Detection of the Fixed Prostheses on Panoramic Images: An Artificial Intelligence Based Study

Melike Yurttas¹, Ozlem Yarbasi², Ridvan Karakurt³, Halil Ayyildiz¹, Elif Bilgir⁴ and Ibrahim Sevki Bayrakdar⁴

Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Kutahya Health Science University, Kutahya, Turkiye Department of Oral and Maxillofacial Radiology, Faculty of Dentistry, Suleyman Demirel University, Isparta, Turkiye Department of Oral and Maxillofacial Radiology, Konya Beyhekim Agiz ve Dis Sagligi Merkezi, Konya, Turkiye Department of Oral and Maxillofacial Radiology, Eskisehir Osmangazi University, Eskisehir, Turkiye

ABSTRACT

Objective: To investigate the effectiveness of using YOLO-v5x in detecting fixed prosthetic restoration in panoramic radiographs. **Study Design:** Descriptive study.

Place and Duration of the Study: Department of Oral and Maxillofacial Radiology, Eskisehir Osmangazi University, Eskisehir, Turkiye from November 2022 to April 2023.

Methodology: For the labelling of fixed prosthetic restorations, 8,000 panoramic radiographs were evaluated using the YOLOv5x architecture. In creating the dataset for this study, fixed prosthetic restorations were categorised as dental implant, pontic, crown, and implant-supported crown on dental panoramic radiographs. The labelled images were then randomly split into three groups: 80% for training, 10% for validation, and 10% for testing. The labelled panoramic images constituted the model's training dataset, and leveraging the knowledge acquired during this learning stage, the model generated predictions in the testing phase. **Results:** The majority of labelling data were dedicated to crown restorations. The precision and sensitivity values of YOLOv5x were 0.99 and 0.98 for crowns, 0.98 and 0.99 for implants, 0.99 and 0.99 for pontics, and 0.99 and 0.99 for implant-supported crowns, respectively.

Conclusion: The results obtained in this study demonstrate a satisfactory success rate of YOLO-v5x in detecting dental prosthetic restorations. The high precision and sensitivity of the model indicate its strong potential to enhance clinical professional performance and contribute to the development of more efficient dental health services.

Key Words: Artificial intelligence, Dentistry, Dental prosthesis, Panoramic radiography.

How to cite this article: Yurttas M, Yarbasi O, Karakurt R, Ayyildiz H, Bilgir E, Bayrakdar IS. Detection of the Fixed Prostheses on Panoramic Images: An Artificial Intelligence Based Study. J Coll Physicians Surg Pak 2024; **34(08)**:922-926.

INTRODUCTION

Prosthetic dentistry diagnoses and preserves the function, comfort, appearance, and health of the oral structures of dental patients with missing or absent teeth. It restores missing teeth and structures by replacing them with artificial ones.^{1,2} Fixed prosthetic restorations are dental prostheses, fabricated to replace missing teeth in dental patients. Due to advantages, such as being more socially and psychologically practical, providing comfort, and occupying less space in the oral cavity, fixed prosthetic restorations are preferred more than removable prosthetics.

Correspondence to: Dr. Melike Yurttas, Department of Oral and Maxillofacial Radiology, Kutahya Health Science University, Kutahya, Turkiye E-mail: basarannm@gmail.com

... Received: February 20, 2024; Revised: July 25, 2024; Accepted: August 02, 2024 DOI: https://doi.org/10.29271/jcpsp.2024.08.922

Artificial intelligence (AI) software has gained momentum in many fields of medicine and dentistry and deep learning (DL), one of the AI methods, has found widespread use in dentistry in recent years. DL is a learning method based specifically on multilayered artificial neural networks (ANN). These networks consist of layers that work similarly to the nerve cells in the human brain and can process data. The ANN specialised in dealing with grid-like topology data, such as 2D and 3D images, are called convolutional neural networks (CNN).³ CNNs were used in dentistry in tooth classification and segmentation, anatomical landmark and caries detection, periodontal bone loss, and vertical foot fracture detection etc.⁴⁻¹⁰ In the past, various imaging methods such as 2D (e.g., periapical, panoramic radiographs) and 3D (cone beam computed tomography) were used, and dental restoration detection was even performed using intraoral photographs. $6-10$ In majority of these studies, CNNs were found to be successful, demonstrating an accuracy rate of over 90% in tasks, such as dental landmark detection, cavity detection, object classification, and disease diagnosis. Using DL methods may provide more precise and accurate diagnoses and can reduce the workload of dentists. Additionally, detecting and diagnosing teeth and restorations

can help dentists keep electronic records of their patient's oral health over time and spot possible problems before they worsen. Furthermore, digital profiling of teeth and restorations can also be used for personal identification in forensic dentistry or in the aftermath of a major catastrophe. 11

You only look once (YOLO) is a novel DL method employed for object detection in medical imaging.¹² Compared to traditional CNNs, YOLO is claimed to be faster, more efficient, and easy to use, making it the preferred choice for real-time object detection. YOLO divides the image into a grid and predicts bounding boxes and class probabilities for each cell.¹² YOLO-v5x is one of the latest and most advanced versions of YOLO-series. In literature, numerous studies have utilised commonly used CNN models such as Denti.AI, ResNet, U-Net, etc.^{9-11,13} However, object detection-focused models, such as YOLO-v5, have limited and unsupported research on dental radiography data. YOLO-v5 could be successful in object detection in dentistry, given its speed, ease of use, and other features. Therefore, the objective of this study was to determine the detection success of YOLO-v5x in dental radiographs by examining fixed prosthetic restorations on panoramic radiographs.

METHODOLOGY

In this retrospective study, segmentation models for dental fixed prosthetic restorations (CranioCatch, Eskisehir-Turkiye) were developed using the YOLO-v5x architecture implemented in PyTorch, based on anonymised panoramic radiographs. The research protocol was approved by the University's Non-Interventional Clinical Research Ethics Board (Decision Date and Approval Number: 04.10.2022/22) and followed the principles of the Declaration of Helsinki. A total of 10,000 anonymised dental panoramic radiographs were randomly selected from the university database from November 2022 to April 2023. The panoramic radiographs were obtained from individuals aged 18 years and over who presented with various dental complaints. All dental panoramic radiographs included in the study were captured using a Planmeca Promax 2D panoramic dental imaging device (Planmeca, Helsinki, Finland) with settings at 68 kVp, 16 mA, and a 13-second exposure. Panoramic radiographs exhibiting artefacts resulting from patient movement, improper positioning, or superposition of foreign subjects were excluded from the database, as they could potentially lead to inaccurate evaluations.

The labelling process is conducted hierarchically, by the researchers with a minimum of 10 years of experience. Subsequently, an oral and maxillofacial radiologist (E.B., with 10 years of experience) has reviewed, refined, and approved all the labels using CranioCatch labelling software (Eskisehir, Turkiye). During the creation of the dataset for the study, fixed prosthetic restorations on dental panoramic radiographs were labelled using a polygonal segmentation method as dental implant, pontic, crown, and implant-supported crown (Figure 1). A total of 8,000 panoramic images were included in the study. Among them, 34,082 crowns were labelled on 7,158 panoramic images, 5,127 implants on 1,543 images, 16,862 pontics on 5,223 images, and

2,703 implant-supported crowns on 954 images. The labelled images were randomly split into three groups: 80% for training, 10% for validation, and 10% for testing. The labelled panoramic images constituted the model's training dataset, and leveraging the knowledge acquired during this learning stage, the model generated predictions in the testing phase.

Figure 1: Fixed prosthetic restorations on panoramic radiographs using the YOLO-v5x AI implant (A) crown (B) implant-supported crown (C) pontic (D).

The software was developed using the PyTorch library in the Python programming language (version 3.6.1; Python Software Foundation, Wilmington, DE, USA) and employed 2D CNN architectures with 500 training epochs. YOLO-v5x was utilised for the training of fixed prosthetic restoration segmentation. The YOLOv5x architecture consists of input, backbone, and neck parts. In the input section, the image is given to the model. In the backbone part, features are extracted from the image. In the neck section, an intermediate layer called neck has been added while estimating objects and more information is requested here. YOLO-v5x hyperparameters used in training included; image size: 1280*640, batch size: 4, learning rate: 0.01, optimiser: SGD, anchor t: 4.0, epoch count = 500 (early stop 145), hyperparameters used for augmentation, mosaic $= 1.0$, scale $= 0.9$, copypaste = 0.1 , hsv $s = 0.7$, hsv $v = 0.4$, and translate = 0.1.

The training process took place in the Eskisehir Osmangazi University, Faculty of Dentistry, Dental-AI Laboratory, utilising the following computer equipment: Dell PowerEdge T640 Calculation Server, Dell PowerEdge T640 GPU Calculation Server, and Dell PowerEdge R540 Storage Server (all manufactured by Dell Inc., Texas, USA). While the training durations vary, each epoch approximately lasts 4 minutes, leading to an estimated total duration of 580 minutes for 145 epochs.

A confusion matrix is a table that is used to evaluate the performance of a classification model. The confusion matrix can be used to calculate various performance metrics such as sensitivity, precision, and F1 score. These metrics can help in evaluating the effectiveness of a classification model and identifying areas for improvement.

Table I: Distribution of the data and training parameters.

The precision values of YOLO- v5x were 0.99 for crowns, 0.98 for implants, 0.99 for pontics, and 0.99 for implant-supported crowns. The sensitivity scores of the YOLOv5x were 0.98 for crowns, 0.99 for implants, 0.99 for pontics, and 0.99 for implant-supported crowns. Considering the F1 scores, the AI models were more successful in determining pontics and implant-supported crowns, with scores of 0.9946 and 0.9942, respectively. Table II provides a summary of the obtained success values.

Table II: The sensitivity, precision, and F1 score values of the YOLO-v5x.

Sensitivity true positive rate (TPR) was defined as the model's ability to predict the true positives and also known as the true positive rate (TPR) or recall.

Precision positive predictive value (PPV) was defined as how many of the samples labelled as positive by the model were actually positive. F1 Score was calculated as $2TP / (2TP + FP)$ $+$ FN $)$.

RESULTS

The YOLO-v5x architecture utilised as the AI model in this study, demonstrated success in the classification and detection of fixed prostheses. For the evaluation of fixed prostheses by using YOLO-v5x architecture, most data were used for crown restorations (Table I).

The precision values of YOLO- v5x were 0.99 for crowns, 0.98 for implants, 0.99 for pontics, and 0.99 for implantsupported crowns. The sensitivity scores of the YOLOv5x were 0.98 for crowns, 0.99 for implants, 0.99 for pontics, and 0.99 for implant-supported crowns. Considering the F1 scores, the AI models were more successful in determining pontics and implant-supported crowns, with scores of 0.9946 and 0.9942, respectively. Table II provides a summary of the obtained success values.

DISCUSSION

Dental prostheses play a crucial role in enhancing the function, appearance, health, and comfort of the oral and maxillofacial structures in patients with missing teeth for various reasons. Fixed prostheses are commonly employed for this purpose in dentistry.¹⁴ Dental radiographs are essential for both diagnostic and treatment planning. Dentists often rely on panoramic radiographs as an easy, fast, and cost-effective method for accurate diagnosis and treatment planning. However, panoramic radiographs, being twodimensional and distorted, with superimpositions of anatomical structures, can pose challenges in evaluating the radiographs.¹⁵ Despite these disadvantages, panoramic radiographs are still widely used by dentists worldwide, and panoramic radiographs have been mentioned in many AI studies.^{6,8-10,16} In this study, panoramic radiographs, commonly used by dentists for diagnostic purposes, were evaluated.

In recent years, AI systems, which have gained considerable attention, have found applications in diverse fields such as medicine, engineering, and education. Within dentistry, AI systems have been employed for various purposes, including patient data analysis, treatment plans, caries detection, prosthesis design, digital smile design, and image interpretation.¹⁷ Researchers utilised various AI programmes to detect and classify dental restorations. Rubiu et al. studied teeth segmentation by Mask Region-based Convolutional Neural Network (Mask-RCNN) on 1,000 panoramic radiographs. The model achieved detection accuracy on the test set 98.4%.¹⁸ Abdalla-Aslan et al. utilised an algorithm which was developed in the Matlab® environment for automatic detection of dental restorations on the 83 panoramic radiographs. The researchers reported that the algorithm's detection sensitivity ranged from 83.1 to 100%, with an overall sensitivity of 94.6%.⁸ Bonfanti-Gris et al. analysed the detection and classification of dental structures and treatments in 300 panoramic radiographs using the Denti.Ai® online software. The neural network showed an overall accuracy of $>80\%$.¹⁰ A recent study compared the performance of faster regions with the convolutional neural networks (R-CNN) and YOLO-V4 for tooth classification in 1,200 panoramic radiographs. The study results demonstrated that the YOLO-V4 method surpassed the Faster R-CNN method in terms of tooth prediction accuracy, detection speed, and the capability to identify both impacted and erupted third molar.¹⁹ Ali et al. employed YOLOv7 to detect teeth and prostheses in 3,138 panoramic radiographs. They reported excellent performance, and the precision of prosthesis was 0.983 .¹¹ The CNN algorithm YOLO-v5x architecture is employed in this study, representing a real-time detection technique with a singlepass categorisation of targeted objects.²⁰ The YOLO-v5x architecture exhibited high detection accuracy for fixed prostheses, with close scores among different types. The lowest F1 score (0.9865) was observed in crown restorations. Based on the success rate of the study, the trained YOLO-v5x model demonstrated an appropriate ability to detect prosthetic restorations.

In studies focusing on the detection of prosthetic restorations, AI systems have demonstrated satisfactory success. Abdalla-Aslan et al. classified dental restorations in 85 panoramic radiographs, achieving 100% accuracy for crowns and 99.9% for dental implants.⁸ In a study by Vinayahalingam et al., diagnostic charting was conducted on 2,000 panoramic radiographs, with reported F1 scores of 0.90 for implants and 0.94 for crowns.¹⁶ Bonfanti-Gris et al. conducted a study on dental structure classification using 300 panoramic radiographs. They reported positive predictive values of 100 for implants and 89.5 for crowns.¹⁰ However, Altan et al., in their evaluation of 5,126 panoramic radiographs, found precision values of 0.74 for crowns and 0.84 for bridges. The authors suggested that the lower results in their study could be attributed to larger datasets and differences in image quality.²¹ In this study, precision values of YOLO-v5x for crowns, implants, pontics, and implant-supported crowns were very high (0.99, 0.98, 0.99, and 0.99, respectively). These results, as previously mentioned and observed in other studies, support the success of YOLO-v5x in object detection and demonstrate its potential applicability in dentistry. Additionally, the large amount of data used in this study has contributed to the learnability of the YOLO-v, which may have enhanced the success of YOLO-v5x.

In considering the errors of the AI system used in this study, it was observed that the system confused pontics and implant-supported crowns as crowns. Additionally, in a few instances, the system misclassified teeth as implants. The system also encountered challenges in predicting pontics, which were related to the density of the teeth and pontic material. Notably, the system failed to estimate implantsupported crowns in cases where implants were not detected in the images.

AI systems demonstrate promise in dentistry, achieving high success rates in detecting dental structures in panoramic radiographs. Furthermore, it is crucial to note that this success is directly linked to image quality. Optimal settings for kVp, mA, and patient positioning significantly impact both image quality and density. The study by Vinayahalingam et al. found that root remnants had the lowest F1 score.¹⁶ Additionally, Bonfanti-Gris et al. concluded

that the AI system exhibited lower success rates in detecting resin-based restorations compared to metallic restorations.¹⁰ This lower success rate may be attributed to the fact that AI systems perform well in regions where two different area densities are clearly differentiated.⁸

CONCLUSION

The precision values of YOLOv5x were 0.99 for crowns, 0.98 for implants, 0.99 for pontics, and 0.99 for implantsupported crowns. The sensitivity scores of the YOLOv5x were 0.98 for crowns, 0.99 for implants, 0.99 for pontics, and 0.99 for implant-supported crowns. The results demonstrated a satisfactory success rate of YOLOv5x in detecting dental prosthetic restorations. It is inevitable that AI systems will gradually find their way into clinical use. Therefore, contributing to the development of AI systems through further studies with more extensive datasets is crucial.

ETHICAL APPROVAL:

The research protocol was approved by the University's Non-Interventional Clinical Research Ethics Board (Decision Date and Approval Number: 04.10.2022/22).

COMPETING INTEREST:

The authors declared no conflict of interest.

AUTHORS' CONTRIBUTION:

MY: Writing the manuscript, review, and editing.

OY, RK, HA: Writing the manuscript.

EB: Conceptualisation, methodology, data collection, review, and editing.

ISB: Conceptualisation, methodology, data collection, and interpretation.

All authors approved the final version of the manuscript to be published.

REFERENCES

- 1. Pareek M, Kaushik B. Artificial intelligence in prosthodontics: A scoping review on current applications and future possibilities. Int J Adv Med 2022; **9**:367-70. doi: 10.18203/2349-3933.ijam20220444.
- 2. Alshadidi AAF, Alshahrani AA, Aldosari LIN, Chaturvedi S, Saini RS, Hassan SAB, et al. Investigation on the application of artificial intelligence in prosthodontics. Appl Sci 2023; **13(8)**:5004. doi:10.3390/app13085004.
- 3. Gerhardt MDN, Fontenele RC, Leite AF, Lahoud P, Van Gerven A, Willems H, et al. Automated detection and labelling of teeth and small edentulous regions on conebeam computed tomography using convolutional neural networks. J Dent 2022; **122**:104139. doi: 10.1016/ j.jdent. 2022.104139.
- 4. Fukuda M, Inamoto K, Shibata N, Ariji Y, Yanashita Y, Kutsuna S, et al. Evaluation of an artificial intelligence

system for detecting vertical root fracture on panoramic radiography. Oral Radiol 2020; **36(4)**:337-43. doi: 10.1007/ s11282-019-00409-x.

- 5. Tuzoff DV, Tuzova LN, Bornstein MM, Krasnov AS, Kharchenko MA, Nikolenko SI, et al. Tooth detection and numbering in panoramic radiographs using convolutional neural networks. Dentomaxillofac Radiol 2019; **48(4)**: 20180051. doi: 10.1259/dmfr.20180051.
- 6. Basaran M, Celik O, Bayrakdar IS, Bilgir E, Orhan K, Odabas A, et al. Diagnostic charting of panoramic radiography using deep-learning artificial intelligence system. Oral Radiol 2022; **38(3)**:363-9. doi: 10.1007/s11282-021-005 72-0.
- 7. Chen CC, Wu YF, Aung LM, Lin JC, Ngo ST, Su JN, et al. Automatic recognition of teeth and periodontal bone loss measurement in digital radiographs using deep-learning artificial intelligence J Dent Sci 2023; **18(3)**:1301-9. doi: 10.1016/j.jds.2023.03.020.
- 8. Abdalla-Aslan R, Yeshua T, Kabla D, Leichter I, Nadler C. 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 2020; **130(5**):593-602. doi: 10. 1016/j.oooo.2020.05.012.
- 9. Engels P, Meyer O, Schonewolf J, Schlickenrieder A, Hickel R, Hesenius M, et al. Automated detection of posterior restorations in permanent teeth using artificial intelligence on intraoral photographs. J Dent 2022; **121**:104124. doi: 10.1016/j.jdent.2022.104124.
- 10. Bonfanti-Gris M, Garcia-Canas A, Alonso-Calvo R, Salido Rodriguez-Manzaneque MP, Pradies Ramiro G. Evaluation of an artificial intelligence web-based software to detect and classify dental structures and treatments in panoramic radiographs. J Dent 2022; **126**:104301. doi: 10.1016/ j.jdent.2022.104301.
- 11. Ali MA, Fujita D, Kobashi S. Teeth and prostheses detection in dental panoramic X-rays using CNN-based object detector and a priori knowledge-based algorithm. Sci Rep 2023; **13(1)**:16542. doi: 10.1038/s41598-023-43591-z.
- 12. Redmon J, Divvala S, Girshick R, Farhadi A. You only look once: Unified, real-time object detection. In Proceedings of

the IEEE conference on computer vision and pattern recognition. 2016 p. 779-88. doi: 10-48550/arXiv.1506. 02640.

- 13. Gardiyanoglu E, Unsal G, Akkaya N, Aksoy S, Orhan K. Automatic segmentation of teeth, crown-bridge restorations, dental implants, restorative fillings, dental caries, residual roots, and root canal fillings on orthopantomographs: Convenience AND PITFAlls. Diagnostics (Basel) 2023; **13(8)**:1487. doi: 10.3390/diagnostics13081487.
- 14. Zhao J, Wang X. Dental prostheses. In advanced ceramics for dentistry. In: Shen JZ, Kosmac T, Eds. Butterworth-Heinemann. Ed. 1st, Waltham, MA; USA; 2014: p. 23-49.
- 15. Perschbacher S. Interpretation of panoramic radiographs. Aust Dent J 2012; **57**:40-5. doi: 10.1111/j.1834- 7819.2011. 01655.x.
- 16. Vinayahalingam S, Goey RS, Kempers S, Schoep Cherici T, Moin DA. Hanisch M. Automated chart filing on panoramic radiographs using deep learning. J Dent 2021; **115**: 103864. doi: 10.1016/j.jdent.2021.103864.
- 17. Chen YW, Stanley K, Att W. Artificial intelligence in dentistry: Current applications and future perspectives. Quintessence Int 2020; **51(3)**:248-57. doi: 10.3290/j.qi. a43952.
- 18. Rubiu G, Bologna M, Cellina M, Ce M, Sala D, Pagani R, et al. Teeth segmentation in panoramic dental X-ray Using mask regional convolutional neural network. Appl Sci 2023; *13(***13)**:7947. doi: 10.3390/app13137947.
- 19. Yilmaz S, Tasyurek M, Amuk M, Celik M, Canger EM. Developing deep learning methods for classification of teeth in dental panoramic radiography. Oral Surg Oral Med Oral Pathol Oral Radiol 2024; **138(1)**:118-27. doi: 10. 1016/j.oooo.2023.02.021.
- 20. Bayraktar Y, Ayan E. Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. Clin Oral Investig 2022; **26(1)**: 623-32. doi: 10.1007/s00784-021-04040-1.
- 21. Altan B, Gunec HG, Cinar S, Kutal S, Gulum S, Aydin KC. Detecting prosthetic restorations using artificial intelligence on panoramic radiographs. Sci Program 2022. doi:10.1155/2022/6384905.

••••••••••