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Detection of dental restorations using no-code artificial intelligence

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ABSTRACT

Objectives: The purpose of this study was to utilize a no-code computer vision platform to develop, train, and evaluate a model specifically designed for segmenting dental restorations on panoramic radiographs.
Methods: One hundred anonymized panoramic radiographs were selected for this study. Accurate labeling of dental restorations was performed by calibrated dental faculty and students, with subsequent final review by an oral radiologist. The radiographs were automatically split within the platform into training (70 %), development (20 %), and testing (10 %) subgroups. The model was trained for 40 epochs using a medium model size. Data augmentation techniques available within the platform, namely horizontal and vertical flip, were utilized on the training set to improve the model's predictions. Post-training, the model was tested for independent predictions. The model's diagnostic validity was assessed through the calculation of sensitivity, specificity, accuracy, precision, F1-score by pixel and by tooth, and by ROC-AUC.
Results: A total of 1,108 restorations were labeled on 960 teeth. At a confidence threshold of 0.95, the model achieved 86.64 % sensitivity, 99.78 % specificity, 99.63 % accuracy, 82.4 % precision and an F1-score of 0.844 by pixel. The model achieved 98.34 % sensitivity, 98.13 % specificity, 98.21 % accuracy, 98.85 % precision and an F1-score of 0.98 by tooth. ROC curve showed high performance with an AUC of 0.978.
Conclusions: The no-code computer vision platform used in this study accurately detected dental restorations on panoramic radiographs. However, further research and validation are required to evaluate the performance of no-code platforms on larger and more diverse datasets, as well as for other detection and segmentation tasks.
Clinical significance: The advent of no-code computer vision holds significant promise in dentistry and dental research by eliminating the requirement for coding skills, democratizing access to artificial intelligence tools, and potentially revolutionizing dental diagnostics.

1. Introduction

Artificial Intelligence (AI) is the science of making computers perform tasks that conventionally require human intelligence [1]. AI has recently seen significant growth due to the availability of large digital datasets and rapid increase in computational power [2].

Machine Learning (ML) and Deep Learning (DL) are integral subsets of AI. ML involves creating algorithms that can automatically learn patterns and make decisions from data, often requiring human-designed feature extraction. On the other hand, DL is a specialized form of ML that enables machines to autonomously discover essential patterns and features for tasks like detection and classification [3]. DL employs multiple layers of non-linear modules to transform raw data into increasingly abstract representations, proving particularly effective in tasks such as image classification and segmentation [4].

The use of AI in dentistry is experiencing a surge in popularity, with the development of several platforms intended to facilitate the diagnosis of dental conditions and aid in treatment planning. Those platforms depend on the concepts of ML and DL which have numerous applications in oral radiology, including caries detection [5], bone loss detection [6], apical lesion detection [7], and root fracture [8]. Therefore, these tools are rapidly becoming indispensable instruments in the field of oral

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health imaging, offering numerous opportunities for enhancing diagnostic precision, streamlining workflow, and improving patient care [9–12].

Deep learning in imaging involves three key tasks: segmentation, object detection and classification. Object detection defines rectangular Regions of Interest (ROIs) to locate objects of interest, while segmentation essentially draws a clear distinction between the objects of interest and the background through labeling precise pixels, hence separating objects from backgrounds. Object detection provides a rough location, while segmentation offers precise object delineation. These tasks are chosen based on the specific imaging application's requirements and complement each other in addressing different objectives. Deep learning in imaging also encompasses a third crucial task: classification. DL systems can aid in both detection and classification, serving a twofold purpose. Firstly, they determine whether an image contains a lesion or anomaly, effectively flagging images that need expert evaluation. Secondly, these systems can classify or categorize the identified anomalies, providing insights into the most probable diagnosis [13].

Despite the increasing interest in this field, several factors hinder the effective deployment of DL models [14,15]. These challenges encompass the necessity of advanced DL knowledge and programming skills, dataset preparation requirements, significant computational demands, and intricate algorithms [16,17]. Furthermore, many of the concepts proposing the integration of DL in dentistry originate from dental researchers, clinicians, or dentists, who often possess limited coding backgrounds. Consequently, the majority of end-users lack the opportunity to independently develop their ideas without substantial external assistance [18]. These complexities often result in the centralization of research and AI applications within a limited number of entities. This prevents a broader dissemination of AI-related applications and research opportunities [19].

No-code computer vision is among the latest breakthroughs in AI that have been developed to overcome the limited coding knowledge. This advancement empowers end-users to develop, train, and test their own AI models, without requiring them to possess extensive expertise in coding or software engineering [20]. No-code computer vision models are developed by annotating the spatial features of an object on multiple images to create an algorithm, without coding. Spatial features may consist of the relationships and arrangements of pixels in an image. Spatial features help users identify the object accurately, as well as its location and relation with other objects in an image. Subsequently, this automated algorithm can detect these features within new images, potentially streamlining the practical aspects of deploying, managing, monitoring, and sustaining ML models in real-world scenarios [21]. By adopting this approach, more professionals can gain the ability to harness the potential of machine learning for diverse applications [22,23].

No-code computer vision has been acknowledged in the literature by other names, such as; code-free machine learning [24], code-free deep learning [25], automated deep learning [26], and automated machine learning [27].The low-code computer vision term have also been reported in the literature. However, unlike no-code platforms, low-code platforms involve some degree of coding but aim to minimize the amount of manual coding required [28].No-code computer vision has been applied and tested in the medical field in diagnosing a diverse range of diseases from medical imaging, including the detection of diabetic retinopathy and open-angle glaucoma using retinal images [18]. It resulted in comparable results to conventional trusted deep learning algorithms and ground truth. However, the authors are not aware of studies that have evaluated the utility of no-code computer vision models in the field of dentistry.

This study aimed to develop, train, and evaluate a no-code model specifically designed for the segmentation of dental restorations on panoramic radiographs using a no-code computer vision platform. The null hypothesis was that the no-code AI model will not be able to differentiate between restorations and other structures on the panoramic radiographs.

2. Materials and methods

Ethical approval from the Institutional Review Board (IRB# HR-4374) was obtained for this study. The study design followed the Checklist for Artificial Intelligence in Medical Imaging (CLAIM) [29].

2.1. Sample selection

To ensure the acquisition of a representative sample, a convenient consecutive sampling methodology was employed in this study. A total of 2500 anonymized panoramic radiographs, collected from the electronic adult patient records of dental school patients between January 2018 and January 2023, were examined. Inclusion criteria specified that the radiographs must be of dentate or partially edentulous patients, aged 18 and older, having a minimum of 8 remaining teeth, and showing at least one dental restoration. Exclusion criteria were applied to ensure that only diagnostically acceptable radiographs were included in the study cohort. This criterion encompassed radiographs featuring severe positional artifacts, orthognathic surgery, plates, screws, lead apron artifact and radiographs depicting severe malocclusion. The first 100 consecutive radiographs that adhered to both the inclusion and exclusion criteria were selected for this study.

2.2. No-code AI platform

For this task, we used LandingLens (Landing AI, Palo Alto, CA, USA) [26] as an example of a no-code platform. We selected this platform as it offered an automated way to split the images, several labeling tools and augmentation techniques. Another advantage is that it is cloud-based, eliminating the need for setting up or managing our own infrastructure. The workflow for users to create a model are as follows:

a) Users can create a new project by selecting the specific task they need (i.e., object detection, segmentation, or classification). The user then uploads a dataset of images to the web-based platform.
b) There are several labeling tools such as bounding box, brush and semiautomatic annotation tools depending on the selected task.
c) After labeling the dataset and assigning classes for the labels, the images are divided into training, validation, and testing subsets. Users can choose whether to have the platform automatically split "auto-split" the images based on a preselected percentage or to manually assign them to each subgroup.
d) Prior to selecting the "train" option to train the model, the user can customize the training settings by selecting data augmentation techniques like horizontal and vertical flip to enhance the diversity of the training sample. A user can also set the number of epochs.
e) Finally, automated training proceeds resulting in the development of a computer vision model which can then be used to further make predictions and fine-tuned, before being deployed upon showing satisfactory results.

2.3. Data labeling and ground truth

The radiographs were uploaded to LandingLens. Following a comprehensive calibration conducted by an oral radiologist, a group consisting of two radiology faculty members and three skilled students diligently performed the labeling of dental restorations. Each annotator labeled dental restorations on 20 radiographs using the brush and semiautomatic "smart" labeling tools (Fig. 1). The group labeled all types of opaque coronal restorations, crowns, gutta-percha, silverpoints, and posts. The labels underwent a final review by an oral and maxillofacial radiologist with three years of experience. The final decision regarding the presence and absence of dental restorations on the

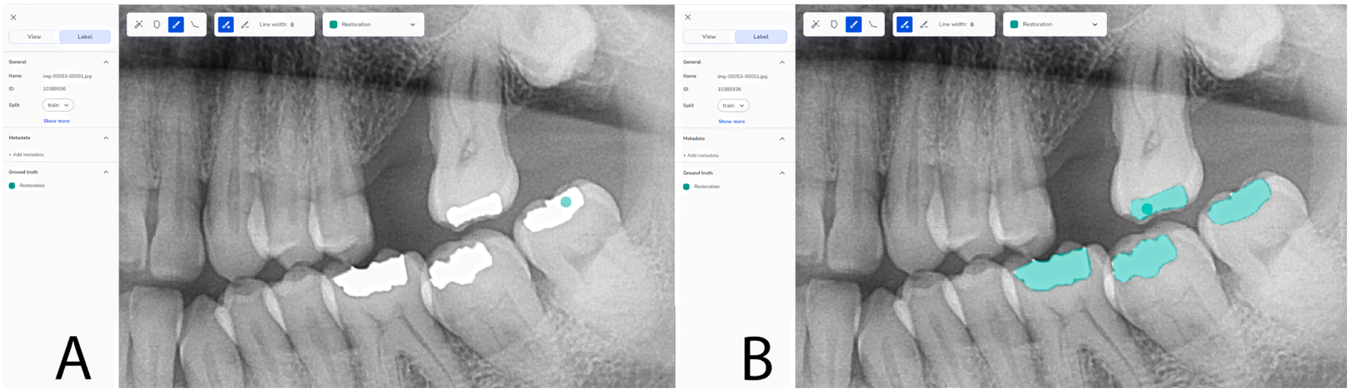

Fig. 1. Data labeling using LandingLens tools. A. Before labeling. B. After labeling. The brush tool was used to label the dental restorations on the panoramic radiographs.

panoramic radiographs was determined by the oral and maxillofacial radiologist. For validation purposes, we randomly chose 20 panoramic radiographs, and rated all teeth in each panoramic image by the oral and maxillofacial radiologist and the five other independent raters using 1 (restoration) or 0 (no restoration). Cohen's Kappa was calculated between the radiologist and the five other raters across all teeth within one patient and averaged them as kappa for that individual. Finally, the average kappa was calculated across all 20 patients, as 0.97 indicating almost perfect agreement, with p value less than 0.1 %. The labeled data was used as ground truth to develop, train and test the no-code computer vision model.

2.4. Developing the no-code computer vision model

The labeled radiographs were automatically and randomly split into a training (70 %), validation (20 %), and testing (10 %) sets using the auto-split feature within LandingLens's platform. Once the samples were divided into these three groups, augmentation was exclusively applied to the training data to enhance diversity for the models to learn from. The validation and testing sets remained unaugmented to ensure accurate model tuning and evaluation on images representative of real-life panoramic images. The model was trained for 40 epochs using a medium-sized model, with the data augmentation parameters preset at a horizontal flip probability of 0.5 and a vertical flip probability of 0.5. Following the training phase, the model underwent testing to make standalone predictions. (Fig. 2).

2.5. Testing the validity of the no-code computer vision model

The model predictions were compared to the labeled ground truth (Fig. 2) initially at the pixel level, and subsequently, on tooth level basis. The pixels and teeth predations were classified into; true positive (TP), false positive (FP), false negative (FN), and true negative (TN). The model's validity was measured through the calculation of sensitivity, specificity, accuracy, precision, and F1-score.

In addition, the model's ability to detect the presence of restorations on panoramic radiographs was evaluated by the computation of a receiver operating characteristic (ROC) curve and measuring the area under the curve (AUC).

3. Results

The panoramic radiographs comprised a total of 66,827,000 pixels. Within this data set, there were 745,545 labeled pixels, indicating the presence of restorative material, and 66,081,455 unlabeled pixels, indicating the absence of restorative material. The cumulative number of teeth shown in these radiographs was 2601 in total. On 960 of these teeth, 1108 restorations were identified, while the remaining 1641 teeth were not restored.

The TP, FP, FN, and TN metrics by pixel are shown in the confusion matrix (Fig. 3). At a confidence threshold of 0.95, the model achieved a sensitivity of 86.64 %. In addition, the model achieved specificity of 99.78 %. The model also achieved an accuracy of 99.63 %. Moreover, the model exhibited a precision of 82.4 % and an F1-score of 0.844.

The TP, FP, FN, and TN metrics by tooth are shown in the confusion

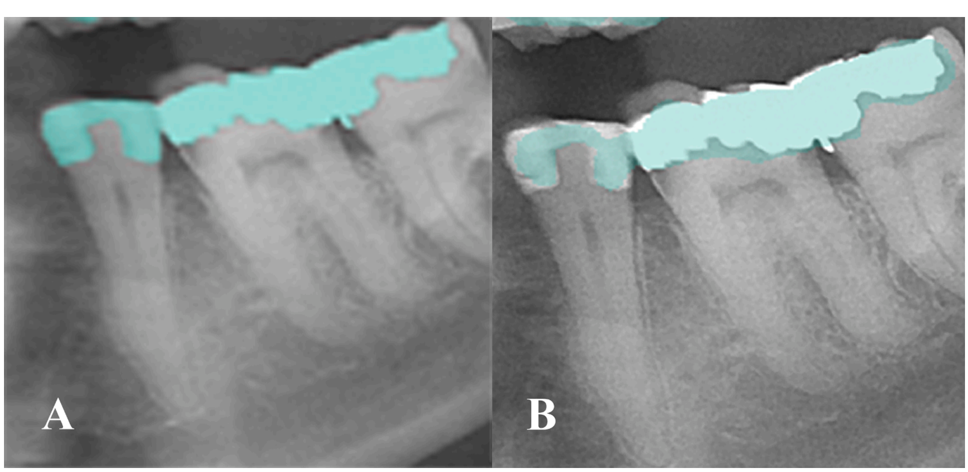

Fig. 2. A. Ground truth. B. Model's prediction. This figure displays mild discrepancies in between the ground truth and model's predictions. The predicted restoration edges show false positive and negative pixels influencing the overall model's accuracy.

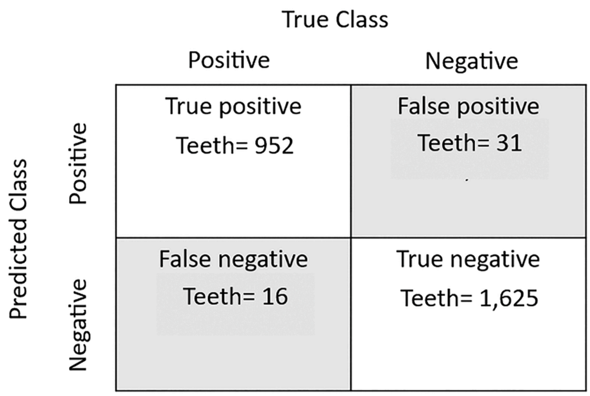

Fig. 3. Confusion matrix of the model's performance on pixel level.

matrix (Fig. 4). At a confidence threshold of 0.95, the model achieved a sensitivity of 98.34 % and a specificity of 98.13 %. The model also achieved an accuracy of 98.21 %. Moreover, the model exhibited a precision of 98.85 % and an F1-score of 0.98. The ROC curve for the model is shown in Fig. 5. The model achieved an AUC of 0.978 ($n = 100$; 95 % CI, 0.959–0.998). Type I and II errors are outlined in Table 1.

4. Discussion

Today, there is a growing interest in no-code deep learning platforms. The primary purpose of these platforms is to facilitate the participation of individuals, such as scientists, radiologists, and clinicians, who do not possess coding proficiency, in the development of deep learning models. Consequently, this may have the potential to enhance the adoption of deep learning in healthcare [30]. This study aimed to develop, train, and evaluate a model specifically designed for the detection of dental restorations on panoramic radiographs using a no-code computer vision platform called LandingLens [31].

The null hypothesis was rejected. As the present study demonstrated the high performance of the no-code AI model, designed for the detection of dental restorations in panoramic radiographs, achieving a sensitivity of 86.64 %, specificity of 99.78 %, accuracy of 99.63 %, precision of 82.4 %, F1-score 0.844 by pixel, and, achieved a sensitivity of 98.34 %, specificity of 98.13 %%, accuracy of 98.21 %, precision of 98.85 % and an F1-score of 0.98 by tooth. These metrics indicate the model's accurate detection of dental restorations in a limited set of panoramic radiographs. Additionally, the model achieved an AUC of 0.978, indicating that the model was frequently able to precisely identify the presence and location of dental restorations on panoramic radiographs.

The elevated specificity and accuracy in pixel-level detection can be

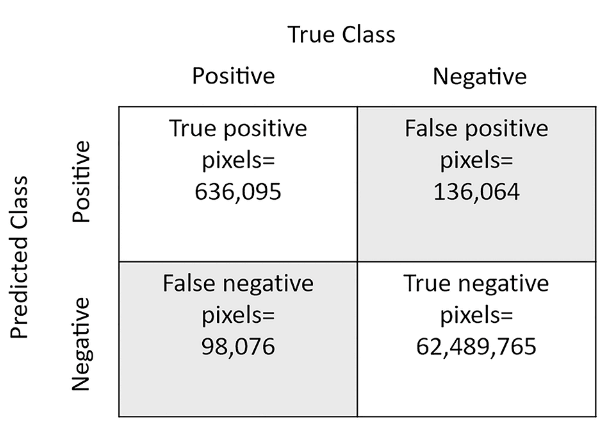

Fig. 4. Confusion matrix of the model's performance on tooth level.

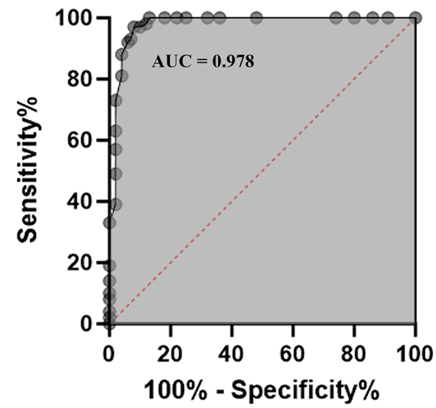

Fig. 5. ROC curve for the model's predictions of dental restorations on panoramic radiographs.

Table 1
Location and frequency of errors.

Type of error	Total	Location	Frequency
Type I - False positive	31	High-density occlusal enamel	16
		Teeth overlap	12
		Mid-root surface	3
Type II - False negative	16	Resin Composite	13
		Gutta percha	3

explained by the abundant true negative (TN) pixels present in panoramic radiographs, largely due to the prevalence of non-tooth structures on this type of radiographic modality. Conversely, the elevated scores in sensitivity, precision, and F1-score observed in tooth-level detection can be attributed to the broader context provided by analyzing the presence or absence of restoration on an entire tooth, as opposed to scrutinizing smaller individual pixels [32].

Nevertheless, the model encountered some difficulties in precisely delineating restoration margins, as evidenced by the presence of false positive and false negative pixels surrounding the predicted restorations (Fig. 6). These difficulties may stem from the similarity in radiographic features between sound and restored enamel and dentin. The model also exhibited both Type I (FP) and Type II (FN) errors. FP errors were primarily associated with high-density occlusal enamel, teeth overlap, and mid-root surface. This finding could be attributed to the similar pixel values compared to dental restorations. In contrast, FN errors were most commonly associated with resin composite restorations and the presence of gutta percha that exabit low pixel values, resembling normal tooth structure.

Several studies have evaluated the segmentation capabilities of deep learning models for detecting various structures in panoramic radiographs. Lee et al. [33] developed a mask-RCNN model to segment teeth on panoramic radiographs, achieving an F1-score of 0.875. Another study by Dayi et al. [34] focused on the automated segmentation of carious lesions and reported a mean F1-score of 0.628. This suggests the challenges associated with accurately segmenting small dental findings in panoramic radiographs.

In the context of dental restorations, various studies have delved into the use of coded deep learning and machine learning models for detecting dental restorations on panoramic radiographs. For instance, Celik et al. employed 10 different deep-learning models in their computer-aided systems, achieving precision and recall between 75.5–97.3 % and 60.5–77.1 %, respectively [35]. Asci et al. and Yeshua et al. obtained results with sensitivities of 95.7 % and 95 %, respectively, with notable errors related to root-canal fillings and dental implants [36, 37]. Top et al.'s evaluation of five CNN algorithms produced accuracies ranging from 75.5 % to92.7 % with a high AUC of 0.989 [38], while

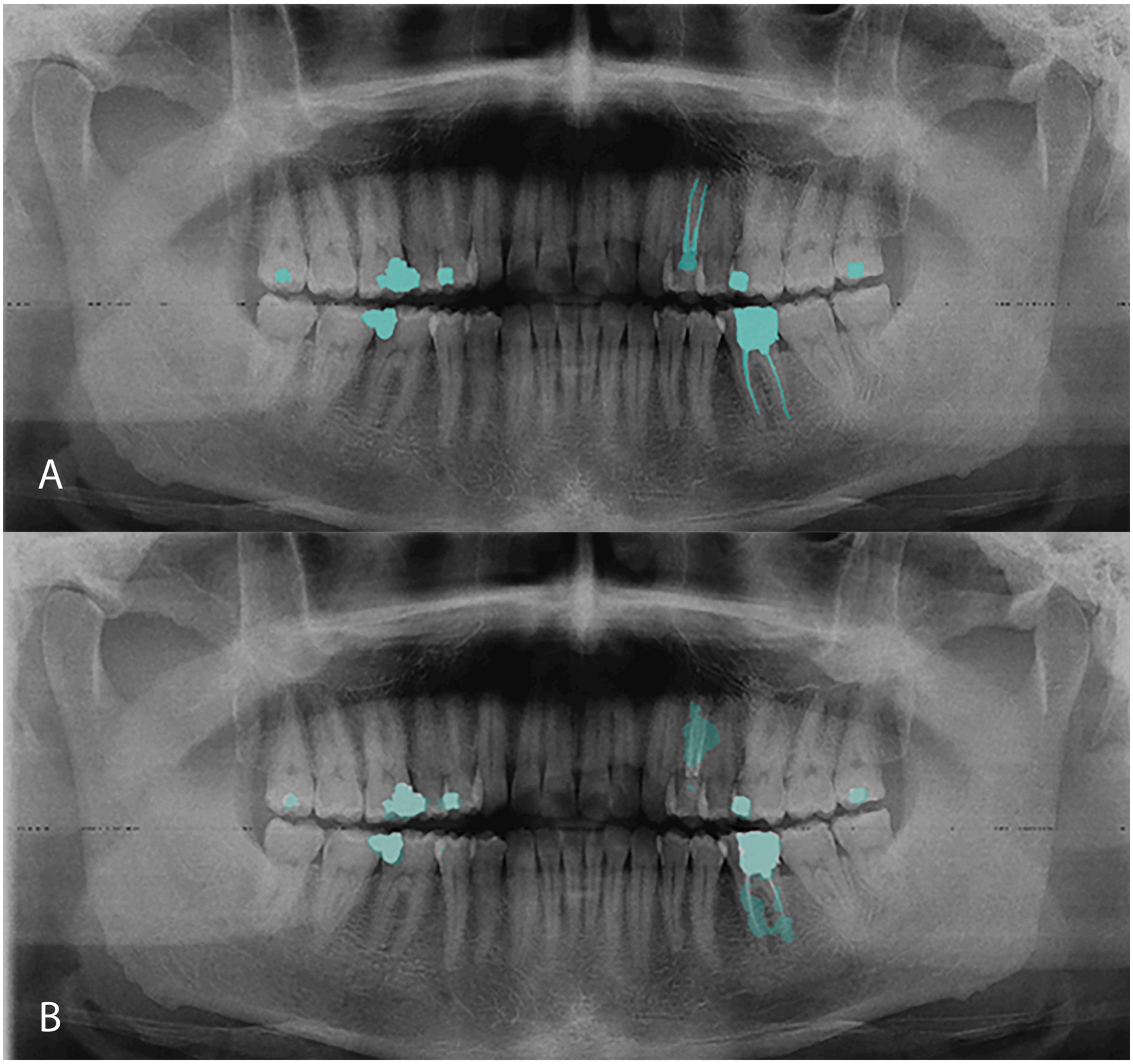

Fig. 6. A. Ground truth. B. Model's predictions. This figure shows two examples of false positive pixels in sites #12 and #19. False positives were mainly associated with the detection of root canal filling material.

Rohrer et al.'s approach of cropping radiographs improved F1 scores from 0.7 to 0.95 [39]. Choi et al.'s model, aimed at detecting natural teeth and dental treatments, reached precision values up to 99.1 % but faced challenges with dental fillings and root canal treatments [40]. Similarly, Abdalla-Aslan et al.'s model detected 94.6 % of restorations with an accuracy of 93.6 %, primarily struggling with composite and root canal fillings [41]. Lastly, Gardiyanoğlu et al. achieved an F1-score of 0.87 and an impressive accuracy of 99 % in segmenting dental restorations. Despite their larger dataset of over 8000 panoramic radiographs compared to our 100, they too found the lowest scores associated with root canal fillings [42].

The results of the aforementioned studies show that various conventionally coded models displayed varying results in detecting dental restoration on panoramic radiographs. Also, a recurring observation is the prevalence of false negative errors in AI models, particularly in relation to resin composite fillings and root canal fillings. This observation is consistent with the findings of our study. It can be concluded that no-code platform was able to match or exceed the performance of a customized model developed with extensive machine learning expertise. Being able to achieve robust performance with less data is highly advantageous, as curating large labeled datasets is one of the major challenges in healthcare AI development. The high accuracy of the tested model in our paper can be attributed to several factors, such as the choice of data augmentation, differences in labeling and in the code-free model architecture used in the platform as well as data preprocessing and model optimization. No-code or low-code computer vision platforms may effectively address the challenges tied to profound machine learning knowledge, expensive training, and operational adeptness. Consequently, no-code AI platforms offer numerous advantages compared to conventional machine learning. These benefits encompass their intuitive nature and the lack of requirement for extensive programming skills. Additionally, no-code computer vision platforms can be deployed more swiftly and easily than traditional machine learning methods. Lastly, findings indicate that these platforms can enhance the precision of dental image segmentation through deep learning, outperforming conventional programming methods [35,42]. To the best of our knowledge, this is the first study to use a no-code platform for developing deep learning models in the field of dentistry. Also limited number of studies evaluated the performance for this approach, especially in case of segmentation task. Successful use of these platforms in medical image classification has already been shown in various recent studies [18,24,43,44].

Santomartino et al. [43] reported that their segmentation model faced challenges stemming from the limitations of no-code platforms. These limitations included the incapacity to handle large dataset sizes, an inability to perform multi-label disease classification, and a restriction on using negative images for training. Consequently, they were unable to achieve successful training of their segmentation model. These identified limitations may be linked to different types of no-code platforms that were not evaluated in the present study. However, they reported that in the context of smaller, balanced and datasets, no-code deep learning platforms demonstrated exceptional performance in single-label, binary classification tasks. On the other hand, Pettersen et al. [45] reported successful use of a no-code pipeline for the segmentation of histopathologic images, reaching dice similarity coefficient of more than 91 % for all the classes. These varying outcomes in different studies might be due to the usage of different platforms for creating deep learning models.

While the study demonstrates the potential of no-code computer vision platforms in radiology, there are limitations that warrant further investigation. For instance, they don't support cross-validation and ensembling, and their model customization options can be limited [43]. Furthermore, this study had several limitations. We worked with a limited dataset size. Additionally, all analyses relied on a single radiographic device, removing variability in intrinsic image properties. Moreover, the generalizability is potentially constrained by the specific age range of our participants and the omission of other dental conditions, such as dental crowding, mixed dentition, and orthodontic appliances, from the dataset. In addition, our research focus was solely on one task: the detection of dental restorations on panoramic radiographs using one no-code computer vision platform. Considering all of these factors, future research should continue by focusing on validating the performance of multiple no-code computer vision platforms on larger and more diverse datasets. This can encompass other deep learning tasks in dentistry, including classification, object detection, and more complex segmentation tasks.

It's essential to highlight that the computer vision platforms developed using this method should not be used for diagnostic purposes i.e., as medical devices, without obtaining FDA clearance. Moreover, while the convenience of adopting technology is apparent, there's a responsibility to thoroughly understand it, including its benefits and potential limitations. Many AI algorithms operate as "black boxes," concealing their internal workings, and perpetuating this lack of transparency carries risks. In essence, caution is necessary when applying AI in critical areas like healthcare [46,47].

5. Conclusion

In conclusion, this study highlights the potential of no-code computer vision platforms in dental radiology, particularly for segmenting dental restorations on panoramic radiographs. The model's performance metrics indicate its accurate segmenting capabilities, which can contribute to advancements in dental imaging and patient care. However, further research and validation are required to evaluate the performance of these platforms for other detection tasks in oral radiology.

Availability of data and materials

The data used for this study are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used [Paraphraser Tool/ QuillBot AI] in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Ethical approval

This study was carried out in accordance with relevant guidelines and regulations. Ethical approval from the Institutional Review Board (IRB) of Marquette University was obtained prior to the study [# HR-4374].

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CRediT authorship contribution statement

Manal Hamdan: Conceptualization, Investigation, Validation, Methodology, Software, Data curation, Funding acquisition, Resources, Supervision, Writing – original draft. **Zaid Badr:** Investigation, Validation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Jennifer Bjork:** Methodology, Software, Visualization, Funding acquisition. **Reagan Saxe:** Methodology, Software, Visualization, Funding acquisition. **Francesca Malensek:** Methodology, Software, Visualization. **Caroline Miller:** Methodology, Software, Visualization. **Rakhi Shah:** Methodology, Software, Visualization. **Shengtong Han:** Data curation, Writing – review & editing. **Hossein Mohammad-Rahimi:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

[1] M. Mupparapu, C.-W. Wu, Y.-C. Chen, Artificial intelligence, machine learning, neural networks, and deep learning: futuristic concepts for new dental diagnosis, Quintessence Int. 49 (2018) 687–688.
[2] S.B. Khanagar, A. Al-Ehaideb, P.C. Maganur, S. Vishwanathaiah, S. Patil, H. A. Baeshen, S.C. Sarode, S. Bhandi, Developments, application, and performance of artificial intelligence in dentistry–a systematic review, J. Dent. Sci. 16 (2021) 508–522.
[3] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444.
[4] G. Chartrand, P.M. Cheng, E. Vorontsov, M. Drozdzal, S. Turcotte, C.J. Pal, S. Kadoury, A. Tang, Deep learning: a primer for radiologists, Radiographics 37 (2017) 2113–2131.
[5] H. Mohammad-Rahimi, S.R. Motamedian, M.H. Rohban, J. Krois, S.E. Uribe, E. Mahmoudinia, R. Rokhshad, M. Nadimi, F. Schwendicke, Deep learning for caries detection: a systematic review, J. Dent. 122 (2022), 104115.
[6] J. Krois, T. Ekert, L. Meinhold, T. Golla, B. Kharbot, A. Wittemeier, C. Dörfer, F. Schwendicke, Deep learning for the radiographic detection of periodontal bone loss, Sci. Rep. 9 (2019) 8495.
[7] T. Ekert, J. Krois, L. Meinhold, K. Elhennawy, R. Emara, T. Golla, F. Schwendicke, Deep learning for the radiographic detection of apical lesions, J. Endod. 45 (2019) 917–922.
[8] M. Fukuda, K. Inamoto, N. Shibata, Y. Ariji, Y. Yanashita, S. Kutsuna, K. Nakata, A. Katsumata, H. Fujita, E. Ariji, Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography, Oral Radiol. 36 (2020) 337–343.
[9] J. Ahn, T.K.K. Ho, J. Kang, J. Gwak, Using artificial intelligence methods for dental image analysis: state-of-the-art reviews, J. Med. Imaging Health Inform. 10 (2020) 2532–2542.

[10] M.H. Hamdan, L. Tuzova, A. Mol, P.Z. Tawil, D. Tuzoff, D.A. Tyndall, The effect of a deep-learning tool on dentists' performances in detecting apical radiolucencies on periapical radiographs, Dentomaxillofac. Radiol. 51 (2022), 20220122.
[11] L.T. Arsiwala-Scheppach, A. Chaurasia, A. Müller, J. Krois, F. Schwendicke, Machine learning in dentistry: a scoping review, J. Clin. Med. 12 (2023) 937.
[12] X. Xie, L. Wang, A. Wang, Artificial neural network modeling for deciding if extractions are necessary prior to orthodontic treatment, Angle Orthod. 80 (2010) 262–266.
[13] A. Babu, J.A. Onesimu, K.M. Sagayam, Artificial intelligence in dentistry: concepts, applications and research challenges, E3S Web Conf. (2021) 1074.
[14] A. Katsumata, Deep learning and artificial intelligence in dental diagnostic imaging, Jpn. Dent. Sci. Rev. 59 (2023) 329–333, https://doi.org/10.1016/j.jdsr.2023.09.004.
[15] J. Amann, A. Blasimme, E. Vayena, D. Frey, V.I. Madai, Explainability for artificial intelligence in healthcare: a multidisciplinary perspective, BMC Med. Inform. Decis. Mak. 20 (2020) 1–9.
[16] F. al Schwendicke, W. Samek, J. Krois, Artificial intelligence in dentistry: chances and challenges, J. Dent. Res. 99 (2020) 769–774.
[17] J. Yanase, E. Triantaphyllou, The seven key challenges for the future of computer-aided diagnosis in medicine, Int. J. Med. Inform. 129 (2019) 413–422.
[18] E. Korot, Z. Guan, D. Ferraz, S.K. Wagner, G. Zhang, X. Liu, L. Faes, N. Pontikos, S. G. Finlayson, H. Khalid, Code-free deep learning for multi-modality medical image classification, Nat. Mach. Intell. 3 (2021) 288–298.
[19] M. Awawdeh, H. Dervis, Artificial Intelligence (Ai) application in dentistry: the knowledge, concerns and challenges of syrian dental care professionals, concerns and challenges of syrian dental care professionals. (n.d.).
[20] C.V.K. Iyer, F. Hou, H. Wang, Y. Wang, K. Oh, S. Ganguli, V. Pandey, Trinity: a No-Code AI platform for complex spatial datasets, in: Proceedings of the 4th ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery, 2021, pp. 33–42.
[21] G.F. Hurlburt, Low-code, no-code, what's under the hood? IT Prof. 23 (2021) 4–7.
[22] W. Villegas-Ch, J. Garc\'\ia-Ortiz, S. Sánchez-Viteri, Identification of the factors that influence university learning with low-code/no-code artificial intelligence techniques, Electronics (Basel) 10 (2021) 1192.
[23] D. Rossi, L. Zhang, Landing AI on networks: an equipment vendor viewpoint on autonomous driving networks, IEEE Trans. Netw. Serv. Manag. 19 (2022) 3670–3684.
[24] S. Touma, F. Antaki, R. Duval, Development of a code-free machine learning model for the classification of cataract surgery phases, Sci. Rep. 12 (2022) 2398.
[25] J. Huemer, M. Kronschläger, M. Ruiss, D. Sim, P.A. Keane, O. Findl, S.K. Wagner, Diagnostic accuracy of code-free deep learning for detection and evaluation of posterior capsule opacification, BMJ Open Ophthalmol. 7 (2022), e000992.
[26] E. Korot, N. Pontikos, X. Liu, S.K. Wagner, L. Faes, J. Huemer, K. Balaskas, A. K. Denniston, A. Khawaja, P.A. Keane, Predicting sex from retinal fundus photographs using automated deep learning, Sci. Rep. 11 (2021) 10286.
[27] G. Tang, Z. Fang, Y. Wang, Global landslide susceptibility prediction based on the automated machine learning (AutoML) framework, Geocarto Int. 38 (2023), 2236576.
[28] K. Rokis, M. Kirikova, Challenges of low-code/no-code software development: a literature review, in: International Conference on Business Informatics Research, 2022, pp. 3–17.
[29] J. Mongan, L. Moy, C.E. Kahn Jr, Checklist for artificial intelligence in medical imaging (CLAIM): a guide for authors and reviewers, Radiol. Artif. Intell. 2 (2020), e200029.
[30] F. Sufi, Algorithms in low-code-no-code for research applications: a practical review, Algorithms 16 (2023) 108.
[31] Computer vision platform and AI software company landing AI, (2023).
[32] R. Parikh, A. Mathai, S. Parikh, G.C. Sekhar, R. Thomas, Understanding and using sensitivity, specificity and predictive values, Indian J. Ophthalmol. 56 (2008) 45.
[33] J.-H. Lee, S.-S. Han, Y.H. Kim, C. Lee, I. Kim, Application of a fully deep convolutional neural network to the automation of tooth segmentation on panoramic radiographs, Oral Surg. Oral Med. Oral Pathol. Oral Radiol. 129 (2020) 635–642.
[34] B. Day, H. Üzen, I.B. Çiçek, Ş.B. Duman, A novel deep learning-based approach for segmentation of different type caries lesions on panoramic radiographs, Diagnostics 13 (2023) 202.
[35] B. Çelik, M.E. Çelik, Automated detection of dental restorations using deep learning on panoramic radiographs, Dentomaxillofac. Radiol. 51 (2022), 20220244.
[36] E. Aşçi, M. Kiliç, Ö. Çelik, I.Ş. Bayrakdar, E. Bilgir, A.F. Aslan, A. Odabaş, K. Orhan, Derin Öğrenme Yöntemi Kullanlarak Geliştirilen Yapay Zekâ Yöntemi ile Panoramik Radyografilerde Dental Restorasyonlarn Otomatik Tespiti ve Snflandrlmas: metodolojik Çalşmalar, Turkiye Klinikleri. Dishekimligi Bilimleri Dergisi. 28 (2022) 329–337.
[37] T. Yeshua, Y. Mandelbaum, R. Abdalla-Aslan, C. Nadler, L. Cohen, L. Zemour, D. Kabla, O. Gleisner, I. Leichter, Automatic detection and classification of dental restorations in panoramic radiographs, Issues Informing Sci. Inf. Technol. 16 (2019) 221–234.
[38] A.E. Top, S. Özdoğan, M. Yeniad, Quantitative level determination of fixed restorations on panoramic radiographs using deep learning, Int. J. Comput. Dent. (2023) 0 (In-Press).
[39] C. Rohrer, J. Krois, J. Patel, H. Meyer-Lueckel, J.A. Rodrigues, F. Schwendicke, Segmentation of dental restorations on panoramic radiographs using deep learning, Diagnostics 12 (2022) 1316.
[40] H.R. Choi, T.S. Siadari, J.-E. Kim, K.H. Huh, W.J. Yi, S.-S. Lee, M.-S. Heo, Automatic detection of teeth and dental treatment patterns on dental panoramic radiographs using deep neural networks, Forensic Sci. Res. 7 (2022) 456–466.
[41] R. Abdalla-Aslan, T. Yeshua, D. Kabla, I. Leichter, C. Nadler, An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography, Oral Surg. Oral Med. Oral Pathol. Oral Radiol. 130 (2020) 593–602.
[42] E. Gardiyanoğlu, G. Ünsal, N. Akkaya, S. Aksoy, K. Orhan, Automatic segmentation of teeth, crown–bridge restorations, dental implants, restorative fillings, dental caries, residual roots, and root canal fillings on orthopantomographs: convenience and pitfalls, Diagnostics 13 (2023) 1487.
[43] S.M. Santomartino, N. Hafezi-Nejad, V.S. Parekh, P.H. Yi, Performance and usability of code-free deep learning for chest radiograph classification, object detection, and segmentation, Radiol. Artif. Intell. 5 (2023), e220062.
[44] S.K. Wagner, B. Liefers, M. Radia, G. Zhang, R. Struyven, L. Faes, J. Than, S. Balal, C. Hennings, C. Kilduff, Development and international validation of custom-engineered and code-free deep-learning models for detection of plus disease in retinopathy of prematurity: a retrospective study, Lancet Digit. Health 5 (2023) e340–e349.
[45] H.S. Pettersen, I. Belevich, E.S. Røyset, E. Smistad, M.R. Simpson, E. Jokitalo, I. Reinertsen, I. Bakke, A. Pedersen, Code-free development and deployment of deep segmentation models for digital pathology, Front. Med. (Lausanne) 8 (2022), 816281.
[46] R. Rokhshad, M. Ducret, A. Chaurasia, T. Karteva, M. Radenkovic, J. Roganovic, M. Hamdan, H. Mohammad-Rahimi, J. Krois, P. Lahoud, Ethical considerations on artificial intelligence in dentistry: a framework and checklist, J. Dent. (2023), 104593.
[47] G. Currie, K.E. Hawk, E.M. Rohren, Ethical principles for the application of artificial intelligence (AI) in nuclear medicine, Eur. J. Nucl. Med. Mol. Imaging 47 (2020) 748–752.