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Detection Performance of an Artificial Intelligence Model in Identifying Anatomical Landmarks on Dental Panoramic Radiographs

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ABSTRACT

Manual identification of panoramic radiographs has limitations due to distortion, superimposition, and individual anatomical variations, so more objective supporting technology such as artificial intelligence (AI) is needed. The purpose of this study was to determine the level of AI detection performance in determining anatomical landmarks in panoramic radiographs. This descriptive study used a purposive sampling method. A total sample of 653 radiographs was used. The radiographs were labeled at nine anatomical landmarks and then analyzed using the YOLOv8 deep learning algorithm. The level of AI detection performance was evaluated using precision, sensitivity (recall), and F1-Score parameters in percentage form. The results showed variations in the level of AI detection performance for each anatomical landmark. The highest detection performance was in the condyloid process, while the mental foramen showed the lowest detection performance. In conclusion, AI shows a high level of detection performance in determining anatomical structures in the jaw and this can be used to assist clinicians in detecting the presence of these anatomical structures.

Keywords: Anatomical Landmarks, Oral Radiology, YOLOv8

ABSTRAK

Identifikasi manual pada radiografi panoramik memiliki keterbatasan karena distorsi, superimposisi, dan variasi anatomi individu, sehingga dibutuhkan teknologi pendukung yang lebih objektif seperti kecerdasan buatan (AI). Tujuan penelitian ini adalah untuk menentukan tingkat kinerja deteksi AI dalam menentukan penanda anatomi pada radiografi panoramik. Studi deskriptif ini menggunakan metode pengambilan sampel bertujuan. Sebanyak 653 radiografi digunakan sebagai sampel. Radiografi diberi label pada sembilan penanda anatomi dan kemudian dianalisis menggunakan algoritma pembelajaran mendalam YOLOv8. Tingkat kinerja deteksi AI dievaluasi menggunakan parameter presisi, sensitivitas (recall), dan F1-Score dalam bentuk persentase. Hasil menunjukkan variasi tingkat kinerja deteksi AI untuk setiap penanda anatomi. Kinerja deteksi tertinggi terdapat pada proses kondiloid, sedangkan foramen mental menunjukkan kinerja deteksi terendah. Kesimpulannya, AI menunjukkan tingkat kinerja deteksi yang tinggi dalam menentukan struktur anatomi di rahang dan ini dapat digunakan untuk membantu dokter dalam mendeteksi keberadaan struktur anatomi tersebut.

Keywords: *Landmark* Anatomis, Radiologi Oral, YOLOv8

1. Introduction

Panoramic radiographs are an important diagnostic tool in dental practice, providing a broad visualization of the dentoalveolar structures, maxillofacial region, and surrounding hard tissues of the oral cavity. These radiographs are often used to evaluate the presence and position of permanent and unerupted deciduous teeth, detect abnormalities in jaw growth and development, as well as facilitate early diagnosis of dentofacial abnormalities [1,2]. A crucial aspect of interpretation is the accurate identification of anatomical landmarks, including the mental foramen, mandibular canal, mandibular ramus, anterior nasal spine, and maxillary sinus [1,3]. Despite the widespread clinical use, the manual process of identifying anatomical landmarks often faces various challenges, including poor radiograph quality due to artifacts or distortion, individual anatomical variations, and apparent overlapping anatomical structures, leading to diagnostic errors [4]. Lesions or abnormalities that obscure landmarks also make identifying anatomical landmarks more difficult, creating a need for methods that improve the efficiency and detection performance [5,6].

In recent years, the development of Artificial Intelligence (AI) technology, particularly deep learning methods based on convolutional neural networks (CNN), has shown great potential in dental radiology [7,8]. Various studies have shown the ability of AI to detect as well as classify tooth structures and bone anatomy in intraoral and extraoral radiographs [7,9,10]. In 2023, Bağ et al. evaluated AI-based detection of nine anatomical landmarks on 981 pediatric radiographs, including maxillary sinus, orbit, mandibular canal, mental foramen, mandibular foramen, mandibular incisura, articular eminence, condylar process, and coronoid process. The results showed that the AI achieved high sensitivity in detection performance [1]. Chen et al. (2019) stated that region-based convolutional neural networks (R-CNN) accurately detected teeth, achieving high precision and intersection over union (IoU) value [9]. Furthermore, Krois et al. (2019) reported that CNNs performed comparably to specialist dentists in assessing periodontal bone resorption on panoramic radiographs [7]. Park et al. (2019) stated that CNNs were more reliable than Single Shot Detectors (SSDs) in detecting cephalometric landmarks [11]. Similarly, Hiraiwa et al. (2019) stated that a deep learning system showed high performance in determining the number of distal roots in mandibular first molars using CBCT as the reference standard [4].

The application of AI in identifying patient anatomical landmarks is expected to reduce manual workload, minimize examiner errors, and accelerate the diagnostic process or clinical planning. However, widespread implementation in clinical dental practice requires rigorous evaluation of AI detection performance in recognizing specific anatomical landmarks [7,12]. Although previous studies have shown the feasibility of AI-based landmark detection on panoramic radiographs, there is limited information on the performance of You Only Look Once version 8 (YOLOv8) in detecting multiple anatomical landmarks in adult panoramic radiographs. Therefore, this study aims to determine the detection performance of YOLOv8-based AI model in identifying nine anatomical landmarks on panoramic radiographs. The results are expected to provide insight into the reliability of AI technology as a diagnostic tool in dentistry and serve as a basis for developing AI-based clinical applications [7,13].

2. Material and Methods

This descriptive study used panoramic radiographs obtained from the Radiology Installation of the Dental and Oral Hospital, Universitas Sumatera Utara, Medan, Indonesia. The experiment was conducted from July 2025 to April 2026 and received ethical approval from the Health Research Ethics Committee of the University of North Sumatra, under letter number 937/KEPK/USU/2025. A total of 653 panoramic radiographs of patients aged 20–60 years were selected using a purposive sampling method. Inclusion criteria were radiographs with good image quality, adequate contrast and density, as well as clear depiction of anatomical landmarks. However, radiographs showing pathological lesions, developmental abnormalities, fractures, or post-surgical changes in the maxilla or mandible were excluded. This study evaluated nine anatomical landmarks, which included the maxillary sinus, orbit, palate, nasal septum, mandibular canal, mental foramen, articular eminence, condylar process, and coronoid process. All radiographs were manually labeled to indicate the location of each anatomical landmark using the RoboFlow platform in accordance with the platform's Terms of Use. The labeled dataset was divided into three groups based on their intended use, namely train (80%), validation (10%), and test (10%) data.

Figure 1. RoboFlow annotation interface used for image annotation

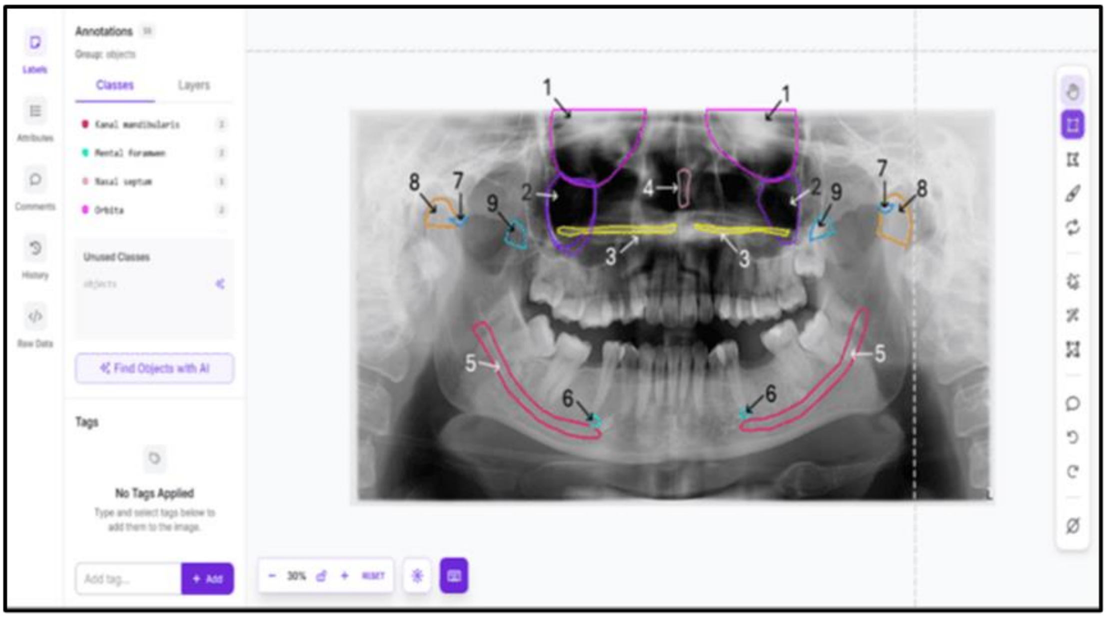

Figure 2. Example of anatomical landmark annotation performed by the authors using RoboFlow platform: 1. Orbit, 2. Maxillary sinus, 3. Palate, 4. Nasal septum, 5. Mandibular canal, 6. Mental foramen, 7. Articular eminence, 8. Condylar process, and 9. Coronoid process

The AI model was developed using the YOLOv8 deep learning algorithm. Detection performance was evaluated using a confusion matrix composed of true positives, false positives, false negatives, and true negatives. The assessment matrix, including precision, sensitivity (recall), and F1-score, was calculated based on the confusion matrix evaluation results and expressed as a percentage to determine the model's detection performance.

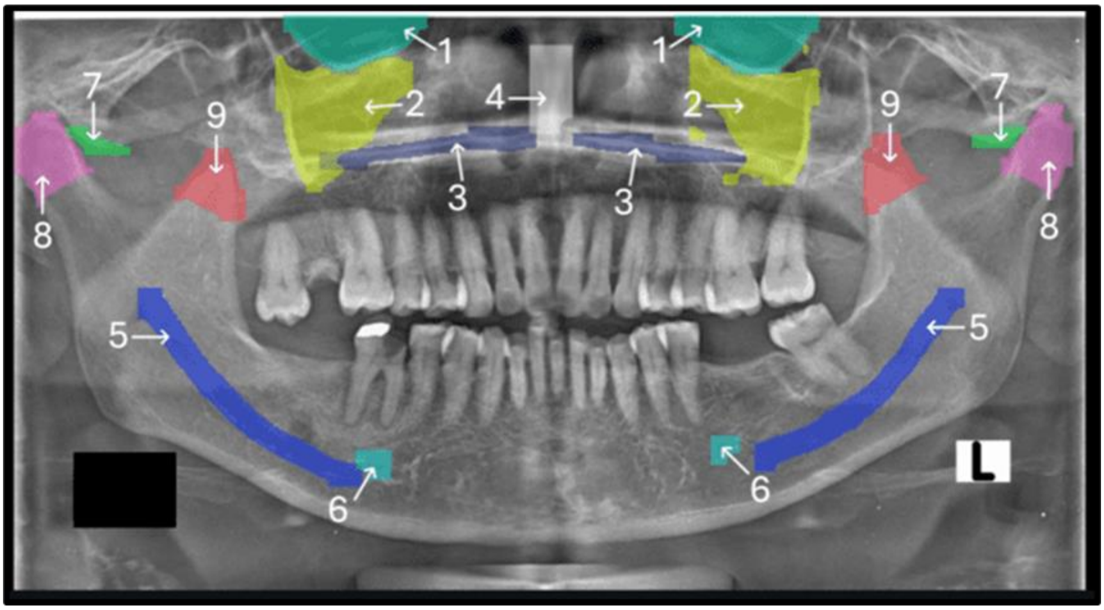

Figure 3. Example of anatomical landmark detection generated by the YOLOv8 model developed in this study: 1. Orbit, 2. Maxillary sinus, 3. Palate, 4. Nasal septum, 5. Mandibular canal, 6. Mental foramen, 7. Articular eminence, 8. Condylar process, and 9. Coronoid process

Cronbach's alpha analysis was performed as a reliability test to evaluate the internal consistency of the anatomical point labeling data. The analysis was conducted by assessing consistency among items, between raters, and over time, thereby reducing the influence of random variation in anatomical process. Furthermore, Pearson Product Moment analysis was performed as a validity test to determine the relationship between each anatomical point variable and the total score. The results of validity and reliability tests were used to evaluate the consistency of the annotation dataset.

3. Result

A total of 653 panoramic radiographs were used as samples in this study. All radiographs met the eligibility criteria, including good image quality, adequate contrast and density, no history of jaw surgery, and absence of pathological conditions in the maxilla or mandible. This study evaluated the detection performance of AI in identifying anatomical landmarks in panoramic radiographs using the YOLOv8 deep learning model. Before model training, the anatomical landmark annotations were evaluated for reliability and validity. The Cronbach's alpha analysis was used to assess the internal consistency of the annotation data, with results presented in Table 1, where a value of 0.767 indicated good internal consistency.

Table 1. Cronbach's Alpha Analysis Results

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.767	.950	10

Table 2 presents the results of the Pearson Product Moment (Inter-Item Correlation Matrix) analysis, which is conducted to measure validity. The results indicated that the condylar process, maxillary sinus, orbit, palate, and articular eminence landmarks had the highest correlation with the total score, at 0.915. The mental foramen landmark had the lowest correlation at 0.571.

Table 2. Results of the Pearson Product Moment Test Analysis (Inter-Item Correlation Matrix)

Anatomical Landmark	Condylar process	Maxillary sinus	Orbit	Mandibular Canal	Palate	Coronoid process	Articular eminence	Mental foramen	Nasal septum	Total
Condylar process	1.000	1.000	1.000	.700	1.000	.565	1.000	.269	.565	.915

Maxillary sinus	1.000	1.000	1.000	.700	1.000	.565	1.000	.269	.565	.915
Orbit	1.000	1.000	1.000	.700	1.000	.565	1.000	.269	.565	.915
Mandibular canal	.700	.700	.700	1.000	.700	.378	.700	.384	.378	.770
Palate	1.000	1.000	1.000	.700	1.000	.565	1.000	.269	.565	.915
Coronoid process	.565	.565	.565	.378	.565	1.000	.565	.069	.291	.605
Articular eminence	1.000	1.000	1.000	.700	1.000	.565	1.000	.269	.565	.915
Mental foramen	.269	.269	.269	.384	.269	.069	.269	1.000	.272	.571
Nasal septum	.565	.565	.565	.378	.565	.291	.565	.272	1.000	.669
Total	.915	.915	.915	.770	.915	.605	.915	.571	.669	1.000

The Pearson Product Moment Test (Item-Total Statistics) analysis was conducted to measure validity. As presented in Table 3, the results showed that all items had Corrected Item-Total Correlation values greater than 0.3, indicating that anatomical landmarks used in this study accurately measured the observed variables. However, none of the Cronbach's Alpha values for item deletion significantly exceeded the overall value of 0.767, indicating that no anatomical landmark needed to be removed from the dataset.

Table 3. Results of the Pearson Product Moment Test Analysis (Item-Total Statistics)

Anatomical Landmark	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Condylar process	16.0600	6.547	.906	.	.744
Maxillary sinus	16.0600	6.547	.906	.	.744
Orbit	16.0600	6.547	.906	.	.744
Palate	16.0600	6.547	.906	.	.744
Articular eminence	16.0600	6.547	.906	.	.744
Mandibular canal	16.0800	6.442	.738	.	.742
Nasal septum	16.1000	6.418	.614	.	.743
Coronoid process	16.1000	6.500	.544	.	.748
Mental foramen	16.2600	6.115	.451	.	.746
Total	8.5200	1.806	1.000	.	.857

Table 4 shows the data grouping used in the development of the YOLOv8 AI model. The labeled radiograph dataset was categorized into three groups, namely train (80%), validation (10%), and test (10%). Data allocation was based on the total number of labels for the nine anatomical landmarks analyzed in this study, namely the condylar processes, maxillary sinus, orbit, mandibular canal, nasal septum, palate, coronoid processes, articular eminence, and mental foramen.

Table 4. Data Grouping in the Development of the YOLOv8 AI Model

Anatomical Landmark	Number of Labels	Data Groups		
		Train (80%)	Validation (10%)	Test (10%)
Condylar process	1.267	1013	127	127
Maxillary sinus	1.271	1017	127	127
Orbit	1.044	836	104	104
Mandibular canal	1.095	875	110	110
Nasal septum	544	436	54	54
Palate	1.299	1039	130	130

Coronoid process	568	454	57	57
Articular eminence	1.131	905	113	113
Mental foramen	882	706	88	88

Table 5 shows the grouping of confusion matrix elements. Model performance evaluation was performed using a confusion matrix consisting of true positives (TP), false positives (FP), and false negatives (FN). Based on these values, precision, sensitivity (recall), and F1-Score parameters were calculated to assess the ability of the AI model to detect each anatomical landmark.

Table 5. Confusion Matrix Elements Grouping

Anatomical Landmark	Confusion Matrix Elements		
	True Positive (TP)	False Positive (FP)	False Negative (FN)
Condylar process	126	3	1
Maxillary sinus	124	9	3
Orbit	101	10	3
Mandibular canal	103	15	7
Nasal septum	47	8	7
Palate	104	42	26
Coronoid process	38	26	19
Articular eminence	70	49	43
Mental foramen	33	33	55

Table 6 shows the precision assessment matrix for each anatomical landmark, which is obtained by dividing the number of TP by the sum of TP and FP. Based on the results, the landmark with the highest precision value was the condylar process (98%), followed by the maxillary sinus (93%) and the orbit (91%). Meanwhile, the lowest precision value was found at the mental foramen (50%).

Table 6. Anatomical Landmark Precision Assessment Matrix

Anatomical Landmark	True Positive (TP)	False Positive (FP)	Precision (%)
Condylar process	126	3	98
Maxillary sinus	124	9	93
Orbit	101	10	91
Mandibular canal	103	15	87
Nasal septum	47	8	85
Palate	104	42	71
Coronoid process	38	26	59
Articular eminence	70	49	59
Mental foramen	33	55	50

Table 7 shows the recall assessment matrix for each anatomical landmark, which is obtained by dividing the number of TP by the sum of TP and FN. The highest recall values were obtained for the condylar process (99%), the maxillary sinus (98%), and the orbit (97%), while mental foramen (38%) showed the lowest.

Table 7. Anatomical Landmark Recall Assessment Matrix

Anatomical Landmark	True Positive (TP)	False Negative (FN)	Recall (%)
Condylar process	126	1	99
Maxillary sinus	124	3	98
Orbit	101	3	97

Mandibular canal	103	7	94
Nasal septum	47	7	87
Palate	104	26	80
Coronoid process	38	19	66
Articular eminence	70	43	62
Mental foramen	33	55	38

Table 8 shows the F1-score assessment matrix for each anatomical landmark. The F1-score combines precision and sensitivity (recall) into a single metric by calculating the harmonic mean of both measures, thereby providing a balanced assessment of model performance. The result showed that the condylar process had the highest F1-score at 98%, followed by the maxillary sinus (96%), the orbit (94%), and the mandibular canal (91%), while mental foramen had the lowest at 43%.

Table 8. Anatomical Landmark F1-Score Assessment Matrix

Anatomical Landmark	Precision (%)	Recall (%)	F1-Score (%)
Condylar process	98	99	98
Maxillary sinus	93	98	96
Orbit	91	97	94
Mandibular canal	87	94	91
Nasal septum	85	87	86
Palate	71	80	75
Coronoid process	59	66	62
Articular eminence	59	62	60
Mental foramen	50	38	43

Table 9 shows mean values of each assessment metric, namely precision, recall, and F1-score, obtained from the model evaluation results. These values are used to describe the model's overall classification performance, including the accuracy of positive predictions (precision), the ability to identify all positive data (recall), and the balance between precision and recall (F1-score).

Table 9. Mean of Assessment Matrix

Assessment Matrix	Mean (%)
Precision	77
Sensitivity/Recall	80.11
F1-Score	78.33

4. Discussion

This study evaluated the detection performance of AI in identifying anatomical landmarks in panoramic radiographs using the YOLOv8 deep learning algorithm. The results showed that the performance of AI model varied for each anatomical landmark due to morphological characteristics, structural size, and the clarity of radiographic boundaries [1]. This is consistent with the state-of-the-art implementations of YOLOv8 in panoramic radiography, which show exceptional capability in segmenting major landmarks like the mandibular canal and maxillary sinus [10].

In this study, the condylar process showed the highest precision, recall, and F1-score values, indicating consistently accurate detection by the AI model. The high detection performance rate can be attributed to the structure relatively large size and clear radiographic boundaries in panoramic radiographs. Anatomical structures with distinct contours and high contrast against surrounding tissue tend to be more easily recognized by deep learning-based object detection models because the algorithm can more consistently identify edge and contour patterns. Similarly, Bağ et al. reported that anatomical structures with distinct radiopaque boundaries and anatomically consistent morphology were more easily recognized by CNN-based deep learning models, particularly the YOLO-v5x AI model [1,7].

The maxillary sinus, orbit, and mandibular canal showed excellent detection performance, with very high precision, recall, and F1-score values. The high values are attributed to the large size, distinctive shape, and clear cortical boundaries that contrast with the surrounding tissue. The consistent position also facilitates the deep learning system's ability to recognize recurring visual patterns across multiple radiographs [1,5,6]. These results were consistent with the values obtained by Bağ et al., who reported near-perfect F1-scores for anatomical structures with distinct radiopaque boundaries, relatively large size, and consistent morphology using YOLO-v5x AI model. A balance between precision and sensitivity was also achieved in structures with high contrast and distinct visual patterns compared to small or complex structures [1].

The nasal septum shows relatively high precision, recall, and F1-score values. This structure appears as a vertical radiopaque line in the center of the nasal cavity on panoramic radiographs, thereby showing a relatively clear linear pattern. The characteristics observed facilitate deep learning-based object detection algorithms such as YOLOv8 in recognizing anatomical patterns on radiographs [14,15]. However, the detection performance of the nasal septum remains lower than the condylar process and maxillary sinus due to individual anatomical variations. Similarly, Bağ et al. reported that structures with consistent anatomical patterns tended to be more easily detected by AI systems on panoramic radiographs [1,5].

Several landmarks, such as the palate, coronoid process, and articular eminence, show lower precision and recall. The detection of these landmarks is affected by the superimposition of other anatomical structures on panoramic radiographs, poor contrast, and individual anatomical variations. Additionally, variations in the patient's head position during panoramic radiograph acquisition can affect the anatomical projection, causing differences in structural appearance [4,6,16]. A previous study by Bağ et al. also found that anatomical structures with less distinct radiopaque boundaries, complex contours, and inconsistent anatomical patterns showed slightly lower sensitivity values than those with larger and more consistent morphology [1]. These results correlate with universal challenges documented in medical YOLO applications, where low contrast, data imbalance, and small target sizes remain persistent challenges that require future architectural modifications [17].

Mental foramen showed the lowest detection performance due to its small anatomical size and significant positional variation between individuals. Generally, mental foramen often overlaps with premolar roots or alveolar bone, making manual and AI-based detection processes difficult [3,5]. According to Bağ et al., large landmarks with distinct radiographic boundaries, such as the orbit and maxillary sinus, showed high F1-scores in automated detection using AI [1]. In comparison, structures with small sizes, such as the mental foramen, tended to have lower detection performance due to the limitations of the object size and the possible superimposition of the surrounding anatomical structures [18].

Before the model training process, this study conducted reliability and validity tests on the anatomical landmark labeling data. Reliability testing using Cronbach's Alpha showed a coefficient value of 0.767, which exceeded the minimum acceptable threshold of 0.70. This indicates that the instrument measuring the detection performance of anatomical landmarks has good reliability [1]. A Cronbach's alpha coefficient above this threshold confirms that the internal consistency of the labeled datasets is acceptable and reliable for training complex object detection models [19].

The validity test was conducted using the Pearson Product-Moment (Inter-Item Correlation Matrix). The results showed that the highest correlation with the total score was achieved by the landmarks of the condylar process, maxillary sinus, orbit, palate, and articular eminence at 0.915, indicating a very strong relationship between variables and the annotation dataset. The high correlation values likely reflect the relatively distinct radiographic boundaries of these anatomical landmarks, which facilitate consistent annotation and AI recognition. In comparison, lower correlation values for other landmarks may be attributed to smaller anatomical size or frequent superimposition with adjacent structures, reducing annotation consistency and detection performance. The correlation analysis indicates that most anatomical landmarks were strongly associated with the overall dataset, supporting the validity of the annotation process [1].

The Pearson Product-Moment (Item-Total Statistics) test showed that no item deletion significantly exceeded the overall Cronbach's Alpha of 0.767, indicating that all items were retained. The results indicated that all anatomical landmarks could be used to measure the AI's detection_performance in identifying anatomical landmarks on panoramic radiographs. Similarly, Bağ et al. reported that the clarity and consistency of anatomical structures on panoramic radiographs influenced the reliability of anatomical landmark identification by both human observers and AI models. Based on the results obtained, the dataset used to create the YOLOv8 AI model met the requirements for reliability and validity [1].

The results indicate that AI has great potential to assist in the identification of anatomical landmarks on panoramic radiographs. This potential is strongly supported by global evidence indicating that automated segmentation of maxillofacial hard tissues yields consistent results, establishing AI as a reliable secondary diagnostic tool [20]. The use of this technology can increase efficiency and reduce subjectivity in the interpretation of dental radiographs [10]. However, further model development is required to improve detection performance for anatomical structures with small size, poorly defined radiographic boundaries, and high morphological variation. Despite the significant contribution, several limitations should be considered when interpreting the results. In this study, the single-center design can limit the generalizability of the model because the training data reflect the imaging characteristics, equipment, and acquisition protocols of a single institution. The lack of external validation indicates that the reported model performance only reflects the capabilities of internal data. Furthermore, the absence of comparison with human readers suggests the lack of empirical evidence showing that YOLOv8's performance is equivalent to or superior to dental radiologists. Class imbalance in the dataset may cause the model to be biased toward the majority class. Therefore, future studies are recommended to include multi-center datasets, external validation using geographically and technically independent data, reader studies involving multiple dental radiologists, and strategies to mitigate class imbalance, such as oversampling, focal loss, or class-weighted loss [4,12,17].

5. Conclusion

In conclusion, YOLOv8 achieves high detection performance for large, distinct anatomical landmarks, including condylar process, maxillary sinus, and orbit. However, the model shows lower accuracy for smaller and more variable structures such as the mental foramen, with a recall of 38%. These results indicate that AI-assisted detection has strong potential to support the identification of prominent maxillofacial anatomical landmarks on panoramic radiographs. Moreover, further model refinement and clinical validation are required before achieving reliable application to small or clinically critical anatomical landmarks.

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7. Conflict of Interest

The authors declare that there is no conflict of interest.

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