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# A novel collaborative learning model for mixed dentition and fillings segmentation in panoramic radiographs

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ABSTRACT

*Introduction:* It is critical for dentists to identify and differentiate primary and permanent teeth, fillings, dental restorations and areas with pathological findings when reviewing dental radiographs to ensure that an accurate diagnosis is made and the optimal treatment can be planned. Unfortunately, dental radiographs are sometimes read incorrectly due to human error or low-quality images. While secondary or group review can help catch errors, many dentists work in practice alone and/or do not have time to review all of their patients' radiographs with another dentist. Artificial intelligence may facilitate the accurate interpretation of radiographs. To help support the review of panoramic radiographs, we developed a novel collaborative learning model that simultaneously identifies and differentiates primary and permanent teeth and detects fillings.
*Methods:* We used publicly accessible dental panoramic radiographic images and images obtained from the University of Missouri–Kansas City, School of Dentistry to develop and optimize two high-performance classifiers: (1) a system for tooth segmentation that can differentiate primary and permanent teeth and (2) a system to detect dental fillings.
*Results:* By utilizing these high-performance classifiers, we created models that can identify primary and permanent teeth (mean average precision [mAP] 95.32 % and performance [F-1] 92.50 %), as well as their associated dental fillings (mAP 91.53 % and F-1 91.00 %). We also designed a novel method for collaborative learning that utilizes these two classifiers to enhance recognition performance (mAP 94.09 % and F-1 93.41 %).
*Conclusions:* Our model improves upon the existing machine learning models to simultaneously identify and differentiate primary and permanent teeth, and to identify any associated fillings.
*Clinical Significance:* Human error can lead to incorrect readings of panoramic radiographs. By developing artificial intelligence and machine learning methods to analyze panoramic radiographs, dentists can use this information to support their radiograph interpretations, help communicate the information to patients, and assist dental students learning to read radiographs.

## 1. Introduction

Dental radiographs are pivotal diagnostic tools, empowering dentists to meticulously discern between primary teeth and permanent teeth, fillings, and other types of dental restorations and pathologies. An inaccurate interpretation can lead to unwarranted appointments or incorrect treatments. Although secondary review by other dentists can mitigate these discrepancies, the solitary nature of many dentists' practices makes consistent peer reviews elusive.

Integrating artificial intelligence and machine learning (AI/ML) into healthcare has inaugurated transformative shifts in image diagnostics, decision-making, and how procedures are planned [24,28,37]. By introducing these advances into dentistry, there's a substantial potential to elevate diagnostic accuracy, especially in detecting and therefore

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treating oral, dental, and craniofacial conditions. The indispensability of an autonomous system that proficiently pinpoints teeth and dental restorations has been underscored in an array of studies [3,5,11,30,32].

AI encompasses computer systems engineered to execute tasks typically necessitating human intelligence, such as visual perception and decision-making. In dental research, ML, an AI sub-set, concentrates on devising algorithms that can learn from data to make predictions or decisions without explicit programming, improving their performance as they encounter more data. Deep Learning (DL), a machine learning subfield, employs artificial neural networks to model intricate data patterns [38]. These networks can autonomously process and represent data across multiple layers, rendering them particularly apt for tasks like dental image analysis. The primary distinction between machine learning and deep learning is that deep learning models can manage more complex data patterns and learn more effectively from extensive datasets [39].

Dental applications typically involve two primary image analysis tasks: classification and segmentation. Classification assigns dental images to distinct categories, such as healthy or diseased. In contrast, image segmentation divides digital dental images, like radiographs or Cone Beam Computed Tomography (CBCT) images, into several segments, simplifying or modifying the image representation to make it more meaningful and easier to analyze. This method is particularly beneficial for detecting and diagnosing dental concerns like cavities, gum disease, and tooth decay. Various modalities, including two dimensional (2D) radiographs and 3D CBCT images, present different levels of detail and complexity. While 2D radiographs offer a planar representation of dental structures, 3D CBCT images provide a more detailed view of teeth, bones, and soft tissues, enabling better diagnosis and treatment planning.

Many distinct tooth segmentation techniques have been developed. Almost every model reported had an accuracy of at least 75 %, with most having accuracies >95 % [9,25,33,40,44]. For example, a mask region-based convolutional neural network (CNN) (Mask R-CNN) has been shown to be able to segment every tooth for automatic tooth segmentation based on panoramic radiographs [14,23]. Another deep neural network has been used to obtain the binary mask of the teeth to statistically identify form and space changes and thereby improve the segmentation quality [41]. A different model used a deep CNN for accurate and autonomous segmentation which was considered to be suitable for dental computer-aided design (CAD) systems [43]. Another 3D system for tooth segregation, the TSegNet approach, was evaluated and showed faster and more accurate segmentation, even accounting for uncertainties caused by missing, crowded, or misaligned teeth [7]. Even though when different neural networks, including Mask R-CNN, hybrid task cascade (HTC), PANet, and ResNet, were compared to perform tooth numbering and segmentation on difficult dental radiographs the accuracy varied greatly and was reduced when teeth were damaged or otherwise altered [35]. Thus, while some of the reported methods of tooth segmentation show good accuracy under certain conditions, additional work is still needed.

Only a few previous studies have examined the primary dentition. One focused solely on segmenting out the primary dentition [20]. Another segmented out both the primary and permanent dentition, but had a low mean average precision (mAP) [29]. Other studies have evaluated the use of machine learning approaches to identify mesiodens in primary, mixed and permanent dentition, with accuracies ranging from ~87 % to ~98 % [1,12,15]. A recent study used CNN to detect and number both primary and permanent teeth, with relatively high accuracy [19]. And lastly, a study classified patients into those with 32 or more teeth and those with fewer than 32 teeth, and found that the segmentation accuracy was higher for patients with 32 or more teeth, likely due to the greater consistency in the locations of the teeth [18]. Although these models were able to detect primary teeth, better models are needed to detect both primary and mixed (primary + permanent) dentition in panoramic radiographs, and to simultaneously detect both healthy teeth and teeth with pathological findings or restorations.

Research in mixed dentition poses unique challenges [17]. The transitional nature of mixed dentition complicates image analysis due to overlapping structures, varying sizes, and stages of tooth eruption. We hypothesized that by using a novel collaborative learning model based on the Mask R-CNN instance segmentation method [13] that simultaneously identifies and differentiates primary and permanent teeth and detects fillings in panoramic radiographs that it would outperform previously published methods. Our present model consists of two steps: (1) deep learning modeling and inferencing through two bespoke models: one dedicated to primary and permanent tooth segmentation and the other fixated on filling discernment and (2) inference aggregation for multiple tasks, providing a summary of the inferencing outcomes to generate a comprehensive understanding of the tooth locations, categorization, and the presence of fillings. By combining the outcomes of different models, the collaborative model can provide a summary from the inferences of multiple tasks, resulting in superior accuracy.

## 2. Material and method

### 2.1. Datasets

The primary dataset used for tooth and filling segmentation was the Universidade Federal Da Bahia-Universidade Estadual de Santa Cruz (UFBA-UESC) dental dataset [36], which included 368 panoramic radiographs used to train the tooth and filling segmentation models. We also used 80 deidentified panoramic radiographs from the University of Missouri–Kansas City, School of Dentistry. Once a chart was accessed from the University of Missouri–Kansas City, School of Dentistry and the panoramic radiograph was determined to be suitable for study use, a clip of the image was saved without any identifiers to the investigator's password protected files on a drive that only the investigators had access to. No identifiers were recorded. The details of the total number of panoramic radiographs used for training, validation and testing from the datasets are shown in Table 1, as well as the number of panoramic radiographs with fillings. The analysis of these deidentified panoramic radiographs was determined to be exempt by the Institutional Review Board of University of Missouri–Kansas City, (IRB Project Number 2, 068,642; IRB Review Number 334,839).

### 2.2. Modeling and inferencing

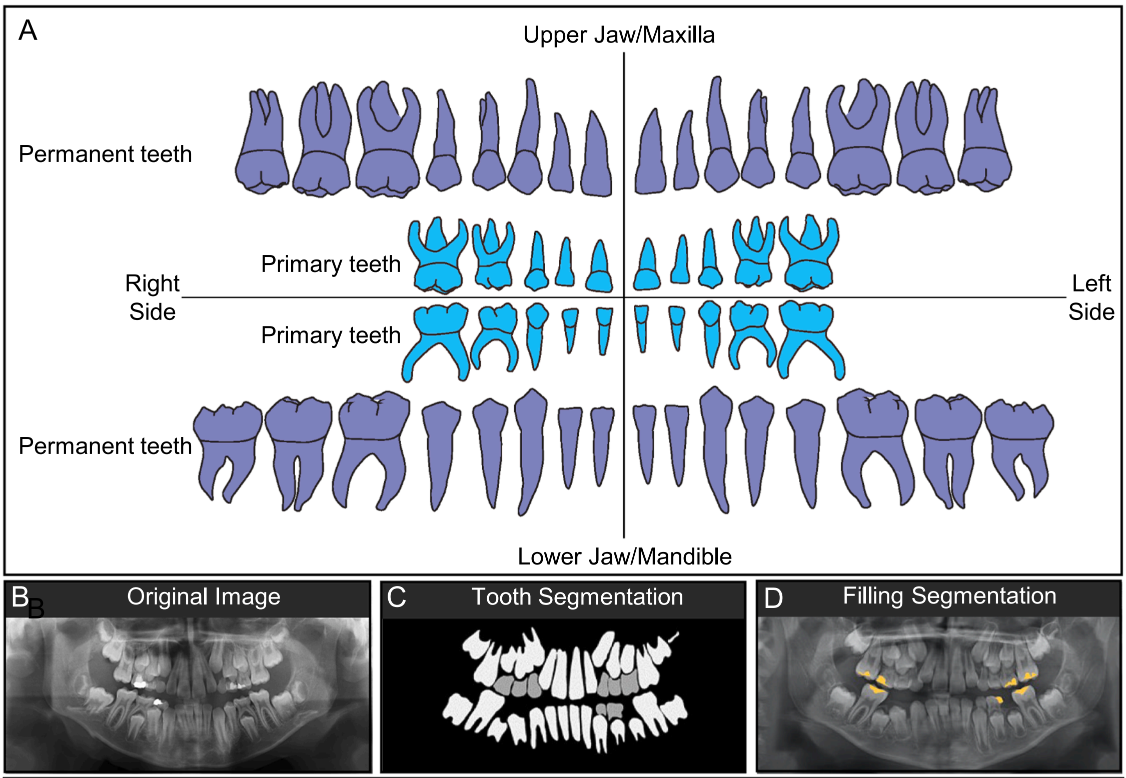
We first developed two distinct models for the segmentation of primary and permanent teeth and for filling segmentation using panoramic radiographs (Fig. 1A). Then we performed inference utilizing these models, and the results were forwarded to the consequence phase for aggregation.

*Model 1: Primary and Permanent Tooth Segmentation Modeling.* To segment teeth, we utilized the Mask R-CNN with the UFBA-UESC & University of Missouri–Kansas City panoramic radiograph datasets. This instance-based segmentation model can handle both segmentation and two-category identifications, and is able to differentiate between primary and permanent teeth. Fig. 1B shows an example of a panoramic radiograph from a patient with mixed dentition and fillings. The tooth segmentation mask for the panoramic radiograph analyzed by our model is annotated for the segmentation of 8 primary and 32 permanent teeth (Fig. 1C). In the model, Mask R-CNN retrieves features from ResNet-101, which performs feature extraction. Subsequently, a feature pyramid network (FPN) with anchors is formed utilizing the regions of interest (ROIs) identified. After aligning the ROIs, the classification and localization of all teeth are carried out based on the regression of the bounding boxes for teeth. Finally, the convolutional network is utilized to identify and segment each tooth, as indicated by the bounding boxes. The tooth

**Table 1**
The datasets used in the present study.

| | UFBA-UESC | | | UMKC | | |
|---|---|---|---|---|---|---|
| | Training | Validation | Testing | Training | Validation | Testing |
| Number of Panoramic Radiographs | 368 | 246 | 65 | 80 | 29 | 35 |
| Number with Fillings | 117 | 60 | 65 | 70 | 40 | 35 |

UFBA-UESC: Universidade Federal Da Bahia-Universidade Estadual de Santa Cruz (UFBA-UESC) dental dataset described by [36].
UMKC: University of Missouri-Kansas City.




E

| Model | Training | Validation | Testing | Epochs | Time (min) |
|---|---|---|---|---|---|
| Tooth Segmentation | 275 images | 50 images | 90 images | 300 | 45 |
| Filling Segmentation | 187 images | 50 images | 90 images | 300 | 30 |

F

$$Precision = \frac{TP}{TP+FP} \qquad F1 = \frac{2 \times Recall \times Precision}{Recall + Precision} \qquad AveP = \frac{\sum_{k=1}^{n} P(k) \times rel(k)}{D}$$

$$Recall = \frac{TP}{TP+FN} \qquad Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \qquad mAP = \frac{\sum_{q=1}^{Q} \overline{AveP(q)}}{Q}$$

**Fig. 1.** An overview of the models. **(A)** The panoramic appearance of the full primary dentition (light blue) and permanent dentition (purple) is shown. **(B)** A panoramic radiograph of a patient with mixed dentition and fillings present. **(C)** The tooth segmentation mask of (B) with permanent teeth segmented in white and primary teeth segmented in gray. **(D)** The filling segmentation mask overlaying (B). **(E)** An overview of the tooth segmentation and filling segmentation models, including the number of images used for training, testing and validation, as well as the Epoch number and time. **(F)** The equations used to determine the precision, recall, F1 score, accuracy, average precision measure (AveP) and mean average precision (mAP). TP - true positive (correct segmentation), TN - true negative, FP - false positive, FN - false negative, D - the total number of relevant documents, rel(k) - an indicator function equal to one if the item at rank k is a relevant document (and is set as zero otherwise), and Q - total number of inquiries.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

segmentation model was created using the panoramic radiograph datasets and Facebook Research's Detectron2 Library for python 3.7 [26,42].

*Model 2: Filling Segmentation Modeling.* Deep CNN methodologies are among the most effective and practical methods for identifying fillings. We used the Mask R-CNN (initially described by He et al. 2017) for filling segmentation. Dental panoramic radiographs were manually annotated to identify fillings and were used for segmentation learning for detection. The filling segmentation mask for the panoramic radiograph shown in Fig. 1B was analyzed by our model, and was annotated for 7 fillings (Fig. 1D).

Individual detection models for tooth segmentation and filling segmentation were developed separately by using the benchmark dataset from the UFBA-UESC [36]. Training the tooth segmentation model with the panoramic radiographs required around 448 annotated training images, 275 for validation and 100 testing images with primary and permanent teeth (Fig. 1E). For filling segmentation, 187 images were used for training, 100 for validation, and 100 were used for testing the model (Fig. 1E). All types of fillings were annotated (amalgam, composite, glass ionomer etc.), but other types of restorations were not annotated for this analysis (implants, crowns, etc.). Around 100 pediatric images were utilized to evaluate the collaborative model, which was developed by combining the output from the two distinct segmentation models.

### 2.3. Collaborative learning

The collaborative model's initial stage involves concurrent inference from the two models, followed by aggregation of the predictions of these models, and finally the generation of a summary of the results. The present collaborative model's novel design allows it to draw inferences from multiple models using a single input for a variety of relevant tasks, in this case, tooth segmentation and filling segmentation. It then provides a summary of data from the different models. A collaboration model is capable of doing multiple tasks with a low dependence on the individual models selected. At this stage, the accuracy is determined as the weighted average of the accuracy of the distinct models. The initial weights are equal for each model, but the weight can be changed after analyzing the contributions of each individual model. The integrated inference summary is saved in a standard format (Microsoft COCO) that can be used for further analyses.

### 2.4. Training phase

In this phase, the deep learning model was exposed to a large dataset containing labeled examples of teeth and fillings. The model learned to recognize patterns and relationships within the data by iteratively adjusting its parameters based on the difference between its predictions and the true labels for independent teeth segmentation and filling detection models. This process employed an optimization algorithm, which minimizes the model's error on the training data.

### 2.5. Validation phase

While the model is being trained, it is essential to monitor its performance on a separate dataset not used for training. The validation set allows us to determine if the model is overfitting, which occurs when a model becomes too specialized to the training data and fails to generalize well to new, unseen data. By evaluating the model on the validation set, we fine-tuned hyperparameters such as learning rate, batch size, and model architecture to strike a balance between fitting the training data and generalizing it to new data for teeth segmentation and filling detection.

### 2.6. Testing (post-processing) phase

After the model was trained and optimized using the validation set, it was assessed on a third, independent dataset called the test set. This step provided an unbiased estimate of the model's performance in real-world scenarios, as the test data has not been seen by the model during training or validation. For our collaborative model, this unique step involved post-processing with these models by summarizing the outcomes of the two different models and tuning their results by applying post-processing rules, for example, filling occurs within the top portion of the tooth segmentation outcomes. The test set was used only once, and its results are reported as the final performance metrics for the model, such as mean average precision (mAP) and F1 score based on precision and recall.

### 2.7. Evaluation measures

In the present study, we evaluated both individual models (tooth segmentation with primary versus permanent identification and filling segmentation) as well as collaborative models. We employed a variety of metrics to assess the performance of the models, including the accuracy, precision, recall, performance (F1 score), and mean average precision (mAP) (Fig. 1F).

## 3. Results

### 3.1. Collaborative model derived from the tooth and filling segmentation models

Collaborative inference was performed by combining the outputs of the two segmentation models (see Fig. 1). We validated our findings using images that were not included in the training data, including 246 from the UFBA-UESC dataset and 29 from the University of Missouri–Kansas City dataset, which was approximately 33 % of the panoramic radiographs. After detecting and labeling teeth, a performance accuracy of approximately 95 % was obtained for the tooth segmentation, including the identification of primary versus permanent teeth (Table 2). Individual cases illustrating the efficacy of the model are described below.

### 3.2. Case 1: permanent dentition

A panoramic radiograph of a patient with only permanent dentition is shown in Fig. 2A. The tooth segmentation model successfully identified all 32 permanent teeth in the tooth segmentation mask and an accuracy of 98.15 % (Fig. 2B). The filling segmentation model confirmed that there were no fillings in the filling segmentation mask and an accuracy of 99.45 % (Fig. 2C). The collaborative model had an accuracy of 98.86 % for this case (Fig. 2D & E). The collaborative F-1 score of 99.18 % and mAP of 98.86 % are shown in Table 2.

### 3.3. Case 2: permanent dentition with fillings

Fig. 2F shows a panoramic radiograph from a patient with only permanent dentition present and fillings in the permanent dentition. The tooth segmentation model successfully identified all 32 permanent teeth in the tooth segmentation mask and an accuracy of 98.67 % (Fig. 2G). The filling segmentation model identified all 8 fillings in the filling segmentation mask and an accuracy of 99.33 % (Fig. 2H). The collaborative model showed an accuracy of 99.04 % for this case (Fig. 2I & J). The collaborative F-1 score of 99.28 % and mAP of 99.04 % are also shown in Table 2.

### 3.4. Case 3: mixed dentition

Case 3 examined a panoramic radiograph from a patient with a mixed dentition, where both primary and permanent teeth were present (Fig. 3A). The tooth segmentation model could identify all 32 permanent teeth and 8 primary teeth in the tooth segmentation mask and an accuracy of 97.89 % (Fig. 3B). The filling segmentation model confirmed that there were no fillings in the filling segmentation mask and an accuracy of 99.57 % (Fig. 3C). The collaborative model showed an accuracy of 99.03 % for this case (Fig. 3D & E). The collaborative F-1 score of 99.30 % and mAP of 99.03 % are shown in Table 2.

**Table 2**
The performance of the individual and collaborative models for tooth and filling segmentation.

| | Average number | | | Tooth Segmentation Model | | Filling Segmentation Model | | Collaborative Model | |
|---|---|---|---|---|---|---|---|---|---|
| | Primary teeth | Permanent teeth | Fillings | mAP | F-1 | Map | F-1 | mAP | F-1 |
| Overall | 1264 (# of teeth) | 8593 (# of teeth) | 2490(# of filling) | 95.32 % | 92.50 % | 91.53 % | 91 % | 94.09 % | 93.41 % |
| Example Case 1 (shown in Fig. 2) | 32 | 0 | 0 | 98.15 % | 98.63 % | 99.45 % | 99.74 % | 98.86 % | 99.18 % |
| Example Case 2 (shown in Fig. 2) | 32 | 0 | 8 | 98.67 % | 98.75 % | 99.33 % | 99.65 % | 99.04 % | 99.28 % |
| Example Case 3 (shown in Fig. 3) | 32 | 8 | 0 | 97.89 % | 98.45 % | 99.57 % | 99.67 % | 99.03 % | 99.30 % |
| Example Case 4 (shown in Fig. 3) | 32 | 9 | 5 | 97.54 % | 98.15 % | 99.24 % | 99.54 % | 98.67 % | 99.07 % |

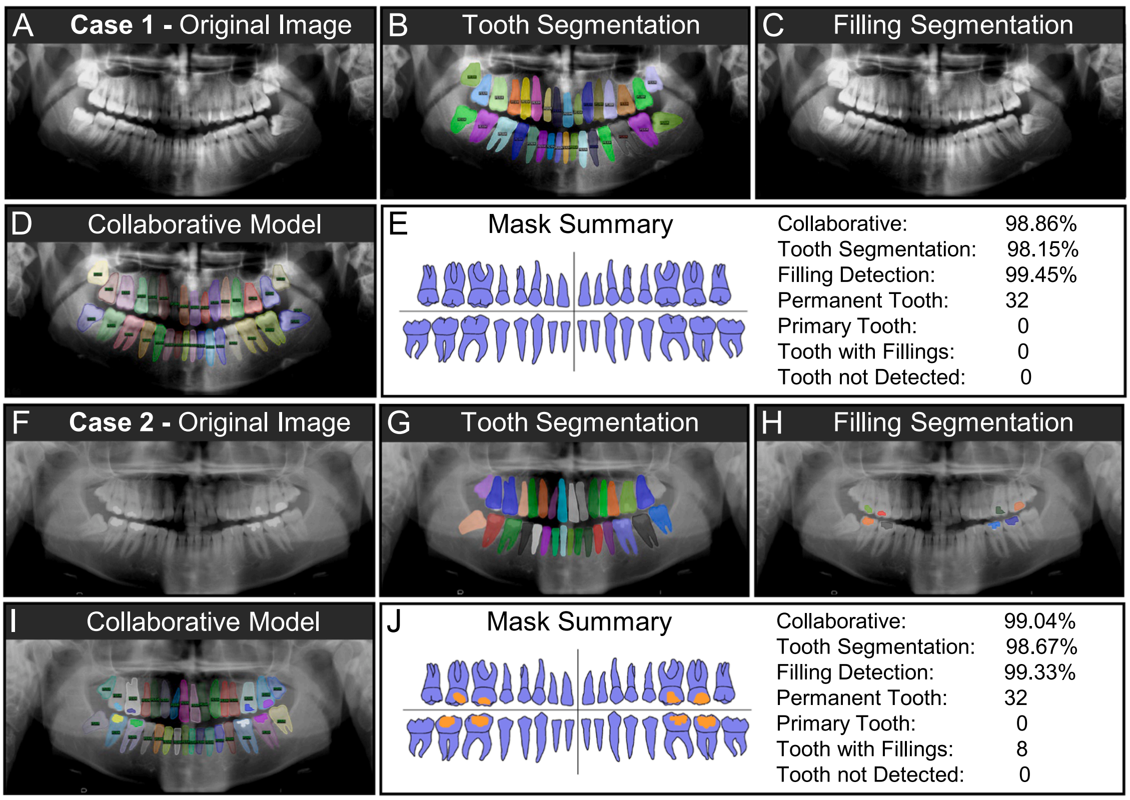



**Fig. 2.** Example cases of permanent dentition and permanent dentition with fillings. **Case 1: (A)** The original panoramic radiograph of a patient with only permanent dentition. **(B)** The tooth segmentation mask overlaying (A). **(C)** The filling segmentation mask overlaying (A) – no fillings were noted. **(D)** The collaborative model mask overlaying (A). **(E)** A mask summary showing that all 32 permanent teeth were identified (shown in purple) and listing the accuracies of the models. **Case 2: (F)** The original panoramic radiograph of a patient with only permanent dentition and multiple fillings. **(G)** The tooth segmentation mask overlaying (F). **(H)** The filling segmentation mask overlaying (F) – four fillings were noted. **(I)** The collaborative model mask overlaying (F). **(J)** A mask summary showing all 32 permanent teeth (purple) with 4 fillings (identified in orange), and listing the accuracies of the models.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

### *3.5. Case 4: mixed dentition with fillings*

A panoramic radiograph from a patient with mixed dentition and fillings in the primary dentition is shown in Fig. 3F. The tooth segmentation identified all 32 permanent teeth and 9 primary teeth in the tooth segmentation mask and an accuracy of 97.54 % (Fig. 3G). The filling segmentation model identified all 5 fillings in the primary teeth in the filling segmentation mask and an accuracy of 99.24 % (Fig. 3H). Finally, the collaborative model showed an accuracy of 98.67 % for this case (Fig. 3I & J). The collaborative F-1 score of 99.07 % and mAP of 98.67 % are shown Table 2.

## 4. Discussion

Our hypothesis that by using a novel collaborative learning model that simultaneously identifies and differentiates primary and permanent teeth and detects fillings in panoramic radiographs that it would outperform previously published methods proved to be correct. The results show that the accuracy of our present model was comparable to (or superior to) that of the previous tooth segmentation approaches for panoramic radiographs. Moreover, we enhanced the F1 score from an average of 92.5 % for the tooth segmentation model alone to 93.41 % for the collaborative model (Table 2). We are currently working to enhance the performance of our collaborative learning model by optimizing the models' inferencing and weighting functions, as well as improving collaboration strategies.

The growing importance of dental imaging applications in recent years has driven the development of innovative deep learning models. Deep learning ensembles, for instance, offer a novel collaborative approach among deep learning models, with the goal of enhancing overall accuracy by merging the outputs of multiple models. Such collaborations can be applied to a single task or a series of tasks using techniques like voting or weight averaging [4,10,27,31,34,44]. However, ensemble deep learning methods, which have been proposed to

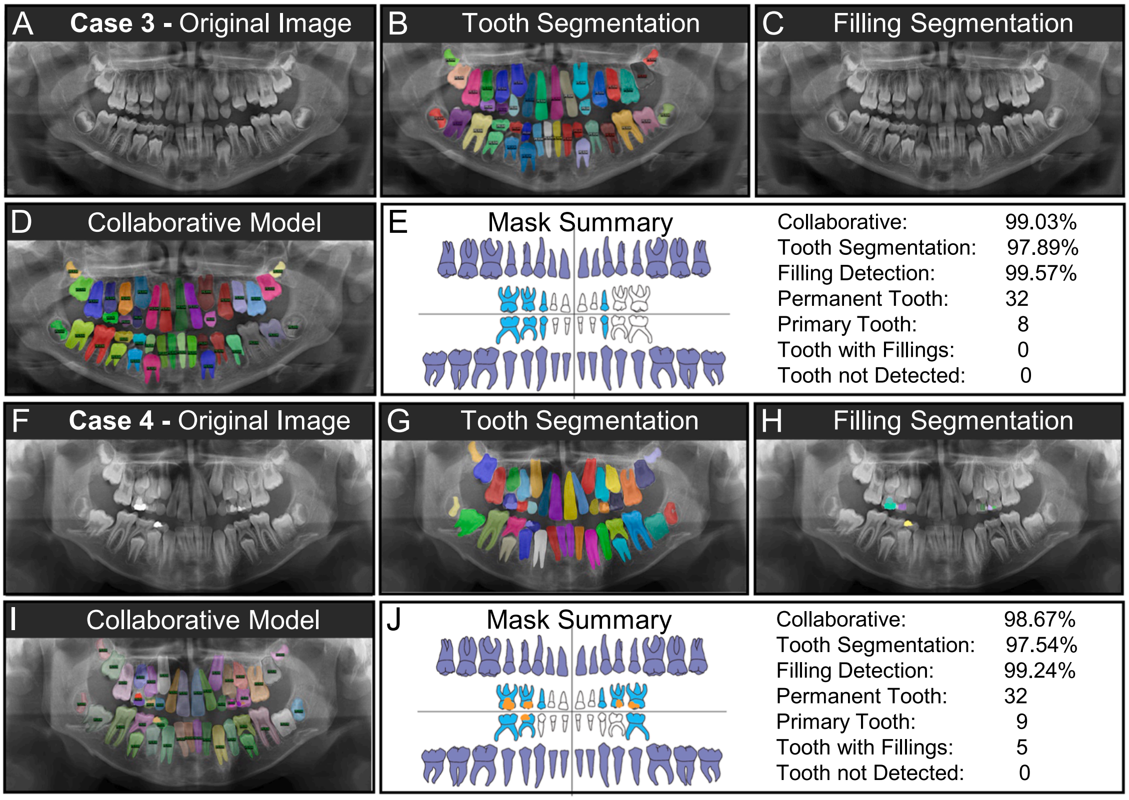



**Fig. 3.** Example cases of mixed dentition and mixed dentition with fillings. **Case 3: (A)** The original panoramic radiograph of a patient with mixed (primary + permanent) dentition. **(B)** The tooth segmentation mask overlaying (A). **(C)** The filling segmentation mask overlaying (A) – no fillings were noted. **(D)** The collaborative model mask overlaying (A). **(E)** A mask summary showing all 32 permanent teeth (purple) and 8 primary teeth (blue). The accuracies of the models are also shown. **Case 4: (F)** The original panoramic radiograph of a patient with a mixed dentition with multiple fillings. **(G)** The tooth segmentation mask overlaying (F). **(H)** The filling segmentation mask overlaying (F) – five fillings were noted. **(I)** The collaborative model mask overlaying (F). **(J)** A mask summary showing all 32 permanent teeth (purple), 9 primary teeth (blue), and 5 fillings (orange), in addition to the accuracies of the models.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

examine the relationship between group accuracy and measurement variance, may not be suitable for multiple tasks, such as tooth segmentation and teeth numbering (identification), required in the dental domain [21].

Our previous work addressed the lack of collaborative models that enhance learning performance by presenting a collaborative learning method combining independent tooth segmentation and identification models for adult teeth using panoramic radiographs [6]. This approach highlighted the advantages of collaborative learning in tooth recognition and numbering. The experimental data showed that the collaborative model significantly outperformed individual models. Our models surpassed state-of-the-art research and effectively managed complex dental scenarios. However, this work primarily focused on adult teeth cases within the 32-teeth adult domain.

This current paper expands on our previous work by applying it to mixed dentistry domains, which include both adult and child teeth. These domains pose greater challenges due to the coexistence of primary and permanent teeth in surface and underlying areas, as well as the limited visibility of some permanent teeth. The comparative evaluation involves individual models for adult teeth, collaborative models for adult teeth, and collaborative models for mixed dentistry. In mixed dentistry, we address more teeth, including 32 permanent teeth and 20 primary teeth (a total of 52 teeth across two different types - primary and permanent teeth). Consequently, the performance of the collaborative model dealing with mixed dentistry is slightly lower than that of adult teeth dentistry.

Table 1 presents a performance comparison of the models for adult teeth segmentation, mixed dentition segmentation, and filling detection. The individual model achieved a segmentation accuracy of 96.00 % for adult teeth and 95.32 % for mixed dentition. In contrast, the collaborative model demonstrated superior performance with a tooth segmentation accuracy of 98.77 %. For filling detection, the individual model scored 91.04 %, mixed dentition reached 91.53 %, and the collaborative model achieved the highest accuracy at 94.09 %.

Our proposed model is distinct from existing models in that it executes multiple tasks and generates a summary of each individual model's findings. There have only been a few studies that have segmented primary teeth, and most of these have focused on identifying specific abnormalities (e.g., mesiodens) [1,12,15,19,20,29]. Moreover, while various deep learning methods have been developed to detect fillings, to our knowledge, the present model is the first to detect fillings in both primary and permanent teeth. Our present method also performed as well as or better than the previous deep learning models for tooth and filling segmentation by providing the collaborative model ([8] and [7,9,23,25,33,35,40,41,43,44]).

In a recent study by Vinayahalingam et al., a deep learning approach was employed to detect, segment, and label teeth, crowns, fillings, root canal fillings, implants, and root remnants on panoramic radiographs [40]. This method was tested on 200 panoramic radiographs after being validated on a set of 1800 panoramic radiographs, achieving F1 scores of 0.993, 0.952, and 0.97 respectively. The impressive accuracy of this approach showcases its potential for automatic chart filing and assisting clinicians in summarizing radiological findings. However, our work builds on this by detecting, segmenting, and differentiating between primary and permanent teeth. This additional feature of our model is handy for dentists, especially in pediatric dentistry.

Kwon et al. utilized deep learning to diagnose odontogenic cysts and tumors in panoramic radiographs, achieving high accuracy with the CNN model using an augmented dataset. While their research illustrates the vast potential of deep learning in tackling various dental problems, it primarily focuses on diagnosing cysts and tumors [22]. Our work extends this field by identifying and differentiating primary and permanent teeth and detecting associated dental fillings. This ability of our model broadens its application and significantly enhances its clinical significance.

Aliaga et al. assessed a CNN system's capability for detecting vertical root fractures (VRF) on panoramic radiography [2]. Their CNN-based model detected 267 of 330 VRFs, with a recall of 0.75, precision of 0.93, and an F measure of 0.83. Their work certainly demonstrates the potential of deep learning for detecting fractures. Our research builds upon this work by providing a more comprehensive solution for dental radiography, covering not only fracture detection but also teeth segmentation and filling detection.

Jeon et al. presented a CNN-based system for predicting C-shaped canals in mandibular second molars using panoramic radiographs. Their Xception-based model displayed high diagnostic performance [16]. However, the primary focus of their research was the prediction of C-shaped canals. Our work, while recognizing the value of their research, extends the potential of AI in dentistry by distinguishing between primary and permanent teeth and identifying any associated fillings.

In comparison to these studies, our work contributes to the field by providing a novel collaborative learning model that simultaneously identifies and differentiates between primary and permanent teeth and detects fillings. By leveraging high-performance classifiers, our models achieve impressive accuracy rates, which we believe will significantly assist dentists in their radiograph interpretations, enhance communication with patients, and provide a valuable learning tool for dental students. Our work adds to the current understanding and application of AI in dentistry and pushes the boundaries of what AI can achieve in this field.

Nevertheless, there are several limitations associated with our present method. First, the data presented here were from a relatively small number of patients, and the patient images were from only two geographic regions (Brazil and Central USA). Additional training of the model using more patient images will be undertaken in future studies. As noted above, we are currently working to further improve the accuracy of the model by addressing the relative importance of the different segmentation data and including lower-quality images, as well as images from patients with abnormal dentition. We are also working to include the identification of specific tooth numbers to improve the segmentation and classification of the teeth [6]. Finally, while the present study included various types of fillings, no other dental restorations were evaluated. A more comprehensive model including a wider range of variables would be useful for clinical practice.

## 5. Conclusions

Accurate interpretation of dental radiographs, especially those displaying mixed dentition, remains a cornerstone in dentistry, directly influencing patient diagnosis and subsequent treatment planning. Our research has significantly contributed to this sphere by introducing a collaborative learning model that seamlessly merges two state-of-the-art deep learning systems: one focused on tooth segmentation, with special attention to differentiating between primary and permanent teeth in mixed dentition scenarios, and another emphasizing filling identification. A standout aspect of our approach is the creation of specialized models for both adults and children, further honing its precision in detecting primary teeth amidst the mixed dentition. With our model exhibiting high accuracy in these tasks, we offer a robust solution to mitigate human errors in radiographic readings. Beyond its diagnostic utility for experienced practitioners, our model also serves as a valuable teaching tool for dental students. As we move forward, embracing the power of AI in dental diagnostics, our research paves the way for enhanced patient care, increased diagnostic reliability, and more informed patient-dentist interactions.

## Author contributions

E. Bumann contributed to the conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, supervision, validation, visualization, and drafting, reviewing, and editing the manuscript. S. Al-Qarni & G. Chandrashekar contributed to the conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, and drafting, reviewing, and editing the manuscript. R. Sabzian contributed to the visualization and review and editing of the manuscript. B. Bohaty contributed to the investigation, resources, and reviewing and editing the manuscript. Y. Lee contributed to the conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, visualization, and drafting, reviewing, and editing the manuscript. All authors gave their final approval and agreed to be accountable for all aspects of the work.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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