European Journal of Therapeutics
pISSN: 2564-7784
eISSN: 2564-7040

Eur J Ther. 2023;29(4):748-758.
https://doi.org/10.58600/eurjther1817

Original Research

Analytical Comparison of Maxillary Sinus Segmentation Performance in Panoramic Radiographs Utilizing Various YOLO Versions

Firdevs Aşantoğrol[1], Burak Tunahan Çiftçi[1]

[1]Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Gaziantep University, Gaziantep, Turkey

Received: 2023-08-23 / **Accepted**: 2023-09-09 / **Published Online**: 2023-09-09

Correspondence
Burak Tunahan Çiftçi, DDs
Address: Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Gaziantep University, Gaziantep, Turkey
E-mail(s): tunahan279@hotmail.com; tunahan@gantep.edu.tr

ABSTRACT

Objective: In this study, we aimed to evaluate the success of the last three versions of YOLO algorithms, YOLOv5, YOLOv7 and YOLOv8, with segmentation feature in the segmentation of the maxillary sinus in panoramic radiography.

Methods: In this study, a total of 376 participants aged 18 years and above, who had undergone panoramic radiography as part of routine examination at Gaziantep University Faculty of Dentistry, Department of Oral and Maxillofacial Radiology, were included. Polygonal labeling was performed on the obtained images using Roboflow software. The obtained panoramic radiography images were randomly divided into three groups training group (70%), validation group (15%) and test group (15%).

Results: In the evaluation of the test data for maxillary sinus segmentation, sensitivity, precision, and F1 scores are 0.92, 1.0, 0.96 for YOLOv5, 1.0, 1.0, 1.0 for YOLOv7 and 1.0, 1.0, 1.0 for YOLOv8, respectively.

Conclusion: These models have exhibited significant success rates in maxillary sinus segmentation, with YOLOv7 and YOLOv8, the latest iterations, displaying particularly commendable outcomes. This study emphasizes the immense potential and influence of artificial intelligence in medical practices to improve the diagnosis and treatment processes of patients.

Keywords: Maxillary sinus; Segmentation; Artificial intelligence; Deep learning models

INTRODUCTION

There are four pairs of paranasal sinuses in the maxillofacial region and cranium; maxillary, frontal, ethmoid and sphenoid sinuses. These sinuses are air-filled cavities lined with mucosa and connected to the nasal cavity. The nose and paranasal sinuses constitute both a functional unit and an integral component of the respiratory system [1]. Specialized epithelial tissue within these structures filters, warms and humidifies the air we breathe, thereby optimizing its suitability for the exchange of oxygen and carbon dioxide within the lungs [2].

The maxillary sinus, pyramid-shaped and the largest among paranasal sinuses, has its frontal wall formed by the facial surface of the maxilla and indented internally by the canalis sinuosus. The posterior wall is formed by the infratemporal surface, the superior wall is composed of the delicate, triangular orbit floor with the infraorbital groove, and the medial wall separates the sinus from the nasal cavity [3]. In the realm of dentistry, the maxillary sinus assumes particular significance among these structures due to its adjacency to dentoalveolar structures, the prevalence of pathologies, and the potential for the symptoms of these pathologies to be confused with symptoms of dental diseases.

Inflammatory paranasal sinus disease is the most prevalent condition affecting the maxillary sinuses. [4]. Dentists frequently encounter the task of distinguishing between dental diseases and other conditions when the maxillary sinus is implicated. Around 10-12% of instances of inflammatory maxillary sinus disease originate from dental sources. Sinus retention cysts usually occur at the floor of the maxillary sinus and are often detected incidentally on dental radiographs and cross-sectional imaging [5]. Mucoceles are formed by the accumulation of mucus when sinus drainage is obstructed and can occupy the sinus entirely. Additionally, mucoceles may induce bone expansion due to pressure effects [6]. Paranasal sinus osteomas are rare, yet they represent the prevalent benign bone growths within the paranasal region. These growths frequently exhibit no symptoms until they attain a particular size, typically being discovered coincidentally during medical examinations [7]. While malignancies arising from the paranasal sinuses are relatively uncommon, approximately 80% of such malignancies occur in the maxillary sinus [8]. Malignant paranasal sinus diseases typically become apparent in advanced stages when the tumor attains a size that triggers symptoms. The paranasal sinus mucosa, unlike oral mucosa, is not as readily accessible for routine examination, making early mucosal abnormalities harder to detect. Dentists can contribute to the diagnosis of maxillary sinus malignancies. The convergence of patient symptoms and clinical indicators should elicit concerns regarding the potential presence of maxillary sinus malignancy, prompting the need for timely referral to a specialized medical practitioner [9].

Panoramic radiography, employed as a standard imaging modality in dentistry, mostly includes the maxillary sinuses in the field of view. Therefore, dentists play a crucial role in diagnosing these diseases by examining the maxillary sinuses in panoramic radiographs where all these pathologies can be seen.

Main Points;

- The effectiveness of YOLOv5, YOLOv7, and YOLOv8 algorithms in segmenting the maxillary sinus on panoramic radiographic images was evaluated in the present study.
- The latest YOLO versions, YOLOv7 and YOLOv8, attained notably high success rates, whereas the success rate of YOLOv5 was comparatively lower than these versions.
- The realm of oral and maxillofacial radiology has also greatly benefited from the progress of artificial intelligence, offering robust assistance in the identification of anatomical structures and pathological conditions.

In 1956, John McCarthy of Dartmouth College introduced the term "artificial intelligence," which now serves as a general descriptor for machines emulating human intelligence's capabilities and functions [10]. Artificial intelligence has made dramatic advances in many fields in recent years, and medicine is one of the fields where artificial intelligence is currently making great progress [11].

Artificial intelligence is developing in the field of dentistry, as in other fields. Artificial intelligence can perform some tasks in dentistry with more precision, reduced need for personnel and minimized errors; It has proven successful in various tasks, ranging from organizing appointments to assisting in clinical diagnoses and treatment planning [12].

You Only Look Once (YOLO) is a popular and widely used artificial intelligence algorithm [13]. This model is a convolutional neural network based real-time object detection algorithm that is fast and high performing compared to its competitors. Redmon et al. introduced the first version of YOLO in 2015 [14]. Since then, new versions of YOLO have been developed and various features have been added to the algorithm.

In this study, we examined the success of the last three versions of YOLO with segmentation feature in segmenting the maxillary sinus in panoramic radiography. We believe that this study will both help dentists in determining the boundaries of the sinus in panoramic images and shed light on the success rates of YOLOv5, YOLOv7 and YOLOv8 algorithms.

MATERIALS AND METHODS

Patient Selection

For our research, a total of 376 participants, 188 males and 188 females, between the ages of 18 and 50, who had undergone panoramic radiography as part of routine examination at Gaziantep University Faculty of Dentistry, Department of Oral and Maxillofacial Radiology, were included. This study received approval from the Gaziantep University Clinical Studies Ethics Committee (Decision No : 2023/310).

Panoramic Radiography Protocol

Uniform digital panoramic images were captured using a consistent machine (Planmeca Proline XC, Helsinki, Finland) with the subsequent exposure parameters: 64 to 66 kVp; 6 to 9 mA; and an exposure time of 10 seconds. The patients were positioned within the dental panoramic machine, aligning the machine's vertical line with the patient's midsagittal plane, while ensuring that the horizontal line (Frankfurt plane) remained parallel to the floor.

Image Labelling and Model Training

Polygonal labelling was performed on the obtained images using Roboflow software (Roboflow, Inc., Des Moines, Iowa, USA) (Figure 1).

The obtained panoramic radiography images were randomly divided into three groups training group (70%), validation group (15%) and test group (15%).

The obtained panoramic radiography images were resized from 1429x697 pixel size to 640x640 pixel size for the algorithm to work at the best performance. Resizing is a key preprocessing step, ensuring uniformity in image size (640x640 pixels) during dataset integration. This uniformity runs algorithms more quickly during training.

Also, the training data;

- Auto Orientation,
- Horizontal Flipping,
- Vertical Flipping,
- Rotation: Ranging from -15° to +15°,
- Grayscale: Applied to 25% of images,
- Blur: Up to 2.5 pixels was applied and it was aimed to increase the learning success of the model by increasing the number of images.

After these changes were applied to the training data, the number of images in the training, validation and test groups were as follows.

- Education group:786 image
- Verification group: 57 images
- Test group: 57 images

The methodology employed up to this point is outlined in Figure 2 as a summarized template.

Deep Learning Procedure

This study utilized the deep learning PyTorch Library and the open-source Python programming language (version 3.6.1; Python Software Foundation, Wilmington, DE, USA), along with the transfer learning approach. The architectures of YOLOv5, YOLOv7, and YOLOv8 were employed for the purpose of maxillary sinus segmentation.

Model Development

The open-source version of Python programming language (v.3.6.1) and PyTorch library were preferred for the model development process. Model training was performed on a computer with 16 GB RAM and equipped with an NVIDIA Tesla V100 graphics card. All model training was done in 10 epochs (training rounds). Google's COLAB platform was used for training and validation, which provides a virtual Linux computer.

Segmentation

In this study, the success of segmentation of maxillary sinuses in panoramic radiography images with YOLOv5, YOLOv7 and YOLOv8 deep learning models was investigated. Figure 3 illustrates the segmented maxillary sinuses achieved through YOLOv5, YOLOv7, and YOLOv8.

Statistical Analysis

True positive (TP): The maxillary sinus segmented by the model is actually the maxillary sinus.
False negative (FN): This is when the model does not segment the maxillary sinus, but it is actually the maxillary sinus.
False positive (FP): This is when the model segments the maxillary sinus, but it is not actually the maxillary sinus.
Sensitivity, accuracy and F1 score are calculated with these values;

- Sensitivity: Refers to the ability not to miss true positives. That is, it shows how few missed positive cases there are.
- Precision: It expresses the rate at which the values predicted as positive by the model are actually positive. That is, it shows how little the model makes false positives.
- F1 Score: A metric that balances precision and sensitivity. By considering the balance between sensitivity and precision, it helps to better evaluate the performance of the model.
- The Receiver Operating Characteristic (ROC) is a common metric used to evaluate the performance of a classification model. It graphs the true positive rate (TPR) of the model on the y-axis and the false positive rate (FPR) on the x-axis.
- The Area Under the Curve (AUC) represents the area beneath the ROC curve. AUC is a measure used to assess the overall classification performance of the model. The AUC value takes a value between 0 and 1:

If AUC = 0.5, the performance of the model is the same as random forecasting.

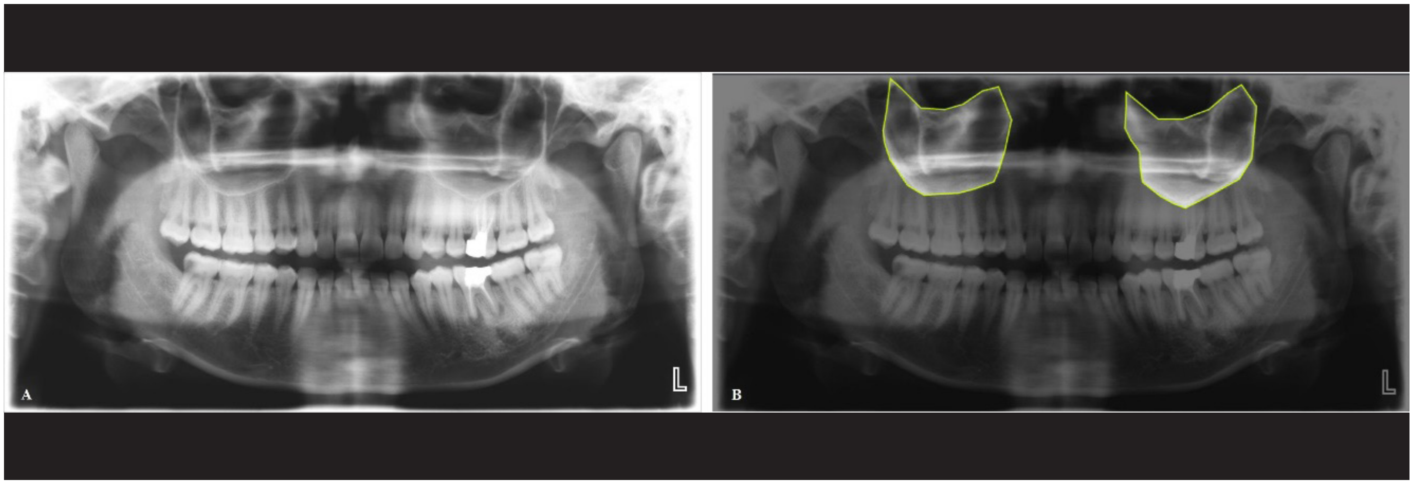

Figure 1. A: Original panoramic image B: Polygonal labelling of images using Roboflow software

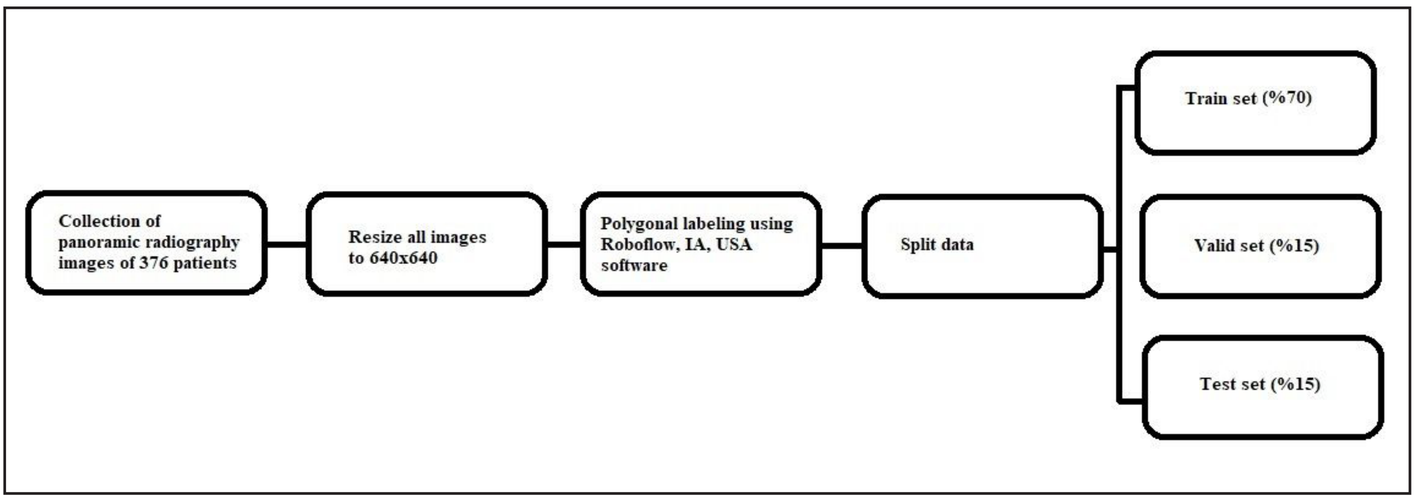

Figure 2. Summarized template of the methodology

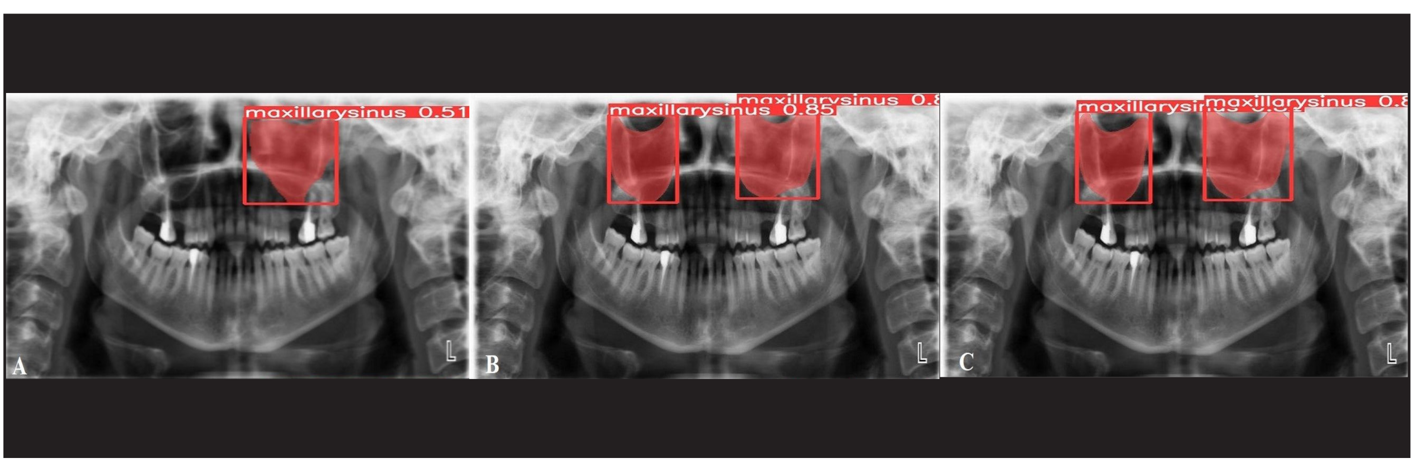

Figure 3. A: Panoramic image segmented utilizing YOLOv5 algorithm B: Panoramic image segmented utilizing YOLOv7 algorithm C: Panoramic image segmented utilizing YOLOv8 algorithm

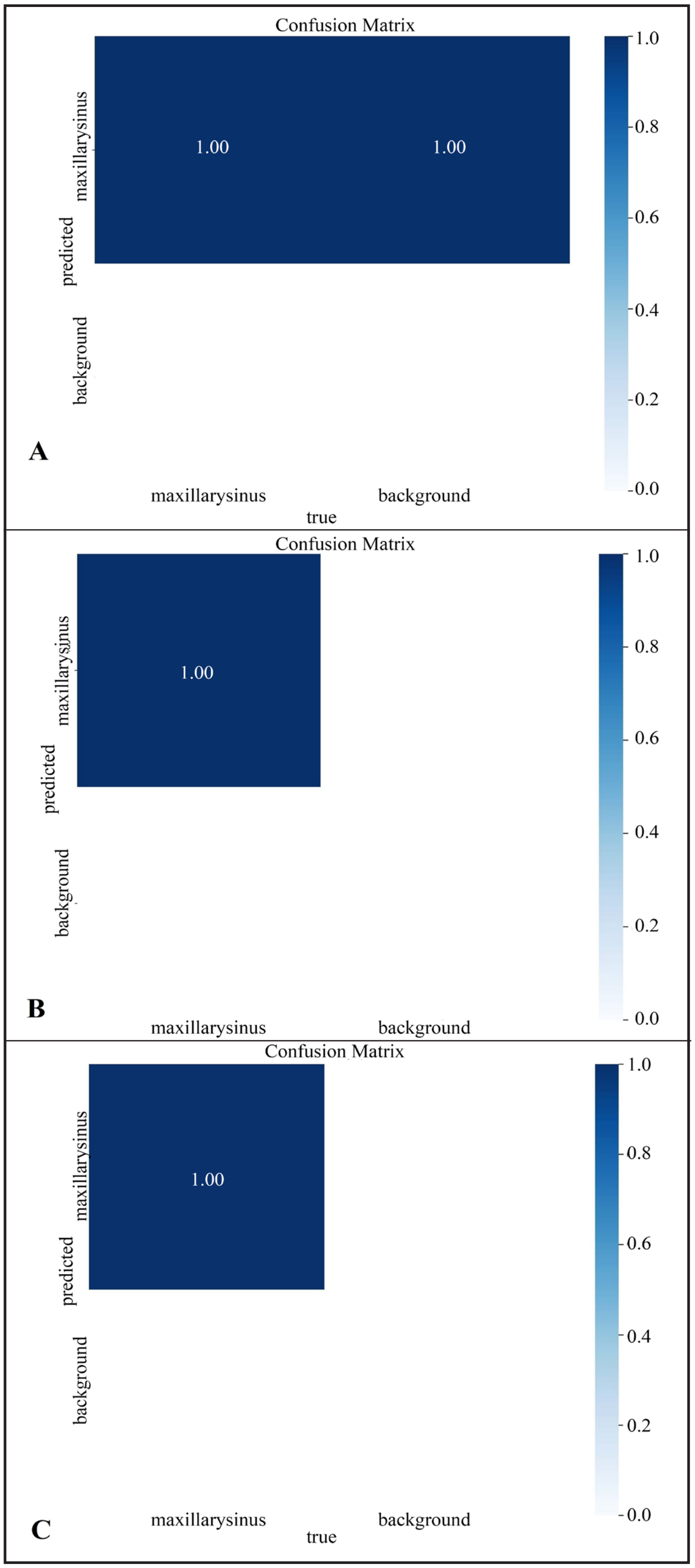

Figure 4. A: Confusion matrix plot for YOLOv5 algorithm B: Confusion matrix plot for YOLOv7 algorithm C: Confusion matrix plot for YOLOv8 algorithm

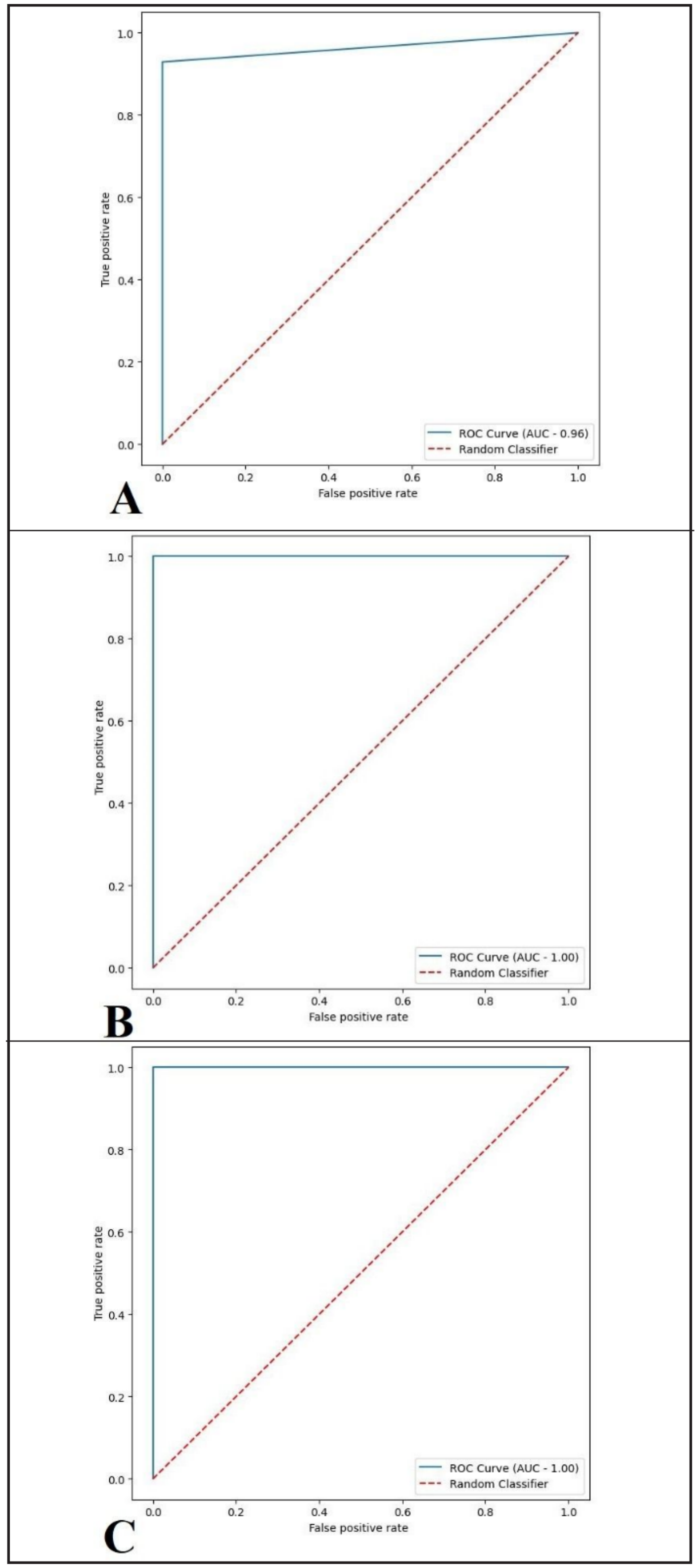

Figure 5. A: Receiver operating characteristic (ROC) curve and area under the curve (AUC) plot for YOLOv5 algorithm B: Receiver operating characteristic (ROC) curve and area under the curve (AUC) plot for YOLOv7 algorithm C: Receiver operating characteristic (ROC) curve and area under the curve (AUC) plot for YOLOv8 algorithm

If AUC > 0.5, the performance of the model is good and indicates that it makes better predictions. As the AUC value increases, the performance of the model improves further.

If AUC < 0.5, the performance of the model is worse than random forecasting. As the AUC value decreases, the performance of the model gets worse.

Higher AUC values indicate that the model has a better discrimination power and better distinguishes between true positive and negative classes.

RESULTS

The confusion matrix plots of YOLOv5, YOLOv7 and YOLOv8 deep learning models for maxillary sinus segmentation are shown in Figure 4.

Figure 5 displays the ROC curves and AUC values for the YOLOv5, YOLOv7, and YOLOv8 deep learning models employed in the segmentation of maxillary sinuses.

In the evaluation of the test data for maxillary sinus segmentation, TP, FP and FN values are 106, 0, 8 for YOLOv5, 114, 0, 0, 0 for YOLOv7 and 114, 0,0 for YOLOv8, respectively. The calculated sensitivity, precision, and F1 scores based on these values are presented in Table 1.

Table 1. F1, Sensitivity and Precision values in the evaluation of test data for maxillary sinus segmentation

	YOLOv5	YOLOv7	YOLOv8
F1	0.96	1.0	1.0
Sensitivity	0.92	1.0	1.0
Precision	1.0	1.0	1.0

DISCUSSION

Artificial intelligence has developed in numerous scientific disciplines in recent years and has become an indispensable part of daily life. The utilization of artificial intelligence in the fields of medicine has aspired not only to aid physicians in diagnosis and treatment within areas such as pharmacology [15], ophthalmology [16], pathology [17], cardiology [18], psychiatry [19], and radiology [20] but also to achieve time and cost efficiencies.

Dentistry is one of the medical fields experiencing rapid and dynamic advancements in new technologies [21]. Within restorative dentistry, artificial intelligence can accurately identify tooth decay or pre-existing restorations and facilitate the selection of the optimal approach for caries removal [22-24]. Artificial intelligence within the field of endodontics can provide valuable assistance in the identification of periapical lesions and root fractures, evaluation of root canal systems, estimation of pulp root cell viability, determination of working length measurements, and prediction of the efficacy of retreatment procedures [25-29]. They can ease diagnosis and treatment planning in orthodontics, identify cephalometric landmarks, conduct anatomical analyses, evaluate growth and development, and assess the outcomes of treatment [30-34]. In oral surgery, artificial neural networks can offer assistance in orthognathic surgical and implant treatment planning, as well as predicting post-extraction complications and detecting bone lesions [35-40]. In the domain of periodontology, these networks have been employed to evaluate both periodontal bone deterioration and the loss of bone around dental implants [41, 42].

The use of artificial intelligence in oral and maxillofacial radiology is becoming increasingly widespread. Studies in this field are frequently used in cone beam computed tomography (CBCT) [28], panoramic radiography [43], intraoral radiography [44], cephalometric radiography [45] and ultrasonography [46] images for the purpose of segmentation [47], detection [48], classification [24]. Thereby, it aims to help physicians identify anatomical structures and diagnose pathologies within this region through its applications.

In the literature, there are many studies on the examination of maxillary sinuses employing artificial intelligence. Ki-Jung et al. [48] aimed to segment the maxillary sinus into distinct components such as maxillary bone, air, and lesions. They subsequently conducted an analysis by juxtaposing these outcomes with evaluations conducted by experts. The study demonstrated that the integration of a deep learning framework can effectively reduce the time required for instructive labeling on limited CBCT datasets. Murata et al. [49] utilized a deep learning system for the diagnosis of maxillary sinusitis. In their study, where they evaluated 800 panoramic images, they indicated that the deep learning system exhibited a notably elevated diagnostic performance for maxillary sinusitis in panoramic radiographs. Morgan et al. [50] developed a CNN model with a 3D U-Net architecture for the automated segmentation of the maxillary sinus in CBCT images. They reported that the CNN model offers a time-efficient, precise, and consistent automated segmentation, which enables the generation of an accurate 3D model for diagnosis and treatment planning purposes. Choi et al. [51] developed a segmentation model for maxillary sinuses employing the U-Net architecture. They determined that the deep learning model exhibited strong performance in effectively segmenting both clear and hazy maxillary sinuses. Kabak et al. [52] conducted a study to assess and compare manual, semi-automatic, and automatic approaches for evaluating maxillary sinus volume using CBCT. They reached the conclusion that the data obtained through the application of artificial intelligence exhibited a strong correlation with the results of sinus morphometry achieved through manual and semi-automatic techniques. Kuwana et al. [53] aimed to determine the performance of deep learning object detection techniques in detecting maxillary sinuses and classifying maxillary sinus pathologies in panoramic radiography. They stated that deep learning can consistently recognize maxillary sinuses and accurately distinguish cysts within the maxillary sinus region and cases of maxillary sinusitis. Youngjune et al. [54] utilized a deep learning algorithm to label maxillary sinuses depicted in Waters radiographs as either sinusitis or normal sinus. They affirmed that the deep learning algorithm has the potential to diagnose maxillary sinusitis in Waters radiographs. Serindere et al. [55] utilized a convolutional neural network (CNN) for the evaluation of maxillary sinusitis in both panoramic radiographs and CBCT images. They concluded that the diagnostic performance of CNN for maxillary sinusitis in panoramic radiographs was moderate, but significantly higher in CBCT images. In their study, Hung et al. [56] employed a CNN algorithm for the automatic detection and segmentation of mucosal thickening and mucous retention cysts in the maxillary sinus using CBCT. They stated that this approach holds the potential to accurately detect and segment these pathological conditions.

The current study examined the success of maxillary sinus segmentation in panoramic radiographs using different versions of the YOLO algorithm. The study concluded that the latest YOLO versions, YOLOv7 and YOLOv8, attained notably high success rates, whereas the success rate of YOLOv5 was comparatively lower than these versions. YOLOv7 was unveiled on ArXiv in July 2022 by the creators of YOLOv4. Similar to YOLOv4, it was trained solely on the MS COCO dataset without the use of pre-trained backbones. YOLOv7 introduced various architectural modifications that enhance accuracy while specifically targeting training time, without impacting the inference rate. These architectural changes likely account for the improved success of YOLOv7 compared to its predecessors. All of these examples from the literature demonstrate how widespread and effective the utilization of artificial intelligence is as a tool in the examination of maxillary sinuses. Artificial intelligence assumes a pivotal role in identifying, segmenting, diagnosing, and strategizing treatment for maxillary sinuses, primarily due to its capableness in image processing and analysis. Deep learning algorithms exhibit high performance, especially in maxillary sinus segmentation and diagnosis and follow-up of sinus diseases. Many studies emphasize the advantages of technology in the field of medicine and the potential of artificial intelligence in clinical applications.

Limitations

This study solely evaluated different versions of YOLO and does not encompass various deep learning architectures. Furthermore, it exclusively focused on the anatomical segmentation of the maxillary sinus and did not assess different sinus pathologies. Addressing these limitations and increasing the sample size in future studies could lead to more beneficial outcomes.

CONCLUSIONS

In conclusion, there are many studies in the literature on the examination of maxillary sinuses with artificial intelligence. The common goal of these studies is to improve the detection, segmentation, diagnosis and treatment planning of maxillary sinuses through the utilization of artificial intelligence techniques. Investigations employing deep learning models like YOLOv5, YOLOv7, and YOLOv8 stand as remarkable indicators of the advancements achieved in this domain. Notably, these models have exhibited significant success rates in maxillary sinus segmentation, with YOLOv7 and YOLOv8, the latest iterations, displaying particularly commendable outcomes. These studies emphasize the immense potential and influence of artificial intelligence in medical practices to improve the diagnosis and treatment processes of patients. The realm of oral and maxillofacial radiology has also greatly benefited from progress of the artificial intelligence, offering robust assistance in the identification of anatomical structures and pathological conditions. These findings suggest that the ongoing and future development of artificial intelligence holds the promise of further refining and enhancing precision and efficacy in healthcare diagnoses and treatments.

Informed Consent: The study is a retrospective study and was carried out by scanning the existing images in the archive system of our department.

Acknowledgments: We would like to thank all individuals whose images we used retrospectively. The writing of this manuscript was performed entirely by the authors and paraphrase was supported by ChatGPT-3.5, an artificial intelligence (AI) application. In the final stage, the version of the manuscript sent to the journal was read and approved by all authors and it was accepted that all responsibilities related to the article belong to all authors.

Conflict of Interest: The authors declare that they have no conflict of interest in the publication.

Funding: The author declared that this study has received no financial support.

Ethical Approval: The presented study has obtained ethical approval from the Institutional Review Board. The decision number assigned to this approval is 2023/310.

Author Contributions: Conception: F.A., B.T.Ç. - Design: F.A., B.T.Ç. - Supervision: F.A.- Materials: F.A., B.T.Ç. - Data Collection and/or Processing: B.T.Ç. - Analysis and/or Interpretation: B.T.Ç. - Literature Review: F.A., B.T.Ç. - Writing: F.A, B.T.Ç. - Critical Review: F.A.

REFERENCES

[1] Krouse JH (2012) The unified airway. Facial Plast Surg 20(1):55-60. https://doi.org/10.1016/j.fsc.2011.10.006

[2] Whyte A, Boeddinghaus R (2019) The maxillary sinus: physiology, development and imaging anatomy. Dentomaxillofac Radiol 48(8):20190205. https://doi.org/10.1259/dmfr.20190205

[3] Standring S (2021) Gray's anatomy E-book: the anatomical basis of clinical practice, 41st edn. Elsevier Health Sciences, London

[4] Parnes SM (2001) Rhinology and Sinus Disease: A Problem-Oriented Approach. Plast Reconstr Surg 108(2):573.

[5] Wang JH, Jang YJ, Lee BJ (2007) Natural course of retention cysts of the maxillary sinus: long-term follow-up results. Laryngoscope 117(2):341-344. https://doi.org/10.1097/01.mlg.0000250777.52882.7a

[6] Capra GG, Carbone PN, Mullin DP (2012) Paranasal sinus mucocele. Head Neck Pathol 6:369-372. https://doi.org/10.1007/s12105-012-0359-2

[7] Gulsen S, Tasdemir A, Mumbuc S (2021) Surgical Approach to Paranasal Sinus Osteomas: Our Experience in 22 Cases. Eur J Ther 27(4):250-256. http://doi.org/10.5152/eurjther.2019-19083

[8] Katzenmeyer K, Pou A (2000) Neoplasms of the Nose and Paranasal Sinus. Dr. Quinn's Online Textbook of Otolaryngology.

[9] Bell GW, Joshi BB, Macleod RI (2011) Maxillary sinus disease: diagnosis and treatment. Br Dent J 210(3):113-118. https://doi.org/10.1038/sj.bdj.2011.47

[10] McCorduck P, Cfe C (2004) Machines who think: A personal inquiry into the history and prospects of artificial intelligence, 2nd edn. CRC Press, New York

[11] Gore JC (2020) Artificial intelligence in medical imaging. Magn Reson Imaging 68. https://doi.org/10.1016/j.mri.2019.12.006

[12] Chen YW, Stanley K, Att W (2020) Artificial intelligence in dentistry: current applications and future perspectives. Quintessence Int 51(3):248-257.

[13] Sultana F, Sufian A, Dutta P (2020) A review of object detection models based on convolutional neural network. Intelligent computing: image processing based applications. 1-16 Springer, Singapore https://doi.org/10.1007/978-981-15-4288-6

[14] Zhiqiang W, Jun L (2017) A review of object detection based on convolutional neural network. Chinese Control Conference (CCC) 36:(11104-11109). https://doi.org/10.23919/ChiCC.2017.8029130

[15] van der Lee M, Swen JJ (2023) Artificial intelligence in pharmacology research and practice. Clin Transl Sci 16(1):31-36. https://doi.org/10.1111/cts.13431

[16] Ting DSW, Pasquale LR, Peng L, Campbell JP, Lee AY, Raman R, Wong TY (2019) Artificial intelligence and deep learning in ophthalmology. Br J Ophthalmol 103(2):167-175. https://doi.org/10.1136/bjophthalmol-2018-313173

[17] Försch S, Klauschen F, Hufnagl P, Roth W (2021) Artificial

intelligence in pathology. Dtsch Arztebl Int 118(12):199. https://doi.org/10.3238%2Farztebl.m2021.0011

[18] Lopez-Jimenez F, Attia Z, Arruda-Olson AM, Carter R, Chareonthaitawee P, Jouni H, Friedman PA (2020, May) Artificial intelligence in cardiology: present and future. In Mayo Clin Proc 95(51):1015-1039. Elsevier. https://doi.org/10.1016/j.mayocp.2020.01.038

[19] Ray A, Bhardwaj A, Malik YK, Singh S, Gupta R (2022) Artificial intelligence and Psychiatry: An overview. Asian J Psychiatr 70:103021. https://doi.org/10.1016/j.ajp.2022.103021

[20] Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJ (2018) Artificial intelligence in radiology. Nat Rev Cancer 18(8):500-510. https://doi.org/10.1038/s41568-018-0016-5

[21] Ossowska A, Kusiak A, Świetlik D (2022) Artificial intelligence in dentistry-Narrative review. Int J Environ Res Public Health 19(6):34-49. https://doi.org/10.3390/ijerph19063449

[22] Javed S, Zakirulla M, Baig RU, Asif SM, Meer AB (2020) Development of artificial neural network model for prediction of post-streptococcus mutans in dental caries. Comput Methods Programs Biomed 186:105-198. https://doi.org/10.1016/j.cmpb.2019.105198

[23] Geetha V, Aprameya KS, Hinduja DM (2020) Dental caries diagnosis in digital radiographs using back-propagation neural network. Health Inf Sci Syst 8:1-14. https://doi.org/10.1007/s13755-019-0096-y

[24] Abdalla-Aslan R, Yeshua T, Kabla D, Leichter I, Nadler C (2020) An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography. Oral Surg Oral Med Oral Pathol Oral Radiol 130(5):593-602. https://doi.org/10.1016/j.oooo.2020.05.012

[25] Saghiri MA, Asgar K, Boukani KK, Lotfi M, Aghili H, Delvarani A, Garcia-Godoy F, (2012) A new approach for locating the minor apical foramen using an artificial neural network. Int Endod J 45(3):257-265. https://doi.org/10.1111/j.1365-2591.2011.01970.x

[26] Ekert T, Krois J, Meinhold L, Elhennawy K, Emara R, Golla T, Schwendicke F (2019) Deep learning for the radiographic detection of apical lesions. J Endod 45(7):917-922. https://doi.org/10.1016/j.joen.2019.03.016

[27] Setzer FC, Shi KJ, Zhang Z, Yan H, Yoon H, Mupparapu M, Li J (2020) Artificial intelligence for the computer-aided detection of periapical lesions in cone-beam computed tomographic images. J Endod 46(7):987-993 https://doi.org/10.1016/j.joen.2020.03.025

[28] Orhan K, Bayrakdar IS, Ezhov M, Kravtsov A, Özyürek T (2020) Evaluation of artificial intelligence for detecting periapical pathosis on cone-beam computed tomography scans. Int Endod J 53(5):680-689. https://doi.org/10.1111/iej.13265

[29] Pauwels R, Brasil DM, Yamasaki MC, Jacobs R, Bosmans H, Freitas DQ, Haiter-Neto F (2021) Artificial intelligence for detection of periapical lesions on intraoral radiographs: Comparison between convolutional neural networks and human observers. Oral Surg Oral Med Oral Pathol Oral Radiol 131(5):610-616. https://doi.org/10.1016/j.oooo.2021.01.018

[30] Li P, Kong D, Tang T, Su D, Yang P, Wang H, Liu Y (2019) Orthodontic treatment planning based on artificial neural networks. Sci Rep 9(1):2037. https://doi.org/10.1038/s41598-018-38439-w

[31] Auconi P, Scazzocchio M, Cozza P, McNamara Jr JA, Franchi L (2015) Prediction of Class III treatment outcomes through orthodontic data mining. Eur J Ortho 37(3):257-267. https://doi.org/10.1093/ejo/cju038

[32] Bianchi J, de Oliveira Ruellas AC, Goncalves JR, Paniagua B, Prieto JC, Styner M, Cevidanes LHS (2020) Osteoarthritis of the Temporomandibular Joint can be diagnosed earlier using biomarkers and machine learning. Sci Rep 10(1):8012. https://doi.org/10.1038/s41598-020-64942-0

[33] Muraev AA, Tsai P, Kibardin I, Oborotistov N, Shirayeva T, Ivanov S, Tuturov N (2020) Frontal cephalometric landmarking: humans vs artificial neural networks. Int J Comput Dent 23(2).

[34] Kök H, Izgi MS, Acilar AM (2021) Determination of growth and development periods in orthodontics with artificial neural network. Ortho Craniofac Res 24: 76-83. https://doi.org/10.1111/ocr.12443

[35] Lu CH, Ko EWC, Liu L, (2009) Improving the video imaging prediction of postsurgical facial profiles with an artificial neural network. J Dent Sci 4(3):118-129. https://doi.org/10.1016/S1991-7902(09)60017-9

[36] Patcas R, Bernini DA, Volokitin A, Agustsson E, Rothe R, Timofte R (2019) Applying artificial intelligence to assess the impact of orthognathic treatment on facial attractiveness and estimated age. Int J Oral Maxillofac Surg 48(1):77-83. https://doi.org/10.1016/j.ijom.2018.07.010

[37] Patcas R, Timofte R, Volokitin A, Agustsson E, Eliades T, Eichenberger M, Bornstein MM (2019) Facial attractiveness of cleft patients: a direct comparison between artificial-intelligence-based scoring and conventional rater groups. Eur J Orthod 41(4):428-433. https://doi.org/10.1093/ejo/cjz007

[38] Kim BS, Yeom HG, Lee JH, Shin WS, Yun JP, Jeong SH, Kim BC (2021) Deep learning-based prediction of paresthesia after third molar extraction: A preliminary study. Diagnostics 11(9):1572. https://doi.org/10.3390/diagnostics11091572

[39] Kurt Bayrakdar S, Orhan K, Bayrakdar IS, Bilgir E, Ezhov M, Gusarev M, Shumilov E (2021) A deep learning approach for dental implant planning in cone-beam computed tomography images. BMC Med Imaging 21(1):86. https://doi.org/10.1186/s12880-021-00618-z

[40] Sukegawa S, Yoshii K, Hara T, Matsuyama T, Yamashita K, Nakano K, Furuki Y (2021) Multi-task deep learning model for classification of dental implant brand and treatment stage using dental panoramic radiograph images. Biomolecules 11(6):815. https://doi.org/10.3390/biom11060815

[41] Krois J, Ekert T, Meinhold L, Golla T, Kharbot B, Wittemeier A, Schwendicke F (2019) Deep learning for the radiographic detection of periodontal bone loss. Sci Rep 9(1):8495. https://doi.org/10.1038/s41598-019-44839-3

[42] Lee CT, Kabir T, Nelson J, Sheng S, Meng HW, Van Dyke TE, Shams S (2022) Use of the deep learning approach to measure alveolar bone level. J Periodontol 49(3):260-269. https://doi.org/10.1111/jcpe.13574

[43] Fukuda M, Inamoto K, Shibata N, Ariji Y, Yanashita Y, Kutsuna S, Ariji E (2020) Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography. Oral Radiol 36:337-343. https://doi.org/10.1007/s11282-019-00409-x

[44] Yasa Y, Çelik Ö, Bayrakdar IS, Pekince A, Orhan K, Akarsu S, Aslan AF (2021) An artificial intelligence proposal to automatic teeth detection and numbering in dental bite-wing radiographs. Acta Odontol Scand 79(4):275-281. https://doi.org/10.1080/00016357.2020.1840624

[45] Çoban G, Öztürk T, Hashimli N, Yağci A (2022) Comparison between cephalometric measurements using digital manual and web-based artificial intelligence cephalometric tracing software. Dental Press J Orthod 27. https://doi.org/10.1590/2177-6709.27.4.e222112.oar

[46] Orhan K, Yazici G, Kolsuz ME, Kafa N, Bayrakdar IS, Çelik Ö (2021) An artificial intelligence hypothetical approach for masseter muscle segmentation on ultrasonography in patients with bruxism. J Adv Oral Res 12(2):206-213. https://doi.org/10.1177/23202068211005611

[47] Leite AF, Gerven AV, Willems H, Beznik T, Lahoud P, Gaêta-Araujo H, Jacobs R (2021) Artificial intelligence-driven novel tool for tooth detection and segmentation on panoramic radiographs. Clin Oral Investig 25:2257-2267. https://doi.org/10.1007/s00784-020-03544-6

[48] Jung SK, Lim HK, Lee S, Cho Y, Song IS (2021) Deep active learning for automatic segmentation of maxillary sinus lesions using a convolutional neural network. Diagnostics (Basel) 11:688. https://doi.org/10.3390/diagnostics11040688

[49] Murata M, Ariji Y, Ohashi Y, Kawai T, Fukuda M, Funakoshi T, Ariji E (2019) Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography. Oral Radiol 35:301-307. https://doi.org/10.1007/s11282-018-0363-7

[50] Morgan N, Van Gerven A, Smolders A, de Faria Vasconcelos K, Willems H, Jacobs R (2022) Convolutional neural network for automatic maxillary sinus segmentation on cone-beam computed tomographic images. Sci Rep 12(1):7523. https://doi.org/10.1038/s41598-022-11483-3

[51] Choi H, Jeon KJ, Kim YH, Ha EG, Lee C, Han SS (2022) Deep learning-based fully automatic segmentation of the maxillary sinus on cone-beam computed tomographic images. Sci Rep 12(1):14009. https://doi.org/10.1038/s41598-022-18436-w

[52] Kabak SL, Karapetyan GM, Melnichenko YM, Savrasova NA, Kosik II (2021) Automated system of the determination of maxillary sinus morphometric parameters. Vest Otorinolaringol 86(2):49-53. https://doi.org/10.17116/otorino20218602149

[53] Kuwana R, Ariji Y, Fukuda M, Kise Y, Nozawa M, Kuwada C, Ariji E (2021) Performance of deep learning object detection technology in the detection and diagnosis of maxillary sinus lesions on panoramic radiographs. Dentomaxillofac Radiol 50(1):20200171. https://doi.org/10.1259/dmfr.20200171

[54] Kim Y, Lee KJ, Sunwoo L, Choi D, Nam CM, Cho J, Kim JH (2019) Deep learning in diagnosis of maxillary sinusitis using conventional radiography. Invest Radiol 54(1):7-15. https://doi.org10.1097/RLI.0000000000000503

[55] Serindere G, Bilgili E, Yesil C, Ozveren N (2022) Evaluation of maxillary sinusitis from panoramic radiographs and cone-beam computed tomographic images using a convolutional neural network. Imaging Sci Dent 52(2):187.

[56] Hung KF, Ai QYH, King AD, Bornstein MM, Wong LM, Leung YY (2022) Automatic detection and segmentation of morphological changes of the maxillary sinus mucosa on cone-beam computed tomography images using a three-dimensional convolutional neural network. Clin Oral Investig 26(5):3987-3998. https://doi.org/10.1007/s00784-021-04365-x

How to Cite;

Aşantoğrol F, Çiftçi BT (2023) Analytical Comparison of Maxillary Sinus Segmentation Performance in Panoramic Radiographs Utilizing Various YOLO Versions. Eur J Ther. 29(4):748-758. https://doi.org/10.58600/eurjther1817