66] S. Vinayahalingam, T. Xi, S. Berge, T. Maal, and G. d. Jong, "Automated detection of third molars and mandibular nerve by deep learning," Scientific Reports, vol. 9, no. 9007, pp. 1-7, 2019.