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Evaluation of tooth development stages with deep learning-based artificial intelligence algorithm

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Abstract

Background This study aims to evaluate the performance of a deep learning system for the evaluation of tooth development stages on images obtained from panoramic radiographs from child patients.

Methods The study collected a total of 1500 images obtained from panoramic radiographs from child patients between the ages of 5 and 14 years. YOLOv5, a convolutional neural network (CNN)-based object detection model, was used to automatically detect the calcification states of teeth. Images obtained from panoramic radiographs from child patients were trained and tested in the YOLOv5 algorithm. True-positive (TP), false-positive (FP), and false-negative (FN) ratios were calculated. A confusion matrix was used to evaluate the performance of the model.

Results Among the 146 test group images with 1022 labels, there were 828 TPs, 308 FPs, and 1 FN. The sensitivity, precision, and F1-score values of the detection model of the tooth stage development model were 0.99, 0.72, and 0.84, respectively.

Conclusions In conclusion, utilizing a deep learning-based approach for the detection of dental development on pediatric panoramic radiographs may facilitate a precise evaluation of the chronological correlation between tooth development stages and age. This can help clinicians make treatment decisions and aid dentists in finding more accurate treatment options.

Keywords Artificial intelligent, Deep learning, Demirjian method, Pedodontic panoramic radiography, Tooth development stages

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Introduction

According to academic research, the process of dental development is a complex phenomenon that lasts from the prenatal stage until the age of twenty [1]. The degree and stages of calcification of teeth provide clinicians with information about abnormal sequences so that timely preventive measures can be taken [2]. Assessment of dental developments is important for evaluating occlusion and growth development, as well as in forensic applications [3]. It is possible to estimate a patient's age by evaluating the development status of their teeth. Additionally, by gathering data from multiple patients, we can determine the dental development status of the population [4, 5]. Demirjian's method determines the development status of teeth and estimate dental age by identifying the stages of seven left mandibular permanent teeth [6]. We selected this method for its internationally recognized validity and reliability in assessing tooth development.

Demirjian's method utilizes dental radiographs to determine the dental development status by converting the developmental stages of each tooth into maturation scores and evaluating them [3]. Panoramic radiographs are extraoral radiographs that provide a general overview of teeth and jaws, and provide the necessary information for diagnosing problems such as dental development, tooth loss, dental caries, periodontal problems, and impacted teeth [7]. Regrettably, the interpretation of these commonly utilized radiographs is challenging and necessitates clinical expertise. Dental problems can be overlooked by even experienced dentists during a radiological examination [8].

Artificial intelligence (AI) applications in dental radiology are being developed to reduce errors in subjective evaluations [7, 9, 10]. Significant progress has been made in the field of AI recently. AI involves machines performing complex tasks that mimic human cognitive functions, including problem-solving, decision-making, and recognition of objects and words [11]. Machine learning, within the realm of AI, involves computers autonomously learning from the accumulation of data [12].

Deep learning (DL), a subset of machine learning, is fundamental to many AI tools for interpreting images. Convolutional neural networks (CNN), a type of DL architecture, extract diverse features through multiple layers of backpropagation algorithms, particularly suited for complex and large-scale image processing [13]. CNNs mimic interconnected neurons in the brain, adept at capturing versatile image features and performing classification tasks. Machine learning, under AI, allows computer models to learn and predict by identifying patterns, much like radiologists analyze cases [12, 14].

In this research, YOLOv5 was used to automate the classification of tooth developmental stages in images obtained from panoramic radiographs from child patients [15–17]. YOLOv5 outperforms other methods with its simplified training and inference on custom datasets. It features rapid training and multiple export options, utilizing a genetic algorithm for anchor box generation and mosaic augmentation to enhance learning from diverse images. YOLOv5' s regression-based approach predicts classes and bounding boxes for entire images in one step, setting it apart in object detection [15–17].

AI techniques such as CNNs show promise in assisting clinicians in the analysis of medical images, disease diagnosis and therapeutic decision-making. AI research utilizing CNNs has also demonstrated advancements within the domain of dentistry. CNNs have shown high performance in maxillary sinusitis diagnosis in panoramic radiography [18], cephalometric landmark detection [19], or root morphological classification [20]. For caries detection, CNNs also showed good performance in periapical [21] and bitewing imaging [22, 23]. The study aims to use deep learning-based AI models on images obtained from panoramic radiographs from child patients to assess tooth development stages in children aged 5–14 years, which are commonly used in dental practice.

Materials and methods

Study design

In this research, the YoloV5 algorithm was used to create models of automatic tooth-developing stages in images obtained from panoramic radiographs from child patients. The purpose of this model was to label. Recep Tayyip Erdoğan University Faculty of Medicine Non-Interventional Clinical Research Ethics Committee granted ethical approval for the study (decision date, meeting number, and decision number: 10.11.2022/203). The research followed the guidelines outlined in the Helsinki Declaration. The present investigation employed a retrospective design, utilizing a collection of images obtained from panoramic radiographs from child patients from individuals between the ages of 5 and 14 years. These radiographs were originally obtained for diverse clinical purposes at the Faculty of Dentistry of Recep Tayyip Erdoğan University.

Preparation of the data set

A total of 1500 images obtained from panoramic radiographs from child patients images were taken using the Planmeca Promax 2D S2 device (Planmeca Oy; Helsinki, Finland) with the parameters of 66 kVp, 8 mA, and 16.6 s. These images were of high quality, showing no image artifacts, tooth deficiencies, or excesses. Additionally, there were no signs of any syndrome within the appropriate age range. The panoramic radiographs evaluated in the study were obtained from patients aged between 5 and 14 years for dental examination and treatment. Sex and age characteristics were recorded for each patient.

Images obtained from panoramic radiographs from child patients with any syndrome, systemic disease, dental anomaly, missing teeth or trauma history were excluded from the study by an Oral, Dental and Maxillofacial Radiologist (D.N.G.) with 5 years of professional experience. Only high-quality images obtained from healthy children during routine examinations were included, contributing to the quality of the study results by adhering to the stages of the Demirjian Method, the tooth development method systematically chosen for evaluation and labelling.

Data labelling

The images obtained from panoramic radiographs from child patients were labelled using the CranioCatch Labelling software (Eskisehir, Turkey) by a Pedodontics Specialist with 4 years of professional experience and also the corresponding author of the study (A.K.), an Oral, Maxillofacial and Dental Radiology Specialist with 5 years of professional experience (D.N.G.), a Pedodontics Specialist trainee with 1.5 years of professional experience (F.Y.). Tags were used to label teeth in the left mandibular area according to the Demirjian tooth development method. Labeling was performed by three researchers: the first labeler, A.K.; the second labeler, D.N.G.; and the third labeler, F.Y; all labels were approved by the joint decision of two Oral, Maxillofacial and Dental Radiology Specialist (İ.Ş.B., and E.B.).

In the labeling process, first the left lower mandibular jaw image was determined by placing it in a box. Then, the boundaries of the teeth in that region were drawn from the crown to the root and matched with the appropriate Demirijan stage. After consensus review by labelers, all data were approved by radiologists, so there is no need for Kappa or concordance testing.

Panoramic radiography images of pediatric patients whose chronological age at the time of image acquisition was between 5 and 14 years were included in the study. However, panoramic radiography images of individuals with craniofacial syndromes, cleft lip and palate, craniofacial bone diseases, and those who underwent orthognathic surgery, and panoramic radiography images with poor quality due to metal artifacts, positioning errors during image acquisition, and other factors causing image distortion were not included in the study.

Demirjian method

There are several methods available for estimating age based on tooth development, including Nolla [24], Moorrees [25], Willems [26], Cameriere [27], and the Demirjian Method [28], which is the one included in this study. We chose to incorporate the Demirjian Method into this study because it is widely recognized as the most used method for age estimation. Initially applied to children in the French-Canadian population, this method has been subsequently validated in diverse populations [28]. This technique differentiates between crown formation stages, denoted as A to D, and root development stages, labelled as E to H [6].

The Demirjian method, which is the most commonly used method in age estimation, was developed in 1973 by Demirjian et al. [28]. It was initially applied to children in the French-Canadian population and subsequently tested in various populations [28]. In this method, the mineralization stages of 7 left mandibular teeth are evaluated according to predetermined scores using panoramic radiographs. Tooth formation is divided into 8 stages (A-H), with specific criteria outlined separately for each tooth. Each stage of the 7 teeth is biologically scored, and the sum of the scores provides an estimate of the maturity of the tooth. The overall maturity score is then converted to dental age according to established gender-specific tables. These standard scores were created separately for each gender [28].

The Demirjian Method Tooth Development [28] (Fig. 1);

Stage A: Cone-shaped or cone-shaped calcification begins at the top of the tooth in single-rooted and multi-rooted teeth. These calcification points are not yet fused.
Stage B: There is fusion in one or more points of calcification points. The outer surface is regular.
Stage C: The occlusal surface undergoes the completion of enamel formation, dentin tissue becomes apparent, and the pulp chamber becomes visible.
Stage D: Crown formation completes at the junction of cementum and enamel, and root formation starts as a needle shape.
Stage E: The straight lines on the walls of the pulp chamber are not continuous due to the pulp horn formation. Molar teeth exhibit a shorter root length than crown height, and the start of the bifurcation point is visible.
Stage F: The length of the root equals or surpasses that of the crown. The division in the root progresses downward, with a crescent shape that ends in a clear and distinct funnel shape.
Stage G: The walls of the root canal are parallel, and the apex point is partially open.
Stage H: The apex of the root canal is entirely sealed, and a consistent periodontal gap is evident around the root.

Developing deep learning algorithms

Deep learning algorithm

The PyTorch implementation of YOLOv5 exhibits distinct characteristics from its predecessors in the YOLO family. It uses the CSP backbone and PA-NET neck, just like in YOLOv4. The model used in YOLOv4 is also used in the head section. The employed activation functions

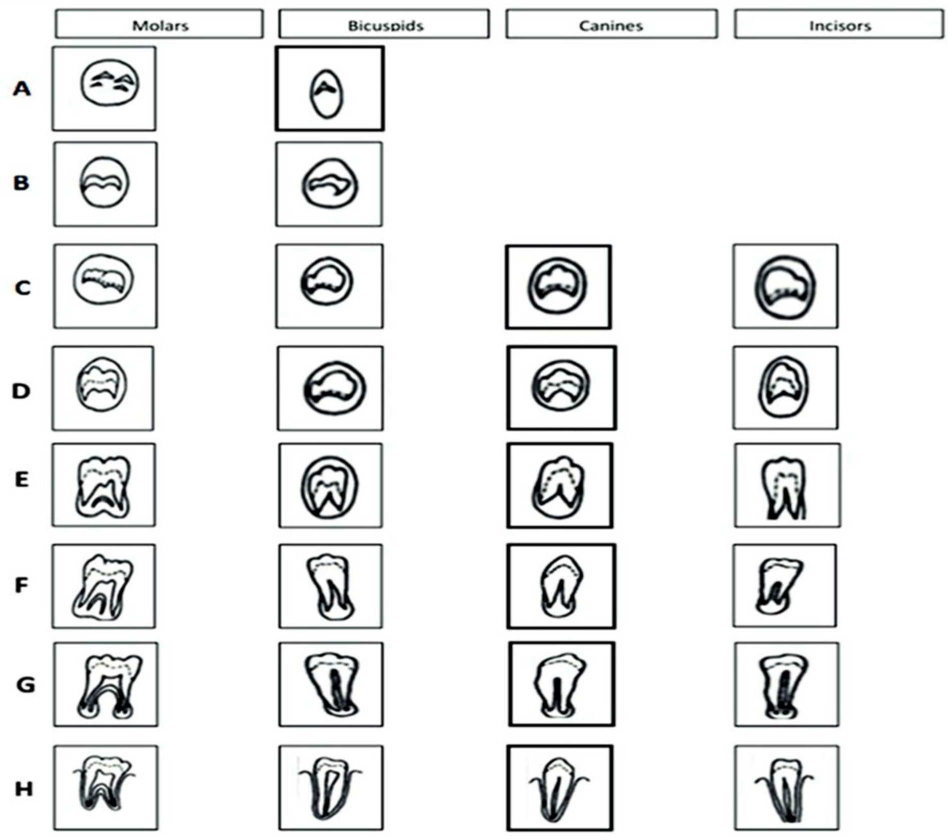

Fig. 1 Tooth development stages in terms of the Demirjian Method

comprise leaky rectified linear units (ReLU) and sigmoids. Within YOLOv5, leaky ReLU is employed in the intermediate and hidden layers, while sigmoid is utilized in the ultimate detection layer. This deep learning model can perform detection and classification operations simultaneously, quickly and accurately. The basic architecture of YOLOv5 is as follows:

Backbone: YOLOv5 uses a "backbone" to perform basic feature extraction. It can be based on models such as ResNet, CSPDarknet, or EfficientNet.

Neck: This stage performs further feature extraction by combining and processing feature maps at various scales.

Head: This part is used to classify objects, determine their locations, and extract possible bounding box coordinates. Multiscale box predictions are often performed here.

The hyperparameters of the Yolov5x model were as follows: hyperparameters used for training; image size: 640, batch size: 16, learning rate: 0.01, optimizer: Stochastic Gradient Descent (SGD), anchor_t: 4.0. Epoch_count=600 (early sr-top 122). Hyperparameters used for augmentation; mosaic=1.0, scale=0.5, copy_paste=0.0, hsv_s=0.7, hsv_v=0.4, translate=0.1.

Pre-processing and training

Panoramic radiography images, with a mixed size totalling 1500, were resized to 1024×512 dpi. The clarity of blurred areas in the images' surroundings was enhanced through the application of the contrast-limited adaptive histogram equalization (CLAHE) technique. The Demirjian method was used to label 56 different external development stages, including 31-A, 31-B, 31-C, 31-D, 31-E, 31-F, 31-G, 31-H, 33-A, 33-B, 33-C, 33-D, 33-E, 33-F, 33-G, 34-H, 35-A, 36-B, 36-C, 36-D, 36-E, 36-F, 36-G, 36-H The diagram depicted in Fig. 2 is presented for reference.

The performance of the multiclass model developed was evaluated using the test dataset, which was not included in the training process. Below is the table displaying the number of labels for each of the 46 classes (Table 1).

In total, 80% of the 1458 data were separated as training (1167), 10% (146) as testing and 10% (145) as validation.

The AI algorithm was developed using Python, an open-source programming language (version 3.6.1; Python Software Foundation, Wilmington, DE, USA). The AI algorithm was developed using the PyTorch library and YoloV5. The training process utilized computer equipment from Eskisehir Osmangazi Faculty of

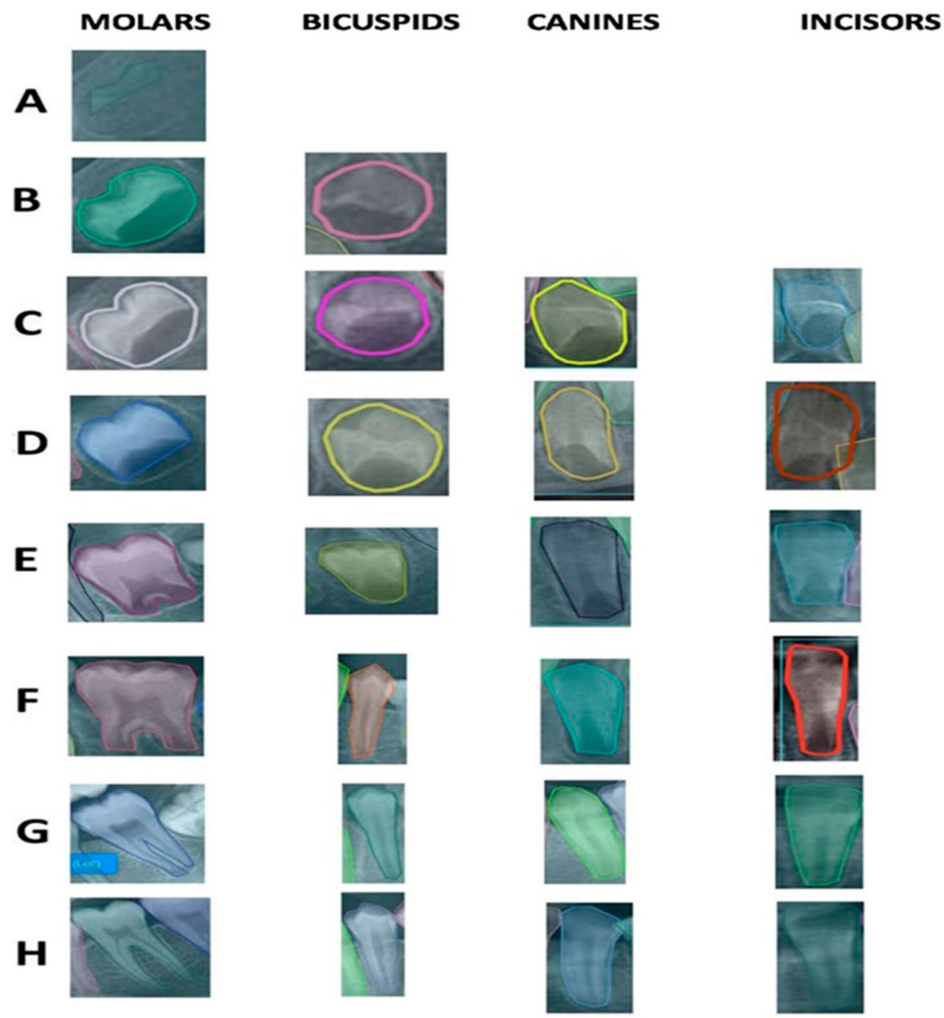

Fig. 2 Labeling of tooth development stages according to the Demirjian Method

Dentistry Dental-AI Laboratory, comprising a Dell PowerEdge T640 Calculation Server, a Dell PowerEdge T640 GPU Calculation Server, and a Dell PowerEdge R540 Storage Server, all manufactured by Dell Inc. (Dell Inc., Texas, USA). Object detection training was performed using YOLOv5, involving 600 epochs and 46 classes (Fig. 3).

The Process of Reaching the Final Prediction of YOLOv5.

- The model detects all objects (e.g. teeth) in an image in a single pass.
- It estimates the bounding boxes and class labels for each object.
- The Non-Maximum Suppression (NMS) process reaches the final predictions by selecting the best predictions.
- As a result, the model produces an output that contains the positions and class labels of the detected teeth.

This process enables YOLOv5 to perform object detection with high accuracy and speed. So the Process of Tooth Detection with YOLOv5;

1. Image Acquisition and Processing:

• The tooth image is acquired, resized, and normalized.

2. Extraction of Feature Maps:

• The image is passed through deep neural network layers to create feature maps.

3. Estimation of Bounding Boxes:

• The image is divided into grid cells and bounding boxes are estimated for each cell.

4. Filtering and Non-Maximum Suppression (NMS):

• Low probability boxes are eliminated, the most reliable boxes are selected with NMS.

5. Final Prediction:

• Tooth classes are determined for the selected boxes and contours are drawn.

6. Output:

Table 1 Numerical values of test, train and valid label counts

Demirjian's method	Test label count	Train label count	Valid label count
31-D	0	2	0
31-E	12	161	23
31-F	27	224	21
31-G	23	194	25
31-H	83	587	77
32-C	0	1	0
32-D	1	27	3
32-E	28	285	34
32-F	28	228	24
32-G	26	197	30
32-H	62	430	55
33-C	0	35	0
33-D	17	159	20
33-E	40	413	55
33-F	47	323	40
33-G	19	107	13
33-H	23	135	19
34-B	0	1	0
34-C	5	63	6
34-D	31	341	44
34-E	52	389	49
34-F	26	173	24
34-G	17	96	14
34-H	14	109	10
35-A	0	1	0
35-B	3	22	3
35-C	14	171	20
35-D	48	400	46
35-E	31	277	37
35-F	25	155	26
35-G	15	81	7
35-H	10	70	7
36-C	0	0	1
36-D	0	5	0
36-E	19	181	21
36-F	29	301	39
36-G	41	285	36
36-H	59	399	51
37-A	1	5	1
37-B	2	37	2
37-C	29	294	38
37-D	42	339	43
37-E	42	333	41
37-F	17	85	11
37-G	9	72	9
37-H	5	16	1
Total Label Count	1022	8209	1026

• Class labels, bounding boxes and confidence scores of the detected teeth are output.

In this way, the YOLOv5 model detects teeth quickly and accurately.

Evaluation of performance

In artificial intelligence studies, it is important that the labeled data is clean. 10% of all labeled data is not used at all in training and is separated as a test data set. After training and validation, the label areas predicted by the developed model are compared with the labels in the test data set to obtain TP, FP, FN values. We developed an algorithm to find the classification of the development stage. The algorithm was trained for this purpose. Therefore, it is not capable of finding negative cases due to the learned positive conditions. Therefore, true negatives were not calculated to evaluate the model success. A confusion matrix was used to evaluate how well a classification mechanism performs by examining the precision and anticipated classifications of data.

True Positive (TP): The proportion of true positive cases correctly identified by the model, while false positive (FP) refers to the proportion of negative instances erroneously identified as positive during classification.

False Negative (FN): The rate of falsely negative cases among positive cases.

After obtaining various metrics, we computed the sensitivity, precision, and F1 score.

Sensitivity: In artificial intelligence studies, sensitivity (or recall) indicates how successfully the model detects true positives (TP - True Positive).

Precision rates the proportion of true positive predictions out of all predicted values.

F1 score: The F1 score is a metric used for assessing segmentation performance that takes into account both precision and recall. Specifically, it considers the extent of overlapping pixels between the predicted and ground truth results. To compute the F1 score, we need to calculate sensitivity and precision (Table 2).

Table 2 displays the calculation of sensitivity, precision, and F1 score.

Results

Of the images obtained from panoramic radiographs from child patients assessed in the study, 811 (54.07%) belonged to girls, while 689 (45.93%) belonged to boys. The average age of the children whose images obtained from panoramic radiographs from child patients were evaluated was 8.43±2.2 years.

On 1167 training images, the root development stages of the left mandibular teeth were detected in all teeth on the image, resulting in the creation of a total of 46 different classes. Out of the 146 images in the test group, 1022 labels were identified. Among these, 828 were TP, 308 were FPs, and only one was a FN. The detection model for tooth stage development had a sensitivity of 0.99, precision of 0.72, and F1-score of 0.84. (Table 3; Figs. 4, 5, 6, 7, 8 and 9).

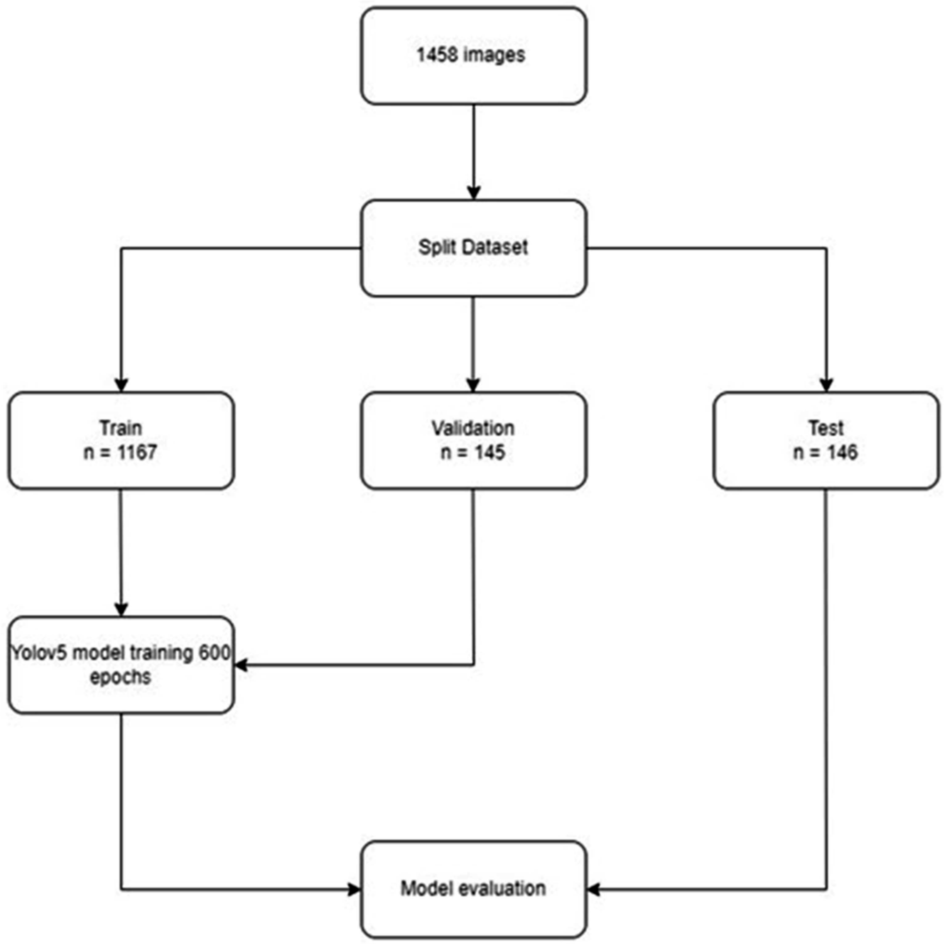

Fig. 3 The diagram of model development stages and 'data not used in training were used for testing purposes to evaluate the success of the model'

Table 2 Calculation of sensitivity, precision, and F1 score after TP, FP, and FN are calculated

Sensitivity	TP/(TP + FN)
Precision	TP/(TP + FP)
F1 score	2TP/(2TP + FP + FN)

Discussion

This study indicates that CNNs-based AI algorithms are promising for accurately and effectively detecting and segmenting tooth development in panoramic radiographs of child patients. Employing a deep learning-based approach to detect dental development in images obtained from panoramic radiographs from child patients may enable precise assessment of the chronological correlation between dental developmental stages and age. This has the potential to assist clinicians in making informed treatment decisions and aid dentists in identifying more accurate treatment options.

AI studies have replaced classical engineering methods and are rapidly improving medical and dental image interpretation through DL and CNNs [29]. The introduction of new technology has inaugurated a fresh era in the fields of diagnosis and treatment planning [30]. Dentists may sometimes provide subjective or incorrect diagnoses. To address this issue, radiologic AI systems are designed to provide automatic, routine, and simplified evaluations for quicker image analysis. This not only saves time for radiologists working on more complex cases, but also facilitates early diagnosis, treatment planning, and information archiving through AI analysis on images obtained from panoramic radiographs [31, 32].

Studies using panoramic radiographs have evaluated various dental issues including alveolar bone loss [33, 34], periodontal disease [35], dental caries [23, 36], apical lesions [37], vertical root fractures [38], root morphology [20], and impacted teeth [10], with moderate to high

Table 3 The results of the AI model success metrics

True positive	False positive	False negative	Sensitivity	Precision	F1 score	Epoch	Learning rate	Model
828	308	1	0,9987	0,7288	0,8427	600	0.01	Yolov5

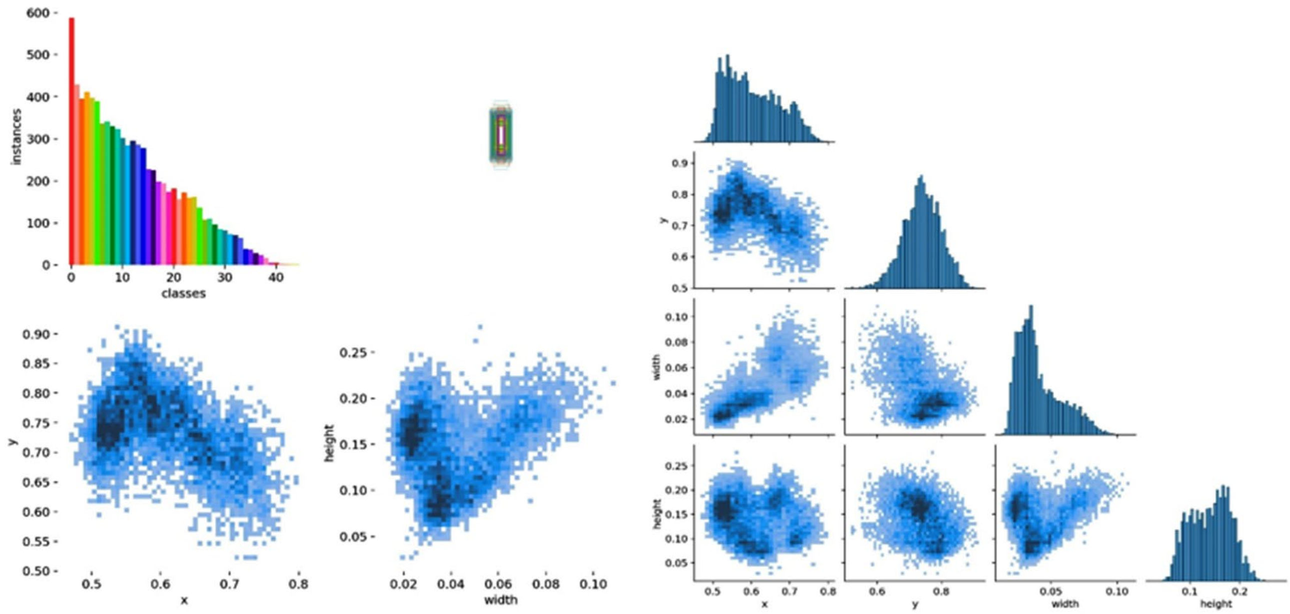

Fig. 4 Label correlogram created using the Demirjian Method. To visually compare labels, they are presented in Fig. 4 as label correlation. The size of the points in the graph represents the confidence score of YOLOv5x for each object. The bigger the point, the higher the confidence score

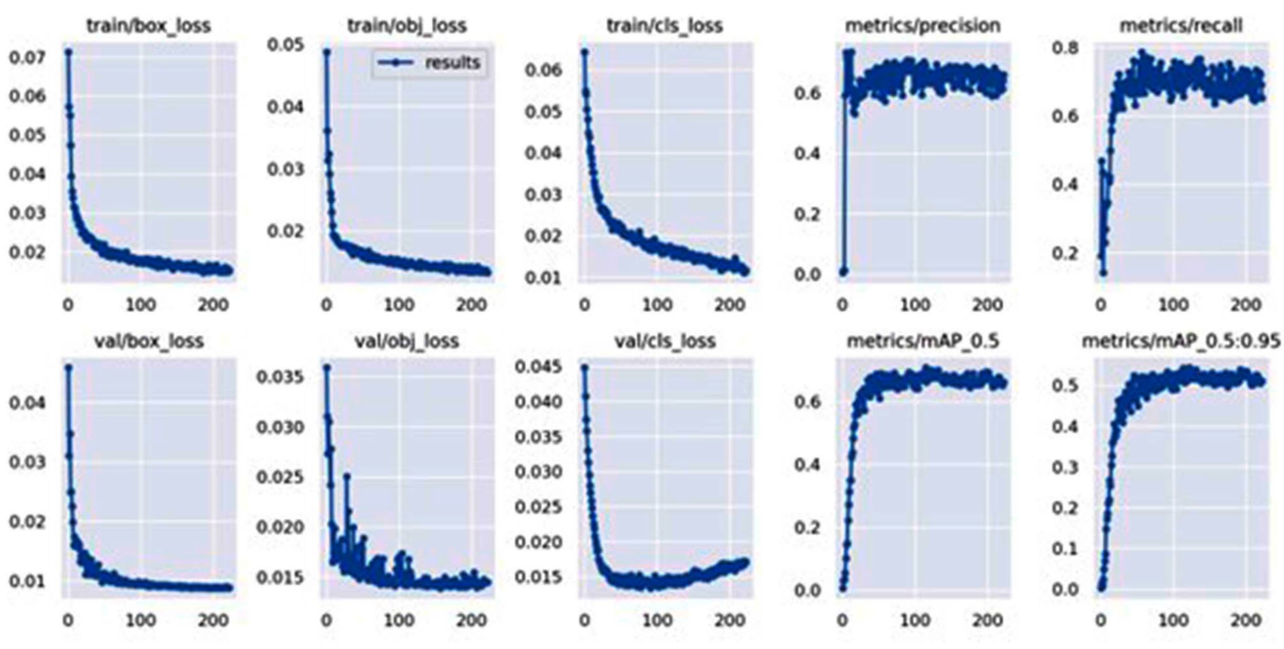

Fig. 5 The training results by YOLOv5 and success metrics. The training results of the evaluations made with YOLOv5 are presented in Fig. 5. In these graphs, the variation of box loss, objectness loss, segmentation loss, classification loss, precision, recall, and mean average precision values were schematized separately for training and validation data sets. Box loss graphs show the size of the center of the area where the relevant parameter is located and how much it covers the relevant area

success rates. No studies have been reported on the use of CNNs for dental development evaluation. Our current study is the first to explore this area. The results of the study show that CNNs are highly effective in identifying dental development, with performance almost identical to that of labelled training data. Moreover, the CNNs system's ability to detect tooth development is comparable to expert-level results.

Demirjian's method is a technique used to determine the developmental stages of permanent teeth in the lower left jaw and estimate dental age [28]. This method is chosen due to its internationally recognized validity and reliability in assessing tooth development. Proposed

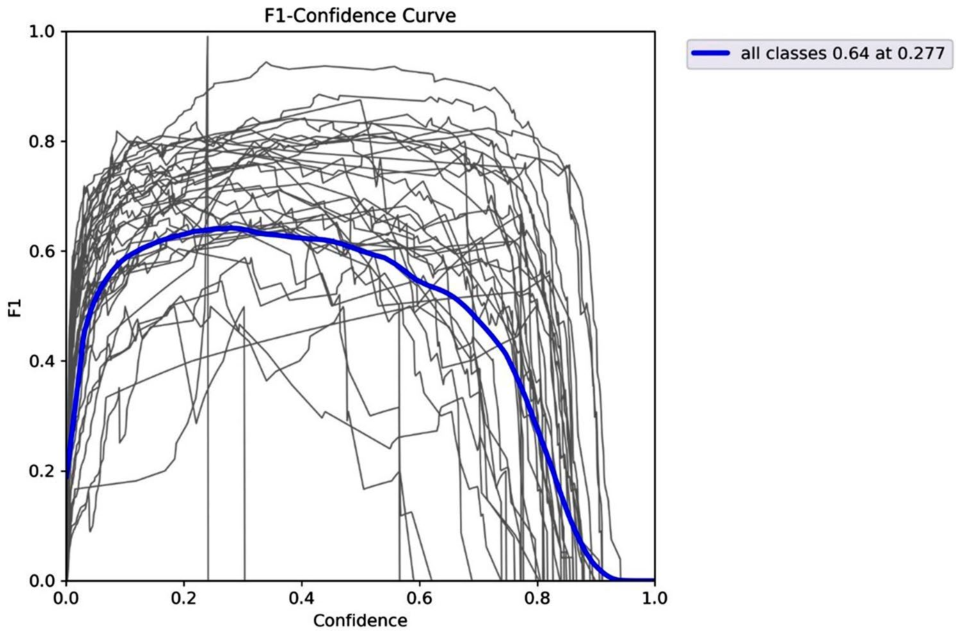

Fig. 6 The graphics of the F1-confidence curve of tooth development stages in terms of Demirjian Method by AI model. F1-confidence curve application measurement was calculated and the application result that the model effectively analyzed are indicated in Fig. 6. Correlograms are a type of two-dimensional (2D) histogram and provide the ability to show each axis of related data relative to the other axis. Thus, the relationship of entire dataset can be viewed at a glance in this graph and the label distributions can be seen. Therefore, the information showing the position (x, y), width, and height of the labels of the relevant parameters was brought together in a graph

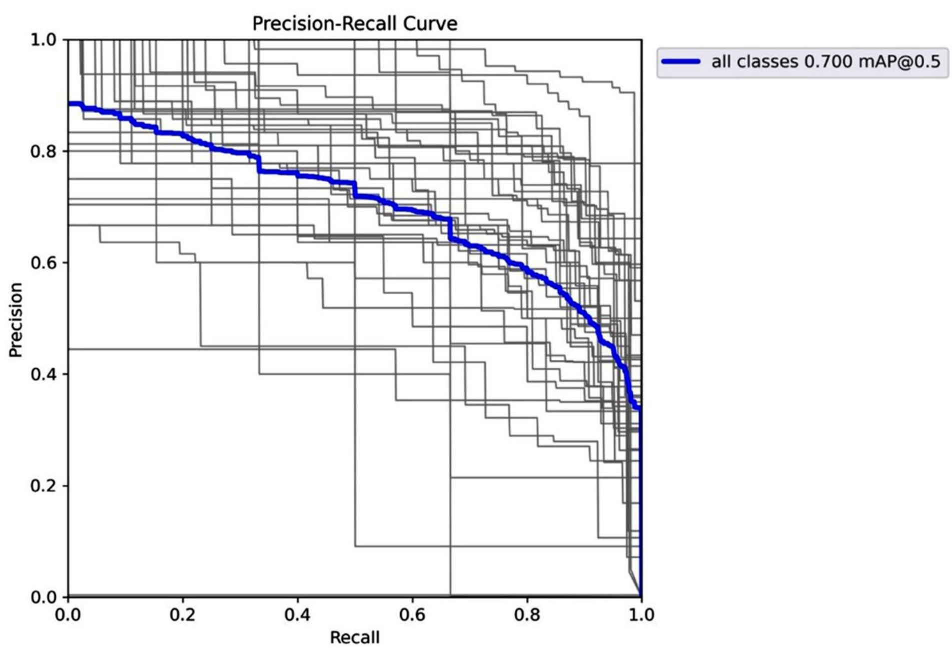

Fig. 7 The graphics of the Precision-Recall curve of tooth development stages in terms of Demirjian Method by AI model. Precision-Recall curve application measurement was calculated and the application result that the model effectively analyzed are indicated in Fig. 7. Correlograms are a type of two-dimensional (2D) histogram and provide the ability to show each axis of related data relative to the other axis. Thus, the relationship of entire dataset can be viewed at a glance in this graph and the label distributions can be seen. Therefore, the information showing the position (x, y), width, and height of the labels of the relevant parameters was brought together in a graph

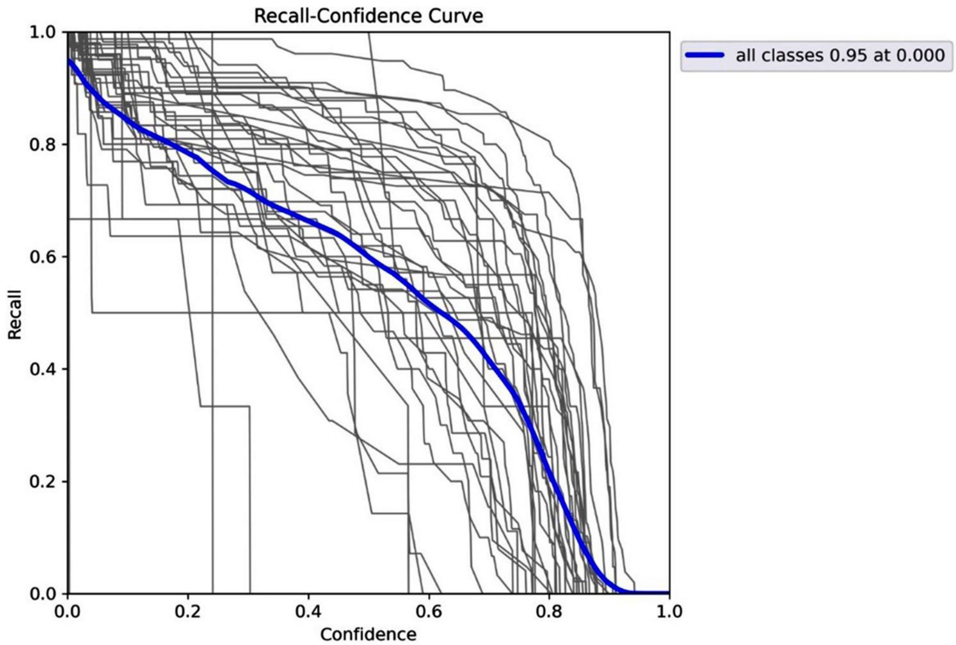

Fig. 8 The graphics of the Recall-Confidence curve of tooth development stages in terms of Demirjian Method by AI model. Recall-Confidence curve application measurement was calculated and the application result that the model effectively analyzed are indicated in Fig. 7. Correlograms are a type of two-dimensional (2D) histogram and provide the ability to show each axis of related data relative to the other axis. Thus, the relationship of entire dataset can be viewed at a glance in this graph and the label distributions can be seen. Therefore, the information showing the position (x, y), width, and height of the labels of the relevant parameters was brought together in a graph

by Demirjian et al. [28], the method for estimating dental age using digital panoramic radiography is currently the most widely applied due to its rationality, convenience, and objectivity. Hostiuc et al. [39] conducted a meta-analysis examining the effectiveness of the Demirjian Method in age estimation. They noted it as one of the most commonly used methods for evaluating tooth development and dental age. Their study showed that, on average, the Demirjian Method tends to overestimate chronological age by approximately six months for both genders, with the least error occurring in the 12–14 and 15–15 age ranges. It was emphasized that caution is necessary when using the method after age 16, as it tends to produce significant errors. Movahedian et al. [40] compared the accuracy of age predictions in children using the Demirjian method and root resorption rates in deciduous teeth. They concluded that both the Demirjian method and root resorption methods are effective and applicable for determining age in children.

The prevailing deep learning approach for handling image data is the deep convolutional neural network architecture. This method is favoured for its capacity to deploy effective self-learning algorithms and harness significant computational power, thereby achieving superior performance in tasks such as detecting, classifying, and quantifying image data [41, 42]. AI research in pediatric dentistry is a developing field. Significant research efforts are dedicated to tooth detection and numbering utilizing CNNs systems [43–45].

Kaya et al. [43] evaluated the effectiveness of a deep learning system using the YOLO Algorithm for the automatic finding and enumeration of teeth on pediatric patients' panoramic radiographs aged 5–13 years, as in the current study. However, they used the Yolov4 model, unlike us. In their study, 4545 data sets were used, and the average precision values were 92.22%, which is higher than this study. Kılıç et al. [44] conducted a study to test how effective a deep learning methodology is in identifying and quantifying primary teeth in panoramic radiographs of children aged 5 to 7 years. They used 421 panoramic images and the quicker R-CNN Inception v2 (COCO) model. The precision values they obtained were 0.95, which was found to be better than the ones obtained in this study.

In pediatric patients, studies in AI have been conducted on images obtained from panoramic radiographs from child patients to explore tooth detection and numbering [26, 46–49]. Duman et al. [32], developed and evaluated an AI model based on CNNs to diagnose taurodontic teeth on on images obtained from panoramic radiographs. Their study aimed to create automated taurodont tooth segmentation via the U-Net model implemented in PyTorch. 434 panoramic images of individuals aged 13 and above were employed to assess the sensitivity, precision, and F1 score values for taurodont tooth

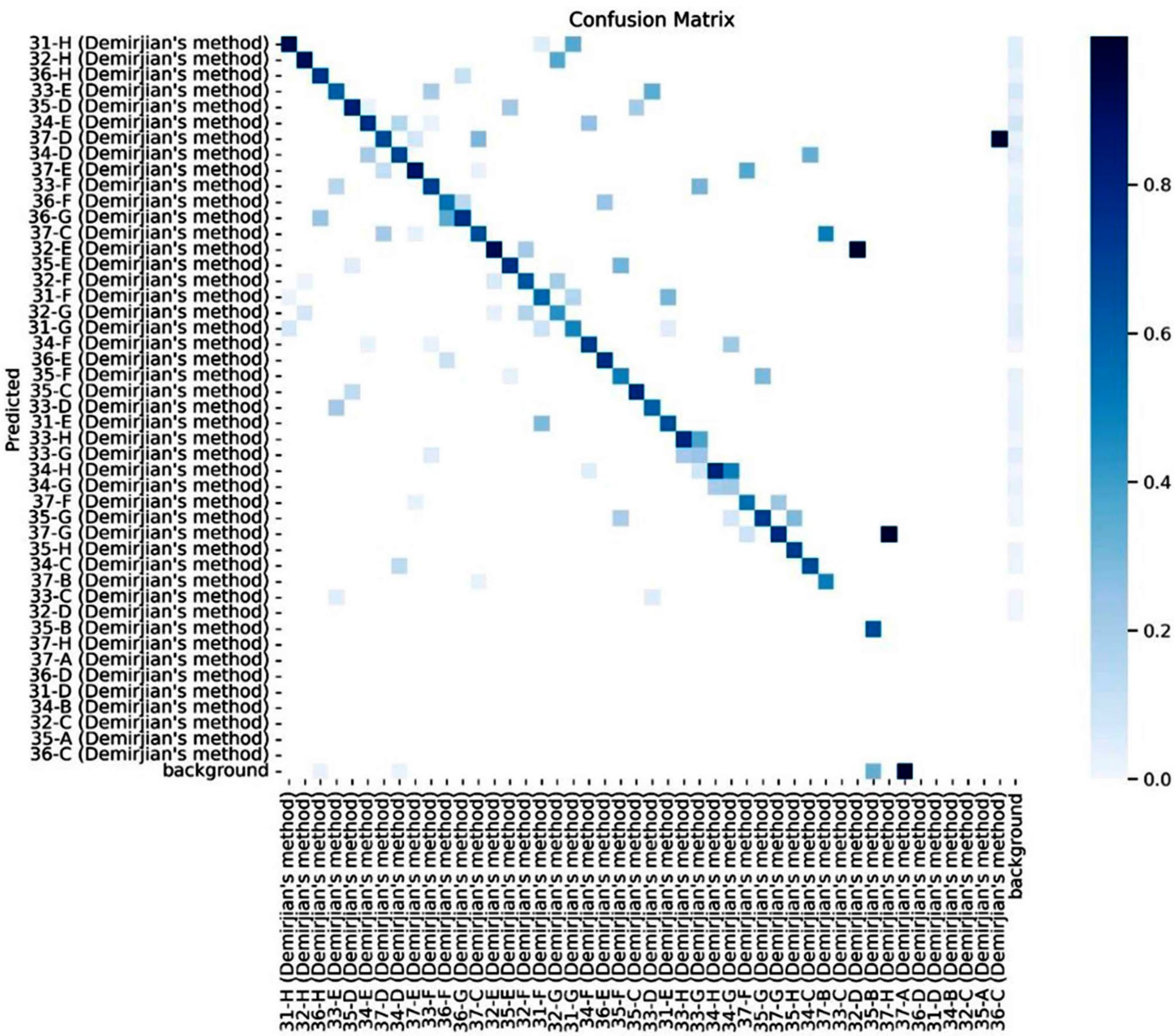

Fig. 9 The confusion matrix showing the YOLOv5 segmentation performance for the test sample. Confusion matrix metrics are shown in Fig. 9. The model's performance metrics include a precision value of 0.72 and an F1 score of 0.84 (Table 3)

segmentation. The results showed that the sensitivity, precision, and F1 score values were 0.86, 0.78, and 0.82, respectively. In this study, we achieved sensitivity, precision and F1 values of 0.99, 0.72 and 0.84 respectively. To obtain these values, we calculated TP, FP and FN values and applied the procedure of calculating success metrics with confusion matrix using these data. These data indicate that our artificial intelligence model evaluating tooth development is effective. Okazaki et al. [49] developed and evaluated deep learning algorithms that can categorize different types of dental abnormalities in panoramic radiographic images. They used 150 data sets and found that the precision rate was 70.8%, which is similar to the result of this study. Liu et al. [48] conducted a study to evaluate the effectiveness of AI in assessing the ectopic eruption of maxillary permanent first molars in panoramic radiographs of children aged 4–9 years. The study utilized a total of 1580 panoramic radiographs, revealing the utility and promise of a deep learning-based automated scanning system.

Recently, the results of studies using AI for dental age estimation have started to enter the literature [3, 51–53]. In their study, Wu et al. [3] conducted a study to compare machine learning techniques with traditional dental development methods, such as the Demirjian method, to estimate dental age. The study used panoramic radiographs of children aged between 2.6 and 17.7 years. A total of 2052 panoramic images were analyzed, and the results showed that machine learning was reliable for individuals aged between 4 and 14 years. Zaborowicz et al. [52] managed a study where they used a deep learning model to estimate the chronological age of between 2 and 12 years old, based on dental and bone parameters extracted from panoramic radiographs. The study examined a total of 619 data sets, with the correlation coefficient R2 ranging between 0.92 and 0.96, signifying a robust correlation between the estimated and actual chronological age.

The present investigation endeavours to identify dental advancements through the utilization of on images obtained from panoramic radiographs from child patients and deep learning methodologies. The study used the YOLOv5 version of the deep learning algorithm. YOLO (You Only Look Once) is an object detection technique that implements CNNs. It was introduced by Redmon et al. [15] and works by converting image pixels into bounding box coordinates and probabilities of classification as a single regression problem. The architecture of YOLO maintains a significant level of average precision while providing extensive training and real-time processing capabilities [54]. Dai et al. [55] employed a deep mesiodens localization network developed within the YOLOv5 framework to understand the nonlinear correlation between image features and mesiodens in images obtained from panoramic radiographs from child patients across primary, mixed, and permanent dentition. Meanwhile, Warin et al. [56] utilized CNNs-based object detection models, specifically Faster R-CNN and YOLOv5, for the identification of mandibular fractures in images obtained from panoramic radiographs from child patients. It can be inferred that in recent years, a limited number of dental research studies have integrated YOLOv5 as a CNNs algorithm, as evidenced in the literature [56–58].

Due to the number of data and the time-consuming nature of the labeling procedure, the labeling procedure in artificial intelligence studies is carried out by different researchers who are experts in their fields. While consensus among researchers is important, passing all labels through an approval mechanism is crucial to prevent data pollution. In our study, before training on the labeled data, we had the labels approved by two independent academics experienced in both artificial intelligence and dentomaxillofacial radiology.

In this investigation, while our current algorithm relying on YOLOv5 demonstrated promising outcomes, there are certain constraints in our research. In this study, we encountered challenges in obtaining sufficient data for all stages of each tooth group, and as a result, we evaluated the performance of the models developed with the available data. The number of samples we worked on, the fact that different researchers took part in labeling and that it was not done by a single source can be counted among the study limitations. Despite these limitations, the findings of our study are promising, indicating the potential for improvement and advancement in this area through further research. Future studies should focus on assessing prediction accuracy with larger datasets, comparing them against diverse dental development methodologies, and exploring alternative CNNs algorithms. Developing advanced methods could enhance the precision of dental development determination. Prospective research initiatives may yield valuable insights for the specified juvenile cohort by evaluating dental maturation, tooth age, and chronological age in combination with AI technologies.

Conclusion

The artificial intelligence algorithm developed to evaluate the performance of the deep learning system for the evaluation of tooth development stages was found to be effective in evaluating tooth development accurately and effectively. It can be said that this result of this study is promising for clinicians to make informed treatment decisions and determine more accurate treatment options.

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Author contributions
A.K., İ.Ş.B. and K.O. wrote the main manucsript text. A.K., D.N.G.,F.Y.Ş., Z.Y. labeled the panoramic radiographs. A.K., İ.Ş.B., Ö.Ç., E.B.,K.O. prepared all figures. All authors reviewed the manuscript.

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Data availability
Data is provided within the manuscript or supplementary information files.

Declarations

Ethical approval and consent to participate
The study was conducted with ethical approval from the Non-Interventional Clinical Research Ethics Committee Presidency of the Recep Tayyip Erdoğan University Faculty of Medicine, (decision date, meeting number and decision number: 10.11.2022/203). In our study, retrospective panoramic radiography archives were scanned and examined. We obtained institutional permission to use data from patients with these radiographs.

Human ethics
The study does not include samples of human tissues. Only radiographic images of the past were used. Institutional permission and ethical approval were obtained for this.

Consent for publication
Not Applicable.

Competing interests
The authors declare no competing interests.

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References

1. Ruiz-Mealin EV, Parekh S, Jones SP, Moles DR, Gill DS. Radiographic study of delayed tooth development in patients with dental agenesis. Am J Orthod Dentofac Orthop. 2012;141(3):307–14.
2. Kamal AT, Shaikh A, Fida M. Assessment of skeletal maturity using the calcification stages of permanent mandibular teeth. Dent Press J Orthod. 2018;23:44. e41-44. e48.
3. Wu TJ, Ling Tsai C, Huang YH, Fan TY, Chen YP. Efficacy of machine learning assisted dental age assessment in local population. Leg Med (Tokyo) Nov. 2022;59:102148.
4. Roberts GJ, McDonald F, Andiappan M, Lucas VS. Dental age estimation (DAE): data management for tooth development stages including the third molar. Appropriate censoring of stage H, the final stage of tooth development. J Forensic Leg Med Nov. 2015;36:177–84.
5. Bjelopavlovic M, Zeigner AK, Hardt J, Petrowski K. Forensic dental age estimation: development of new algorithm based on the minimal necessary databases. J Pers Med 2022;12(8).
6. Moca AE, Ciavoi G, Todor BI et al. Validity of the Demirjian method for dental age estimation in Romanian children. Child (Basel). 2022;9(4).
7. Angelopoulos C, Bedard A, Katz JO, Karamanis S, Parissis N. Digital panoramic radiography: an overview. Paper presented at Seminars in Orthodontics; 2004.
8. Athota A, Babu DBG, Nagalaxmi V, Raghoji S, Waghray S, Reddy CR. A comparative study of digital radiography, panoramic radiography, and computed tomography in dental implant procedures. J Indian Acad Oral Med Radiol. 2017;29(2):106.
9. Peretz B, Gotler M, Kaffe I. Common errors in digital panoramic radiographs of patients with mixed dentition and patients with permanent dentition. Int J Dentistry. 2012;2012.
10. Başaran M, Çelik Ö, Bayrakdar IS, et al. Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system. Oral Radiol. 2022;38(3):363–9.
11. Jacob ESoRcmoNEdSNBABAABCDCFV. What the radiologist should know about artificial intelligence–an ESR white paper. Insights into Imaging. 2019;10(1):44.
12. Nichols JA, Herbert Chan HW, Baker MA. Machine learning: applications of artificial intelligence to imaging and diagnosis. Biophys Rev. 2019;11:111–8.
13. Hwang J-J, Jung Y-H, Cho B-H, Heo M-S. An overview of deep learning in the field of dentistry. Imaging Sci Dentistry. 2019;49(1):1–7.
14. Hung K, Montalvao C, Tanaka R, Kawai T, Bornstein MM. The use and performance of artificial intelligence applications in dental and maxillofacial radiology: a systematic review. Dentomaxillofacial Radiol. 2020;49(1):20190107.
15. Redmon J, Divvala S, Girshick R, Farhadi A. You only look once: Unified, real-time object detection, In Proceedings of the IEEE conference on computer vision and pattern recognition. 2016; 779–788.
16. Altay A, Yılmaz SYOLO, Algoritması Kullanılarak. T Hücrelerinin Sınıflandırılması. İleri Mühendislik Çalışmaları ve Teknolojileri Dergisi,. 2022;(2):66–81.
17. Lei F, Tang F, Li S. Underwater target detection algorithm based on improved YOLOv5. J Mar Sci Eng. 2022;10(3):310.
18. Murata M, Ariji Y, Ohashi Y, Kawai T, Fukuda M, Funakoshi T, et al. Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. Oral Radiol. 2019;35(3):301–7.
19. Arık SÖ, Ibragimov B, Xing L. Fully automated quantitative cephalometry using convolutional neural networks. J Med Imaging (Bellingham). 2017;4(1):014501.
20. Hiraiwa T, Ariji Y, Fukuda M, Kise Y, Nakata K, Katsumata A, et al. A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on panoramic radiography. Dentomaxillofac Radiol. 2019;48(3):20180218.
21. Choi J, Eun H, Kim C. Boosting proximal dental caries detection via combination of variational methods and convolutional neural network. J Signal Process Syst Signal Image Video Technol. 2018;90(1):87–97.
22. Srivastava MM, Kumar P, Pradhan L, Varadarajan S. Detection of tooth caries in bitewing radiographs using deep learning. ArXiv; 2017.
23. Cantu AG, Gehrung S, Krois J, Chaurasia A, Rossi JG, Gaudin R, et al. Detecting caries lesions of different radiographic extension on bitewings using deep learning. J Dent. 2020;100:103425.
24. Nolla CM. The development of the permanent teeth. J Dent Child. 1960;27:254–66.
25. Moorrees CFA, Fanning A, Hunt EE. Age variation of formation stages for ten permanent teeth. J Dent Res. 1963;42:1490–502.
26. Willems G. A review of the most commonly used dental age estimation techniques. J Forensic Odontostomatol. 2001;19(1):9–17.
27. Cameriere R, Ferrante L, Liversidge HM, Prieto JL, Brkic H. Accuracy of age estimation in children using radiograph of developing teeth. Sci Int. 2008;(176);173–7.
28. Demirjian A, Goldstein H, Tanner JM. A new system of dental age assessment. Hum Biol. 1973;45(2):211–27.
29. Carrillo-Perez F, Pecho OE, Morales JC, et al. Applications of artificial intelligence in dentistry: a comprehensive review. J Esthet Restor Dent Jan. 2022;34(1):259–80.
30. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism Apr. 2017;69s:S36–40.
31. Ozden FO, Özgönenel O, Özden B, Aydogdu A. Diagnosis of periodontal diseases using different classification algorithms: a preliminary study. Niger J Clin Pract. 2015;18(3):416–21.
32. Duman S, Yılmaz EF, Eşer G, et al. Detecting the presence of taurodont teeth on panoramic radiographs using a deep learning-based convolutional neural network algorithm. Oral Radiol. 2023;39(1):207–14.
33. Kim J, Lee HS, Song IS, Jung KH. DeNTNet: deep neural transfer network for the detection of periodontal bone loss using panoramic dental radiographs. Sci Rep. 2019;26(1):17615.
34. Krois J, Ekert T, Meinhold L, et al. Deep learning for the radiographic detection of periodontal bone loss. Sci Rep. 2019;11(1):8495.
35. Revilla-León M, Gómez-Polo M, Barmak AB et al. Artificial intelligence models for diagnosing gingivitis and periodontal disease: a systematic review. J Prosthet Dent. 2022.
36. Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. J Dent. 2018;77:106–11.
37. Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T. Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endod J. 2020;53(5):680–9.
38. Fukuda M, Inamoto K, Shibata N, et al. Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiol. 2020;36(4):337–43.
39. Hostiuc S, Edison SE, Diaconescu I, Negoi I, Isaila OM. Accuracy of the Demirjian's method for assessing the age in children, from 1973 to 2020. A meta-analysis. Leg Med. 2021;52:101901.
40. Movahedian N, Abedi S, Memarpour M. Comparison of the Demirjian and root resorption methods to estimate dental age in radiographic images. J Dent Child . 2018;85(2):45–50.
41. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts H. Artificial intelligence in radiology. Nat Rev Cancer Aug. 2018;18(8):500–10.
42. Moawad AW, Fuentes DT, ElBanan MG, et al. Artificial Intelligence in Diagnostic Radiology: where do we stand, challenges, and opportunities. J Comput Assist Tomogr. 2022;01(1):78–90.
43. Kaya E, Gunec HG, Gokyay SS, Kutal S, Gulum S, Ates HF. Proposing a CNN method for primary and permanent tooth detection and enumeration on pediatric dental radiographs. J Clin Pediatr Dent. 2022;1(4):293–8.
44. Kılıc MC, Bayrakdar IS, Çelik Ö, et al. Artificial intelligence system for automatic deciduous tooth detection and numbering in panoramic radiographs. Dentomaxillofac Radiol. 2021;1(6):20200172.
45. Kaya E, Gunec HG, Aydin KC, Urkmez ES, Duranay R, Ates HF. A deep learning approach to permanent tooth germ detection on pediatric panoramic radiographs. Imaging Sci Dent. 2022;52(3):275–81.
46. You W, Hao A, Li S, Wang Y, Xia B. Deep learning-based dental plaque detection on primary teeth: a comparison with clinical assessments. BMC Oral Health. 2020;13(1):141.
47. Kim J, Hwang JJ, Jeong T, Cho BH, Shin J. Deep learning-based identification of mesiodens using automatic maxillary anterior region estimation in panoramic radiography of children. Dentomaxillofac Radiol. 2022;1(7):20210528.
48. Liu J, Liu Y, Li S, Ying S, Zheng L, Zhao Z. Artificial intelligence-aided detection of ectopic eruption of maxillary first molars based on panoramic radiographs. J Dent. 2022;125:104239.
49. Okazaki S, Mine Y, Iwamoto Y, et al. Analysis of the feasibility of using deep learning for multiclass classification of dental anomalies on panoramic radiographs. Dent Mater J. 2022;30(6):889–95.
50. Galibourg A, Cussat-Blanc S, Dumoncel J, Telmon N, Monsarrat P, Maret D. Comparison of different machine learning approaches to predict dental age using Demirjian's staging approach. Int J Legal Med. 2021;135(2):665–75.

51. Lee YH, Won JH, Auh QS, Noh YK. Age group prediction with panoramic radiomorphometric parameters using machine learning algorithms. Sci Rep. 2022;9(1):11703.
52. Zaborowicz M, Zaborowicz K, Biedziak B, Garbowski T. Deep learning neural modelling as a Precise Method in the Assessment of the chronological age of children and adolescents using tooth and bone parameters. Sensors (Basel). 14 2022;22(2).
53. Wu TJ, Tsai CL, Gao QZ, Chen YP, Kuo CF, Huang YH. The application of Artificial-Intelligence-assisted Dental Age Assessment in Children with Growth Delay. J Pers Med. 2022;12(7).
54. Warin K, Limprasert W, Suebnukarn S, Jinaporntham S, Jantana P, Vicharueang S. AI-based analysis of oral lesions using novel deep convolutional neural networks for early detection of oral cancer. PLoS ONE. 2022;17(8):e0273508.
55. Dai X, Jiang X, Jing Q, et al. A one-stage deep learning method for fully automated mesiodens localization on panoramic radiographs. Biomed Signal Process Control. 2023;80:104315.
56. Warin K, Limprasert W, Suebnukarn S, Inglam S, Jantana P, Vicharueang S. Assessment of deep convolutional neural network models for mandibular fracture detection in panoramic radiographs. Int J Oral Maxillofac Surg. 2022;51(11):1488–94.
57. Thulaseedharan A, PS LP. Deep learning based object detection algorithm for the detection of dental diseases and differential treatments. Paper presented at: 2022 IEEE 19th India Council International Conference (INDICON)2022.
58. Gast P. A comparison of YOLOv5 and Detectron2 object detectors in identyf-ing teeth from photographic dental images; 2022.

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