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Deep Learning Detection of Ectopic Canines and Molars in Mixed Dentition

Research Article

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ABSTRACT

Background: Ectopic eruption (EE) during the mixed dentition is a significant dental anomaly that requires early detection to prevent complications that may impact function, aesthetics, and health. Advances in artificial intelligence point to the need for automated methods to detect ectopic canines and molars.

Aim: This study aimed to develop a DL model to automatically detect EE of canines and molars on panoramic radiographs.

Methods: This retrospective study utilised a dataset of panoramic radiographs from pediatric patients in the mixed dentition stage. EE of canines and molars was defined using angular and positional criteria. Images were annotated by calibrated specialists and divided into training, validation, and test sets. Performance was evaluated using precision, recall, F1-score, Dice coefficient, and mean average precision (mAP).

Results: For ectopic canines, precision was 0.786, recall 0.771, F1-score 0.778, Dice coefficient 0.768, and mAP 0.793. For ectopic molars, precision was 0.812, recall 0.650, F1-score 0.722, Dice coefficient 0.757, and mAP 0.719. These results indicate more consistent detection performance for ectopic canines than for molars.

Conclusion: DL demonstrated effective diagnostic capability for detecting EE on panoramic radiographs. This tool has potential to improve early diagnosis, support pediatric dental treatment planning, and enhance radiology education.

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Keywords: Radiography, Panoramic; Image Interpretation, Computer-Assisted; Diagnosis, Computer-Assisted; Pattern Recognition, Automated; Artificial Intelligence; Dental Informatics

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Introduction

The mixed dentition period is a transitional stage in dental development, marked by the exfoliation of primary teeth and the emergence of permanent dentition.[1] The timing and pattern of eruption are crucial for forming functional occlusal relationships; deviations can disrupt development, potentially affecting maxillofacial growth and masticatory function.[2] Serial panoramic radiographs are essential for monitoring the timing, sequence, and spatial progression of dentition and for identifying anomalies early.[3] However, diagnostic accuracy varies by practitioner experience, leading to inconsistencies.[4] Early and precise detection of eruption irregularities is essential for effective clinical intervention.[5]

Among the most significant anomalies during this period are ectopic canines and molars, which deviate from expected eruption paths due to space loss, crowding, or developmental disturbances. If undetected, ectopic eruption (EE) can cause adjacent tooth resorption, delayed eruption, malocclusion, and the need for complex interventions. Accurate radiographic detection during this window is critical for timely diagnosis and treatment.[6,7]

Artificial intelligence (AI) has been applied in pediatric dentistry for tasks like tooth identification, age estimation, and plaque detection.[8–11] However, neural network models for predicting eruption anomalies remain underdeveloped,[12] partly due to the complexity of such diagnoses, where anomalies in number, position, and timing often coexist. Segmenting teeth in mixed dentition on panoramic images is particularly challenging due to superimposition of primary and permanent teeth,[13] along with limitations in image quality from radiation constraints.[14]

The You Only Look Once (YOLO) algorithm is a real-time object detection framework based on Convolutional neural networks (CNNs), utilising a single-stage detection architecture.[15]

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Unlike multi-stage detectors that separate region proposal and classification tasks, YOLO performs object detection in a single pass through the network, enabling faster and more efficient inference without significantly compromising accuracy. This makes it particularly advantageous in clinical scenarios that demand real-time or near-real-time decision support. In dental radiology, YOLO-based models have achieved high performance across numerous studies, including the detection of periodontal bone loss, localization of impacted third molars, and tooth canal segmentation.[16–18] Due to its proven efficiency in radiographic object localization, YOLO presents a promising solution for detecting ectopic canines and molars in mixed dentition—an area that remains relatively underexplored in the current literature.

To our knowledge, this is the first study to use a YOLOv8-based multiclass model to detect ectopic canines and molars in mixed dentition on panoramic radiographs. Prior studies[6,19] focused mainly on molar segmentation using architectures like nnU-Net and did not adopt a multiclass modelling approach. In contrast, our study emphasizes real-time, tooth-specific detection with a multiclass model capable of identifying both ectopic canines and ectopic molars, enhancing clinical applicability. This study aims to develop and evaluate a YOLOv8-based multiclass model for detecting EE of canines and molars in panoramic images, with the goal of improving diagnostic precision and supporting early intervention in pediatric dentistry.

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Material and Methods

Study Design

This retrospective study aimed to develop a computer-aided diagnostic tool using a YOLOv8-based deep learning algorithm for the automatic detection of ectopic canines and ectopic molars in panoramic radiographs of pediatric patients during the mixed dentition period. The manuscript was prepared in accordance with the Checklist for Artificial Intelligence in Medical

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Imaging (CLAIM) and the Standards for the Reporting of Diagnostic Accuracy Studies (STARD). The study protocol was approved by the Non-Interventional Clinical Research Ethics Committee of Inonu University (decision number: 2025/7876). The study was conducted in accordance with the principles outlined in the Declaration of Helsinki.

Radiographic Data Set

All panoramic radiographs were retrospectively retrieved and reviewed from the archives of Eskişehir Osmangazi University Faculty of Dentistry and Inonu University Faculty of Dentistry. Radiographs of pediatric patients in the mixed dentition phase were examined, focusing on permanent canines and first molars. Images showing ectopic canine or molar features were included.

Two diagnostic approaches were adopted for identifying ectopic canines. In the first approach, attention was given to cases in which the angle between the longitudinal axis of the permanent canine and the midline exceeded 30 degrees.[20–22] To measure this angle, the Protractor extension on Google Chrome was used, and teeth presenting an angle greater than 30 degrees were classified as ectopic canines (Figure 1A). As a second approach, Ericson's vertical sector method was applied.[23] Permanent canines located outside their designated sector were defined as ectopic and included in the study (Figure 1B).

For the diagnosis of ectopic molars, panoramic radiographs were evaluated based on the presence of atypical resorption or superimposition of the first permanent molar on the distobuccal root or cervical region of the adjacent second primary molar.[24,25] First permanent molars exhibiting these characteristics were classified as ectopic molars (Figure 1C).

Exclusion criteria included cleft palate, supernumerary teeth, or lesions such as cysts/tumours. Poor-quality images that did not allow for a reliable diagnosis of ectopic canines and molars

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were excluded as well. Additionally, cases with mesial migration in the first molars due to early loss of adjacent teeth were also excluded from the study. This decision was made in accordance with the evaluation approach based on the presence of adjacent teeth in assessing ectopic first molars in our study. Specifically, evaluating molars that have migrated mesially in the absence of adjacent teeth complicates the establishment of a standard and reliable model training criterion. Moreover, such migrations have the potential to alter normal eruption patterns and anatomical reference points, making the detection of true ectopic molars on panoramic radiographs more difficult. Therefore, excluding these cases is expected to help ensure the accuracy and consistency of the model.

Within the scope of the study, a total of 11,827 panoramic radiographs were screened from the archives. Based on the inclusion and exclusion criteria detailed above (absence of ectopic canines or ectopic molars, presence of developmental anomalies, pathology associated with the relevant tooth, etc.), 10,768 radiographs were excluded from the study. A total of 1,059 panoramic radiographs that met the eligibility criteria were included in the analysis. In this study, the unit of analysis was defined as the tooth. On the included radiographs, a total of 1,632 ectopic canines and 245 ectopic molars were evaluated.

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All panoramic radiographs included in the study were acquired using different dental panoramic units with varying imaging parameters.

Ground Truth Labelling

Accurate identification of ectopic canines and molars was essential for establishing the ground truth. Calibration training was provided by two experienced researchers: one with 25 years of experience in oral and maxillofacial radiology and 10 years in AI, and the other with 15 years

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in radiology and 10 years in AI. The diagnostic criteria used—outlined in the "Radiographic Data Set" section—were thoroughly explained.

Following the training, the calibration of the researchers who would be identifying and annotating ectopic canines and molars on panoramic radiographs was evaluated using 20 images not included in the study. In cases where deficiencies were identified, further sessions were conducted using sample cases to reach consensus.

After completing the training, six pediatric dentists and two oral and maxillofacial radiologists retrospectively reviewed the archive and identified images with ectopic teeth. These were anonymized and uploaded to the Craniocatch platform (Craniocatch, Eskişehir, Turkey), a web-based module for annotation. Since one of the authors is the CEO of CranioCatch, several measures were taken to minimize any potential bias related to the annotation platform. First, the dataset was divided at the patient level into training, validation, and test sets, and the test set remained locked throughout model development and was used only for the final evaluation. Second, the annotation platform was used exclusively for image labeling, while model training and performance evaluation were carried out independently using separate scripts and computational environments. Finally, the author affiliated with the annotation platform was not involved in the evaluation process or in the statistical analysis of the results.

Subsequently, the trained researchers annotated the boundaries of the ectopic canines and molars using polygonal segmentation techniques. These segmentations were periodically reviewed by the two experienced researchers who conducted the initial training. In cases of discrepancies or suspected inaccuracies, the two reviewers discussed the findings to reach a consensus. If no agreement could be reached, a third oral and maxillofacial radiologist with expertise in the field—who was not involved in the study—was consulted. If consensus still could not be achieved after this step, the respective panoramic radiograph was excluded from

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the study. No clinical information or reference standard results were accessible to the model or annotators during the training and evaluation processes. The assessors of the reference standard were blinded to the model's predictions and clinical information.

To evaluate interobserver agreement, a subset of panoramic radiographs was independently assessed by the two oral and maxillofacial radiologists who conducted the training and supervised the annotation process. This subset consisted of 50 panoramic radiographs without ectopic teeth and additional 50 panoramic radiographs randomly selected from the study dataset. The observers evaluated each radiograph for the presence or absence of ectopic canines and ectopic molars. Interobserver agreement was quantified using Cohen's kappa coefficient. The analysis demonstrated excellent agreement, with a kappa value of 0.83 for ectopic canine detection and 0.93 for ectopic molar detection.

Development of the Deep Learning Model

Before starting the development phase of a YOLOv8-based deep learning model for the automatic detection and segmentation of ectopic canine and molar teeth on panoramic radiographs, the entire dataset was randomly divided into three parts after completing all annotations: 80% for training, 10% for validation, and 10% for testing. Because a single panoramic radiograph could contain multiple annotated teeth and the performance metrics in this study were calculated on a tooth-level basis, data splitting was performed at the patient level rather than at the annotation level. This approach ensured that all annotations belonging to the same patient were assigned to the same subset, thereby preventing images or annotations from the same patient from appearing in different subsets and minimizing the risk of data leakage between the training, validation, and test sets. After splitting the dataset into training, validation, and test sets, the distribution of images and ectopic tooth annotations was determined. The training set included 849 images with 1,313 ectopic canine and 195 molar

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labels; the validation set contained 105 images with 157 canine and 30 molar labels; and the test set had 105 images with 162 canine and 20 molar labels (Table 1).

Following this step, the training phase began, and the model was trained for 800 epochs using input images with a resolution of 1280×1280 pixels. To improve the model's performance, a data augmentation strategy was applied. The parameters used for this purpose were as follows:

- *Blur(p=0.05, blur_limit=(3, 7))*
- *CLAHE(p=0.05, clip_limit=(1, 2), tile_grid_size=(8, 8))*
- *GaussNoise(p=0.05, var_limit=(2, 600), per_channel=False, mean=0.0, noise_scale_factor=1.0)*
- *ISONoise(p=0.1, intensity=(0.1, 0.2), color_shift=(0.05, 0.08))*
- *MultiplicativeNoise(p=0.1, multiplier=(0.9, 1.2), elementwise=True, per_channel=True)*
- *RandomBrightnessContrast(p=0.05, brightness_limit=(-0.1, 0.1), contrast_limit=(-0.2, 0.2), brightness_by_max=True)*
- *RandomSnow(p=0.05, snow_point_range=(0.1, 0.1), brightness_coeff=0.2)*
- *Sharpen(p=0.05, alpha=(0.1, 0.8), lightness=(0.2, 1.0))*
- *ToSepia(p=0.005)*

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The model was developed using Python (version 3.6.1; Python Software Foundation, Wilmington, DE, USA), an open-source programming language, along with the PyTorch library. In this study, we used instance segmentation architecture of YOLOv8 (YOLOv8-seg) a versatile deep learning architecture applicable to various vision tasks including object detection, instance segmentation, pose estimation, tracking, and classification. YOLOv8-seg is available in five scales—YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large)—which differ in speed, system requirements,

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and performance. We selected YOLOv8x for its superior accuracy, despite higher computational demands.

Early stopping was applied during the training process, with the patience parameter set to 50. Accordingly, training was automatically terminated if no improvement in the validation mAP value was observed for 50 consecutive epochs. The model weights corresponding to the epoch with the highest validation performance were then used for evaluation on the test set. The primary motivation for adopting this approach was to prevent overfitting during training. Although the model was initially configured to be trained for 800 epochs, the early stopping mechanism terminated training at epoch 257. The best validation performance was achieved at epoch 207, and the model weights from this epoch were retained for final testing. Accordingly, the optimal model weights corresponding to the highest validation fitness were automatically retained. For optimization, the AdamW optimizer was used with an initial learning rate of 0.001, $\beta 1$ of 0.9, $\beta 2$ of 0.999, and a decoupled weight decay of 0.0005, aiming to improve convergence speed and enhance model regularization. Model training and data processing were performed on high-performance systems at the Dental-AI Laboratory of Eskişehir Osmangazi University Faculty of Dentistry, including Dell PowerEdge T640 compute and GPU servers and a PowerEdge R540 storage server (Dell Inc., Texas, USA).

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Evaluation of the Model's Performance

To assess the model’s accuracy in detecting ectopic canines and molars, several performance metrics were used. Model performance thresholds were pre-defined prior to the study, and no post-hoc optimization was performed on the results. Accordingly, in line with standard YOLOv8 implementations, an IoU (Intersection over Union) threshold of 0.5 was determined to ensure a balance between sensitivity and precision; detections and segmentations above this threshold were accepted as positive. The model's performance was assessed using true positive

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(TP), false positive (FP), and false negative (FN), indicating correct detection/segmentation, incorrect detection/segmentation, and missed ectopic canines or molars, respectively. Based on these values, key performance metrics such as sensitivity, precision, and F1-score were calculated. In addition, a confusion matrix was used to provide a more detailed view of the model's prediction performance. Since the annotations were performed using polygon-based mask segmentation, the YOLOv8-seg model— which intrinsically performs both object localization and pixel-level segmentation—enabled the evaluation of the model at both the detection and segmentation levels. Accordingly, in addition to the conventional classification metrics, model performance was further assessed using mean Average Precision (mAP) for object-level detection and the Dice Similarity Coefficient (DSC) to quantify pixel-level segmentation accuracy.

Results

Detection Performance and Confidence Threshold Optimization

The model achieved a mean average precision (mAP@0.5) of 0.756 across both target classes. Class-specific mAP scores were 0.793 for ectopic canines and 0.719 for ectopic molars. The F1-confidence curve analysis revealed that the optimal overall F1-score of 0.76 was attained at a confidence threshold of 0.386 (Figure 2). Class-wise F1-scores remained relatively high for ectopic canines, while ectopic molars showed a slightly lower and more variable trend across thresholds.

Precision and recall metrics further reinforced model performance. The highest overall precision score of 1.00 was achieved at a confidence threshold of 0.964 (Figure 2), indicating exceptional reliability at high-confidence predictions. Although ectopic molars exhibited marginally higher precision than ectopic canines at specific thresholds, the final class-specific

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precision was higher for ectopic canines. The maximum recall for all classes (0.80) occurred at the lowest threshold, illustrating the typical trade-off between sensitivity and specificity. Ectopic canines consistently maintained higher recall values than ectopic molars, indicating more robust sensitivity (Figure 2).

Evaluation using class-specific metrics confirmed the performance distribution between classes. Final evaluation metrics demonstrated that ectopic canines achieved a precision of 0.786, recall of 0.771, F1-score of 0.778, and Dice score of 0.768, while ectopic molars reached 0.812 for precision, 0.650 for recall, 0.722 for F1-score, and 0.757 for Dice score (Table 2).

Although the developed model yielded higher F1-scores and mAP values for ectopic canines, it is important to note that the number of ectopic molars in the dataset was significantly lower than that of canines. Clinically, the model demonstrated higher precision for ectopic molars compared to canines, suggesting that it produced fewer false positives for molars. In contrast, the lower precision for canines indicates that the model more frequently mislabelled non-ectopic canines as ectopic, which could potentially lead to overtreatment in clinical settings. Conversely, the model exhibited a lower recall for ectopic molars, meaning it failed to detect some truly ectopic molars, thereby risking undertreatment. Such oversights could allow ectopic molars to go unnoticed, potentially causing damage to adjacent teeth, malocclusion, or space loss. In comparison, the higher recall for ectopic canines reduces the likelihood of such clinical consequences in those cases.

Precision-Recall (PR) curves reflected the detection trends across classes, with ectopic canines exhibiting greater stability and fewer fluctuations than ectopic molars. PR trends for molars showed greater variation, particularly in high-recall regions, suggesting elevated false positive rates when attempting to maximize sensitivity (Figure 2).

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Confusion Matrix Analysis

The normalized confusion matrix revealed classification accuracies of 77% for ectopic canines and 65% for ectopic molars, indicating stronger model reliability in canine detection. Misclassifications were notably more frequent in the molar class, with a predominant tendency toward false negatives (Figure 3). According to the raw confusion matrix, 125 ectopic canines were correctly identified, whereas 34 were misclassified. For ectopic molars, 13 were accurately detected, 2 were incorrectly classified, and 7 were entirely missed, highlighting the increased detection challenge posed by this class (Figure 3).

Qualitative Evaluation

Visual inspection of test predictions confirmed the model's qualitative reliability. High-confidence detections were frequently observed for ectopic canines in well-defined cases. In contrast, predictions for molars occasionally exhibited minor localization errors or lower confidence, particularly in complex or low-contrast regions. Representative examples illustrating these predictions are provided in Figure 4.

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Discussion

EE is a common developmental anomaly in children, especially affecting maxillary canines due to their complex eruption path.[26] While EE can involve any tooth, it most often affects first permanent molars and canines, with mandibular cases being rarer.[27,28] Early panoramic radiographic evaluation during mixed dentition is key to preventing complications like arch length loss and root resorption. This study demonstrated that a YOLOv8-based deep learning model, with a mean average precision of 0.756, showed strong agreement with expert annotations, highlighting its value in early detection.

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Diagnosing EE—whether involving molars or canines—can be highly experience-dependent, particularly in cases with subtle or atypical radiographic features. For instance, mild superimposition of first molars over second primary molars or minor root resorption may not always present clear diagnostic thresholds. Similarly, canines with aberrant eruption trajectories that do not yet show definitive impaction can challenge even experienced clinicians. In the present study, such borderline cases were included in the training dataset based on expert consensus, aiming to capture the full spectrum of EE patterns encountered in clinical practice. This inclusive approach was intended to enhance the model's exposure to varied presentations and improve its generalisability. Despite these diagnostic complexities, the model demonstrated consistent performance, suggesting its potential to support clinicians in identifying early or ambiguous cases of EE more reliably.

In clinical practice, many cases of EE—whether involving molars or canines—may resolve spontaneously, particularly when detected early and managed conservatively. The likelihood of self-correction is often influenced by factors such as the eruptive angulation of the permanent tooth, the degree of resorption in adjacent primary teeth, and the severity of impaction.[19,24,29] These variables are crucial in determining whether immediate intervention is necessary or if observation is appropriate. While the current study focused on the automated detection of EE, it also provides a foundation for future models capable of evaluating eruption dynamics and severity. Advancing such systems could support clinicians in predicting eruption outcomes and developing more personalized treatment strategies for pediatric patients.

Despite the model's strong performance in detecting EE, certain diagnostic limitations remain. Ectopic molars showed lower recall than canines, indicating a higher likelihood of false negatives, particularly in cases with subtle radiographic signs. Conversely, high-confidence predictions for canines may occasionally result in false positives, potentially causing

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unnecessary concern. Such misclassifications, however, can often be resolved through secondary clinical evaluation or referral. Given that eruption status and adjacent root resorption progress over time, follow-up panoramic radiographs are essential in ambiguous cases. Periodic re-evaluation helps identify previously missed cases and allows for monitoring of progression toward impaction, supporting timely and appropriate intervention.

Prior studies on artificial intelligence-assisted detection of EE have primarily concentrated on single-tooth analysis—most commonly the first permanent molars—and have often relied on cropped regions of interest to enhance model sensitivity, or were conducted with lower sample sizes.[6,19,30] In contrast, the present study evaluated both molars and canines directly on full panoramic radiographs, aiming to reflect real clinical scenarios where such targeted cropping is not feasible. This approach, while more representative of routine practice, may partially explain the comparatively lower performance outcomes. Furthermore, the region involving canines is anatomically more complex due to overlapping structures such as the roots of primary lateral incisors and adjacent molars, which adds to the diagnostic challenge. Another distinguishing feature of this study was the involvement of a larger number of pediatric dental specialists with diverse clinical experience in the labeling process. This inclusive strategy allowed the dataset to represent a broader range of radiographic variations, including subtle and ambiguous cases, which may have introduced additional diagnostic complexity. Taken together, these factors underscore the broader scope and practical orientation of the current work, emphasizing applicability over narrowly optimized performance.

This study primarily focused on the development of a computer-aided diagnostic system for detecting EE, with the broader aim of evaluating the applicability of deep learning in diagnostically complex dental scenarios. To enhance the external validity and real-world

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relevance of the findings, the dataset was compiled from multiple clinical centers, encompassing a diverse range of pediatric cases.

Accordingly, the model developed in this study has the potential to be used as a clinical decision-support tool for assisting clinicians in evaluating panoramic radiographs for the presence of ectopic canines and molars. In this context, the model is primarily intended to function as a screening and referral-triage aid rather than as an autonomous diagnostic system. In particular, its relatively balanced performance in detecting ectopic canines—reflected in an F1-score of 0.778—may be especially beneficial for less experienced clinicians or in hospital settings with high patient volumes and rapid case turnover, where swift yet accurate evaluation is required. In such environments, the model could help highlight potentially ectopic teeth and prompt further clinical review or specialist referral when necessary. Although the model demonstrated somewhat lower performance in detecting ectopic molars compared to canines, this is likely attributable to the limited number of ectopic molar cases in the dataset. Nevertheless, the model still achieved an F1-score of 0.722 in this class, suggesting meaningful potential as a diagnostic aid in clinical settings. However, the recall score of 0.650 for ectopic molars—indicating that some actual ectopic molars were misclassified as normal—should also be considered in clinical applications. From a clinical perspective, this suggests that the system may be more suitable as a supportive screening tool operating at a sensitivity-oriented threshold, where the primary goal is to minimize missed cases and ensure that suspicious findings receive additional clinical evaluation. These results reinforce the notion that AI-based diagnostic systems are not intended to replace clinicians, but rather to assist them by reducing cognitive load and improving diagnostic consistency. It should also be noted that the present study did not include a direct comparison with human readers such as general dentists, pediatric dentists, or dentomaxillofacial radiologists. Future studies incorporating reader comparisons and evaluating model performance at clinically meaningful operating thresholds would further

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clarify the practical role of such systems in routine dental imaging workflows. Furthermore, beyond its immediate diagnostic utility, the model may serve as a foundation for large-scale screening programs and contribute to the training of early-career dental professionals by providing consistent and objective diagnostic feedback.

Despite its contributions, this study has limitations. First, the cross-sectional design and lack of longitudinal radiographs preclude the assessment of eruption progression or spontaneous resolution, limiting the model to detection rather than prediction. Furthermore, the model was trained using ectopic canine and molar images selected through specific inclusion and exclusion criteria, without determining the true prevalence of ectopic eruption in the source population. Consequently, it remains unclear how the model will perform during routine screening, where the base rates of ectopic canines and molars can be highly variable. Because the current research is primarily a model development study, the expected positive predictive value and false-positive burden in a real-world clinical workflow remain unknown. Therefore, validating our developed model in routine clinical practice is essential, and the absence of such prospective clinical testing should be considered a major limitation of this study. Second, the two-dimensional nature of panoramic radiographs introduces superimposition and distortion—especially in the canine region—which may reduce accuracy. Third, although the multicentre dataset enhances generalisability and diversity variations in image quality and acquisition parameters may have introduced heterogeneity. Additionally, the imbalance between the number of ectopic canines and ectopic molars in our dataset—especially the relatively low number of ectopic molars—represents a significant limitation, potentially restricting model performance for this class. Considering these limitations, future studies should aim to develop models using prospectively designed datasets with balanced class distributions, incorporating detailed clinical data and not limited to two-dimensional imaging but also integrating three-dimensional imaging data. Such approaches may contribute to the development of AI systems

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that are more suitable for clinical application and offer higher performance. Furthermore, the use of transfer learning methodologies—employing deep learning models previously trained on dental radiographs—may further enhance model performance in future studies.

In conclusion, this study demonstrated the feasibility of using a deep learning–based object detection model to identify EE of canines and molars on panoramic radiographs in the mixed dentition period. By leveraging a diverse, multicentre dataset and maintaining original image integrity without region cropping, the model was designed to reflect real-world diagnostic conditions. Although performance scores were modest compared to segmentation-based approaches focused on single-tooth targets, the broader anatomical scope and practical adaptability of this system highlight its potential clinical value. Given its ability to analyse entire panoramic radiographs without the need for manual preprocessing, the model holds promise as a practical adjunct in routine pediatric dental screenings, particularly in high-volume clinical settings where early identification of EEs can improve patient outcomes. Future efforts should aim to incorporate longitudinal imaging, expand anatomical coverage, and explore predictive modelling to further enhance diagnostic accuracy and individualized treatment planning.

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Bullet Points

- The YOLOv8-based deep learning model can accurately detect ectopic canines on panoramic radiographs of children in the mixed dentition period.
- Despite the limited number of ectopic molars in the dataset, the model also demonstrated clinically acceptable performance in detecting these teeth.
- AI-based methods are not only capable of detecting ectopic canines and molars but also of delineating their boundaries, which may assist in clinical decision-making regarding extraction, continuation of eruption, or assessment of resorption risk in adjacent teeth.

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Statements & Declarations

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Competing interests

Dr. Ibrahim Sevki Bayrakdar is the Co-founder and CEO of CranioCatch, a company specializing in the development of advanced artificial intelligence solutions for use in dentistry and related fields. In his role, he oversees company operations, strategic planning, and product development. Given his professional role and business interests in CranioCatch, there may be a potential conflict of interest regarding the content of this article. While every effort has been made to ensure an objective and balanced perspective, readers are advised to consider this potential influence. Dr. Bayrakdar remains committed to ethical conduct, transparency, and integrity in all academic and professional activities. As other authors, we do not have any conflict of interest to disclose.

Author Contributions

E.G., contributed to conception and design, analysis, interpretation; drafted and critically revised the manuscript. F.N.K., contributed to conception and design, analysis, interpretation; drafted the manuscript. E.M.A., contributed to conception and design, analysis, interpretation; critically revised the manuscript. I.T.G., contributed to conception and design, analysis, interpretation, writing; drafted and critically revised the manuscript. S.Ö., contributed to conception and design, analysis, interpretation; critically revised the manuscript. T.M., contributed to conception and design, analysis, interpretation; drafted the manuscript. A.K., contributed to conception and design, writing, analysis, interpretation; drafted and critically revised the manuscript. B.K., contributed to analysis, interpretation; drafted the manuscript. M.U., contributed to data acquisition and collection, established the study methodology, and participated in manuscript writing. I.S.B., contributed to conception and design, analysis, interpretation; drafted and critically revised the manuscript. Ö.Ç., contributed to design, data acquisition, analysis, interpretation; drafted the manuscript. K.O., contributed to conception and design, analysis, data acquisition, interpretation; critically revised the manuscript. All authors gave final approval and agreed to be accountable for all aspects of the work.

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Ethics approval and consent to participate

The study protocol was approved by the Non-Interventional Clinical Research Ethics Committee of Inonu University (decision number: 2025/7876).

Consent to participate

Informed consent was obtained from all individual participants included in the study and required approval for using their data for this study obtained from Ethics Committee.

Consent to publish

Not Applicable.

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Table 1 Distribution of Images/Patients and Ectopic Tooth Labels Across Training, Validation, and Test Sets

Dataset Split	Number of Images/Patients	Ectopic Canine Labels	Ectopic Molar Labels
Training	849	1313	195
Validation	105	157	30
Test	105	162	20

Table 2 Class-specific evaluation metrics for ectopic canine and molar detection

Class	TP	FP	FN	Precision	Recall	F1-Score	Dice Score	mAP
Ectopic Canine	125	34	37	0.786	0.771	0.778	0.768	0.793
Ectopic Molar	13	3	7	0.812	0.650	0.722	0.757	0.719

TP (True Positive), TN (True Negative), and FN (False Negative) represent correctly detected ectopic teeth, correctly identified non-ectopic teeth, and missed ectopic detections, respectively.

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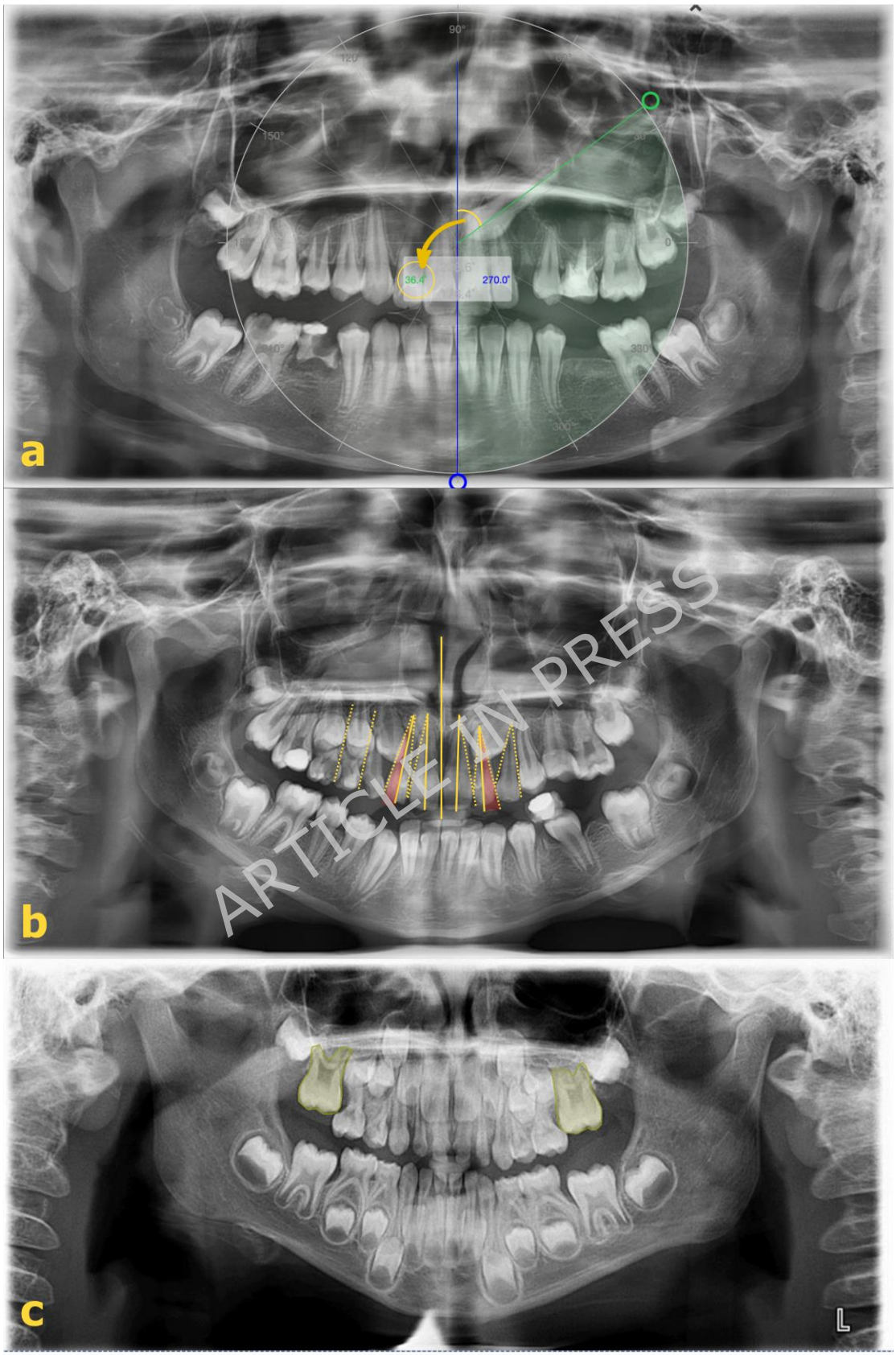
Fig. 1 Figure showing the inclusion criteria for ectopic canines and ectopic molars included in the study: (**A**) an angle greater than 30 degrees between the long axis of the permanent canine and the midline; (**B**) the permanent canine being located outside its designated sector according to Ericson's vertical sector classification; and (**C**) the permanent first molar overlapping with or causing resorption in the distobuccal root or cervical area of the second primary molar

Fig. 2 Performance curves for the detection of ectopic canines and molars. Top left: F1-score versus confidence threshold curves demonstrating detection performance. Top right: Precision–confidence curve. Bottom left: Recall–confidence curve. Bottom right: Precision–recall curves

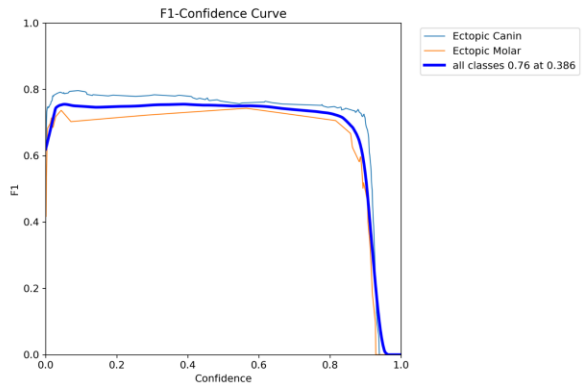
Fig. 3 Normalized Confusion Matrix and Confusion Matrix for Ectopic Canine and Molar Detection

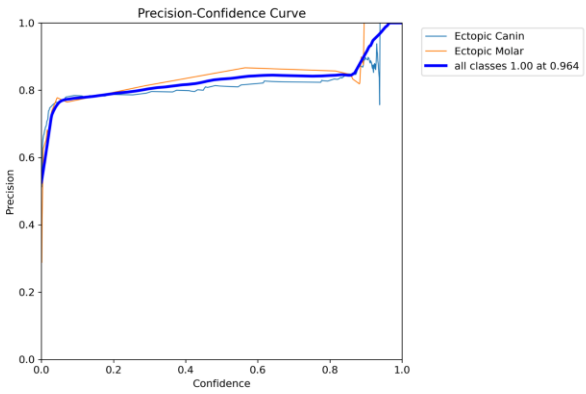
Fig. 4 Visualization comparing the ground truth annotations and YOLOv8-seg model predictions for the detection and segmentation of ectopic canines and molars. Representative examples with high confidence predictions are shown, illustrating the agreement between the model outputs and the reference annotations

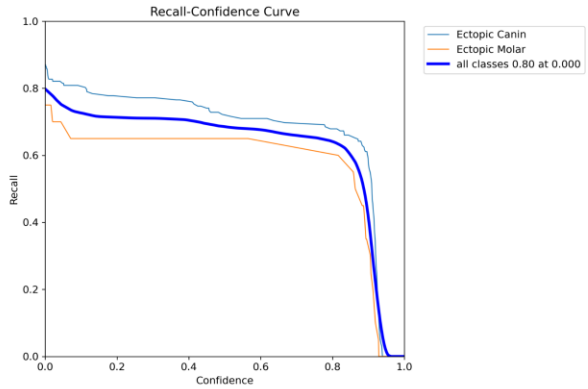
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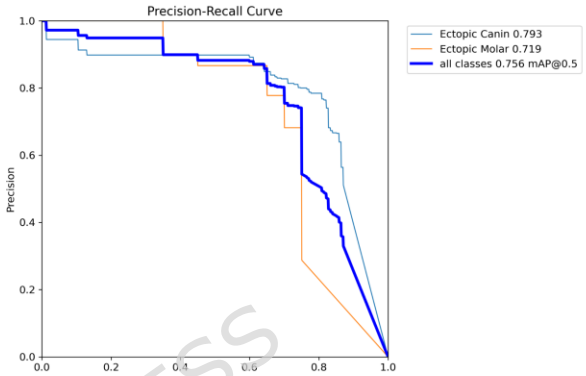


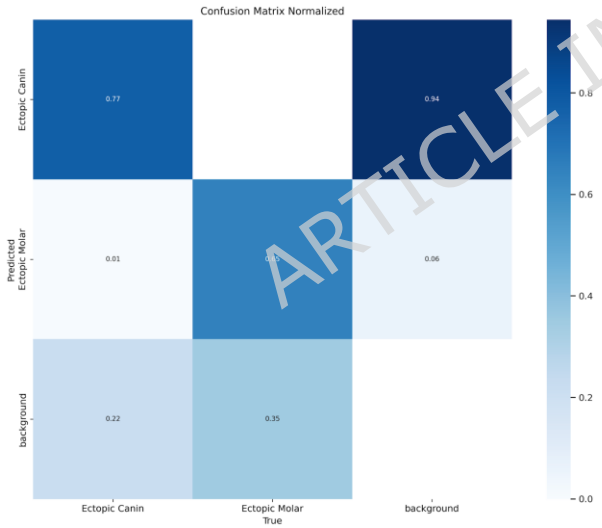
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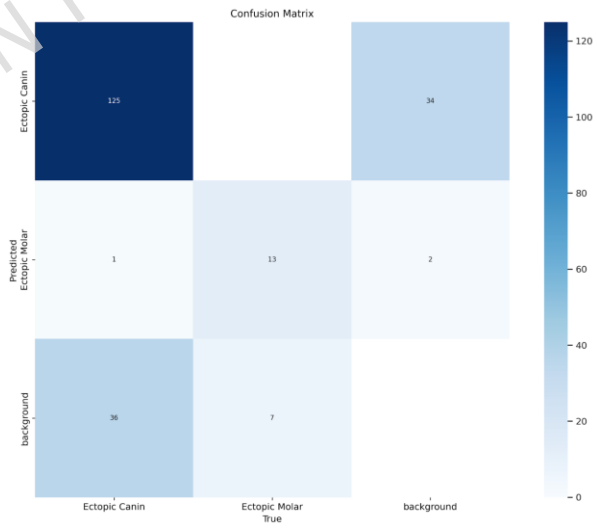




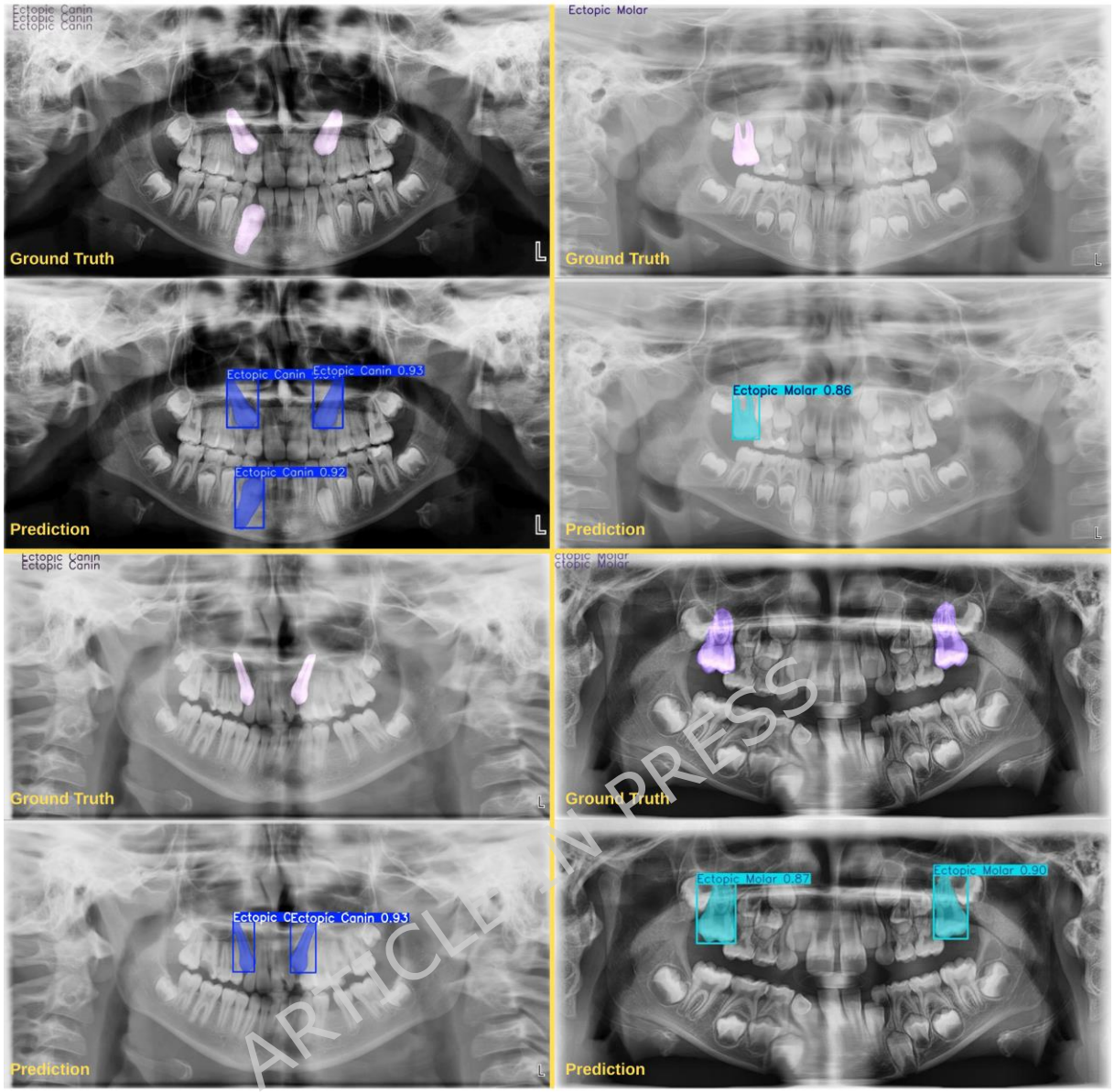








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