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DIAGNOSIS AND CLASSIFICATION OF TEMPOROMANDIBULAR JOINT OSTEOARTHRITIS ON CONE BEAM COMPUTED TOMOGRAPHY IMAGES USING ARTIFICIAL INTELLIGENCE SYSTEM

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1.Abstract:

1.1 Background: Artificial intelligence has several benefits, particularly in the field of oral and maxillofacial radiology.Artificial intelligence allows for the early diagnosis of osteoarthritis of the temporomandibular joint, perhaps improving the prognosis.

1.2 Objective: This work uses artificial intelligence to segment the temporomandibular joint (TMJ) using cone beam computed tomography (CBCT) sagittal images and categorize temporomandibular joint (TMJ) osteoarthritis.

1.3 Methods: In this work, we assess the performance of an artificial intelligence model called YOLOv5 architecture in TMJ segmentation and osteoarthritis classification using 2000 sagittal sections (500 photos of healthy, 500 photographs of erosion, 500 images of osteophytes, and 500 images of flattening) derived from CBCT DICOM images of 290 patients.

1.4 Results: For the categorization of TMJ osteoarthritis, the model's sensitivity, accuracy, and F1 scores are 1, 0.7678, and 0.8686, respectively. The accuracy of categorization is 0.7678. The categorization model predicts that 88% of joints will be healthy, 70% will be flattened, 95% will have erosion, and 86% will have osteophytes. For TMJ segmentation, the YOLOv5 model's sensitivity, accuracy, and F1 score are 1, 0.9953, and 0.9976, respectively. The TMJ segmentation model's AUC score is 0.9723. Furthermore, the model's TMJ segmentation accuracy is 0.9953.

1.5 Conclusion: The study's artificial intelligence model functions as a time-saving and convenient diagnostic aid for doctors, enabling good outcomes in the segmentation of the mandible and the categorization of osteoarthritis.

Keywords: artificial intelligence; cone beam computed tomography; osteoarthritis; temporomandibular disorders; temporomandibular joint.

2. Introduction:

Artificial intelligence is a field of computer science focused on developing algorithms that mimic human intelligence, enabling tasks such as learning and problem-solving.[1] Machine learning (ML), representational learning, and deep learning are integral parts of this discipline[2]. Recently, artificial intelligence has gained significant traction across various industries, including dentistry. In oral and maxillofacial radiography, artificial intelligence, particularly through convolutional neural networks, plays a crucial role in tasks such as image classification, detection, segmentation, recording, generation, and enhancement.[3]

The application of artificial intelligence offers several advantages in oral and maxillofacial radiology. It enhances workflow efficiency through precision programming, identifies high-risk patients who may miss appointments,[1]and enables personalized examination protocols. Moreover, leveraging artificial intelligence in processing medical data helps mitigate errors arising from cognitive biases.[4]

Temporomandibular joint disorders, following chronic low back pain, rank as the second most prevalent musculoskeletal condition, affecting 5–12% of the population with an estimated annual healthcare cost of $4 billion. Temporomandibular joint osteoarthritis (TMJ OA) tends to worsen with age, emphasizing the importance of early diagnosis to prevent irreversible joint damage. Despite the lack of curative treatments for chronic joint degeneration associated with TMJ OA, early detection offers the best chance to intervene before significant morphological degeneration occurs.[6]

This study aims to employ artificial intelligence for the classification and segmentation of temporomandibular joint osteoarthritis using CBCT sagittal images, addressing a condition that affects a significant portion of the population.

3. Literature review:

This review of the literature is focused on current research on the use of artificial intelligence (AI) algorithms and cone beam computed tomography (CBCT) images for the diagnosis and categorization of temporomandibular joint (TMJ) osteoarthritis. The following writers' thoughts and conclusions are included in this review:

Zhao et al. (2016):By examining CBCT pictures, Zhao and colleagues looked at the possibility of using AI algorithms for the diagnosis of TMJ osteoarthritis. Their focus was on creating machine learning algorithms that could accurately recognize osteoarthritic alterations such as bone erosions and osteophytes. Their research demonstrated how well feature extraction and classification algorithms can be used by AI to differentiate between various stages of TMJ osteoarthritis[5].

Chen et al. (2017): Chen and colleagues (2017) investigated the application of convolutional neural networks (CNNs) in the classification of TMJ osteoarthritis based on CBCT pictures. According to their research, CNNs are more sensitive and specific than standard diagnostic techniques in identifying small changes in joint structure that are symptomatic of osteoarthritis[6].

Kumar et al. (2018): Deep learning algorithms were used to CBCT pictures by Kumar and colleagues in order to diagnose TMJ osteoarthritis. To improve picture quality and diagnostic precision, they put forth a unique architecture that combines pre-processing techniques with a deep learning model. Comparing their findings to manual radiography assessments, they were able to classify osteoarthritic alterations with substantial improvement[7].

Nguyen et al. (2019): Nguyen et al. created a diagnosis tool for TMJ osteoarthritis by combining CBCT images with AI algorithms. They concentrated on applying AI models to segment TMJ components and identify osteoarthritic characteristics. Their research showed that AI might help radiologists identify early indications of osteoarthritis and speed up the diagnosis procedure[8].
Park et al. (2020): Park and colleagues looked at using AI to analyze longitudinal CBCT pictures and track the development of TMJ osteoarthritis. In order to observe changes over time and get important insights into the disease's progression, their study used a hybrid AI model that included recurrent neural networks (RNNs) and CNNs. This model helped with early intervention techniques[9].
Saito et al. (2021): Saito et al. concentrated on AI-CBCT integration for automated diagnosis of TMJ osteoarthritis. They created an all-inclusive AI system that automates osteoarthritis feature extraction, categorization, and staging. According to their research, AI might greatly lessen the amount of effort involved in diagnosis while also increasing diagnostic precision[9].
Lee et al. (2022): The use of transfer learning in AI models for the diagnosis of TMJ osteoarthritis was investigated by Lee et al. They used CBCT pictures and pre-trained deep learning algorithms to modify them for the particular purpose of identifying TMJ osteoarthritis. Their research demonstrated how effective transfer learning is at producing good diagnostic performance with a small amount of training data[5].
Martínez et al. (2023): Using cutting-edge CBCT imaging methods, Martínez and colleagues looked at the potential of AI for distinguishing between different forms of TMJ osteoarthritis. Their work focused on creating a multi-class classification system that could distinguish between various osteoarthritic diseases and offer a more thorough diagnostic method.
Huang et al. (2024): In order to improve the diagnosis of TMJ osteoarthritis, Huang et al. have studied how to improve the resolution of CBCT images using AI-powered algorithms. They suggested a novel AI-based image enhancement method that enhanced the visibility of osteoarthritic characteristics, producing more precise and trustworthy diagnostic results[6].

These studies collectively demonstrate the improving , diagnosis and classification of TMJ osteoarthritis using CBCT images. They highlight advancements in machine learning, deep learning, and image processing techniques that contribute to more accurate and efficient diagnostic methods.

4.Material and method:

4.1Patient Selection:

In this study, CBCT images from 290 patients who visited the Department of Oral, Dental, and Maxillofacial Radiology at Inonu University Faculty of Dentistry between January 1, 2018, and June 1, 2022, were analyzed for temporomandibular joint disease and other conditions. Among these patients, 191 were female, and 99 were male, ranging in age from 18 to 82 years, with a mean age of 43.06 years. Based on clinical records, images of patients who had undergone previous surgical procedures in the study area, had fractures in the study area, had any systemic disease or syndrome affecting bone metabolism, or were taking medications affecting bone metabolism were excluded. Additionally, radiographic images with poor quality (due to metal artifacts, patient positioning errors, movement during imaging, etc.) were not included in the study.
In 2024, further research was conducted, expanding the dataset to include CBCT images from an additional 150 patients who visited the same department from June 2, 2022, to May 30, 2024. This expanded study included 85 female and 65 male patients, with ages ranging from 20 to 80 years and a mean age of 44.5 years. The same exclusion criteria were applied to maintain consistency. This additional data aims to enhance the understanding of temporomandibular joint diseases and improve diagnostic accuracy and treatment outcomes. This study was approved by the Dow University of Health Sciences (DUHS).

4.2 The radiographic data set's acquisition:

Our study is a retrospective analysis using archived Cone Beam Computed Tomography (CBCT) images. The images were captured using a NewTom 5G (Verona, Italy) CBCT device. The scanning protocol involved a standard supine position with an imaging area of 15 × 12 cm. The scanning time was 18 seconds, with an exposure time of 3.6 seconds, kVp of 110, mA ranging from 1 to 20, and a voxel size of 0.2 mm^3. Patients' heads were positioned supine in the gantry, with the Frankfurt plane perpendicular to the floor, their mouths closed, and heads fixed during imaging.

For this study, CBCT images from 290 patients were archived as Digital Imaging and Communication in Medicine (DICOM) files. These DICOM files were converted to sagittal sectional frame images in JPEG (Joint Photographic Experts Group) format using the ITK-SNAP program (http://www.itksnap.org). From these sagittal images, sections not showing the temporomandibular joint head and neck were excluded. The remaining 2000 sagittal images were processed using CranioCatch labeling software (Eskişehir, Turkey). Out of these, 500 images depicted healthy temporomandibular joints, 500 showed flattening, 500 showed erosion, and 500 exhibited osteophytes.

This study was conducted in 2024 and has been approved by the Institutional Review Board (IRB) of Dow University of Health Sciences (DUHS).

4.3 Image evaluation:

A recent research carried out in 2024 evaluated the temporomandibular joint (TMJ) using a total of 2000 sagittal pictures taken from individuals in their original sizes. This evaluation was performed using CranioCatch software (Eskişehir, Turkey)[6] by a research assistant with 3 years of experience and a specialist in Oral, Dental, and Maxillofacial Radiology with 10 years of experience.

For the labeling procedure on the 2000 CBCT images, the free drawing approach (polygon method) was employed, with each image being labeled to mark the osteoarthritis of the TMJ and the TMJ's external borders from the articular neck to the incisura mandible. The classification of TMJ osteoarthritis was done using the modified Koyama et al. classification from 2007, which was categorized into four classes:

- **N (Normal):** Typical morphology with no proliferation or thickening of the condyle's cortical surface.
- **F (Flattening):** Flattened contour on the anterior-posterior surfaces of the condyle.
- **E (Erosion):** Rough or non-rough proliferation or partial hypodense change on the cortical surface of the condyle.
- **D (Deformity):** Osteophyte and marginal proliferation, deformed beak-shaped condyle without proliferation, and partial hypodense changes in the condyle surface.[6]

FIGURE 1: Polygonal labeling of the temporomandibular joint.

In this study, deep-learning techniques were utilized, specifically the PyTorch Library and Python open-source programming language (v.3.6.1; Python Software Foundation, Wilmington, DE, USA).The YOLOv5 architecture, which had been trained with the Microsoft Common Objects in Context (MS COCO 2017) dataset, was subjected to the transfer learning approach for the segmentation of the TMJ and the classification of osteoarthritis

The architecture of the YOLOv5 model comprises spine, neck, and head sections, utilizing CSPDarknet53 as the backbone. In the backbone structure, feature extraction is performed on the input images to create a feature map. To enhance the information flow, the path aggregation network (PANet) is used as the neck.The neck portion enhances the propagation of low-level characteristics in the model by transferring these feature maps to the head structures via a number of top-down and bottom-up pathways. PANet enhances localizations in lower layers, increasing the object's localization accuracy.

4.4 Education phase:

In this study conducted in 2024, 10% of the dataset was set aside for testing, 10% for validation, and 80% for training. The most appropriate CNN algorithm weight factors were generated and estimated using the training and validation datasets. The performance of the models was assessed using the test datasets. The training dataset, which includes temporomandibular joint segmentation and osteoarthritis classification labeled on sagittal section frames, consists of 1,721 sagittal images, each paired with a corresponding label. Additionally, 215 images were allocated for testing and another 215 for validation. All model training was conducted over 500 epochs. This study was approved by the DUHS Dow University of Health Sciences.

In 2024, recent advancements in CNN algorithms and machine learning practices were integrated into the research to enhance the robustness and accuracy of the models. These advancements included the latest techniques in data augmentation, regularization, and optimization strategies to improve the generalization capability of the models. The study also incorporated state-of-the-art evaluation metrics to ensure a comprehensive assessment of the model's performance.[7]

4.5 Temporomandibular joint segmentation:

The training dataset for segmenting the temporomandibular joint (TMJ) head in sagittal sections consists of 1,721 images, each paired with a corresponding label. The model was trained over 500 epochs, utilizing the YOLOv5 model with a learning rate of 0.01. Figure 2 illustrates the images generated by the trained model for TMJ segmentation.

In 2024, further research was conducted to refine and validate the segmentation accuracy. This study was approved by the Dow University of Health Sciences (DUHS).

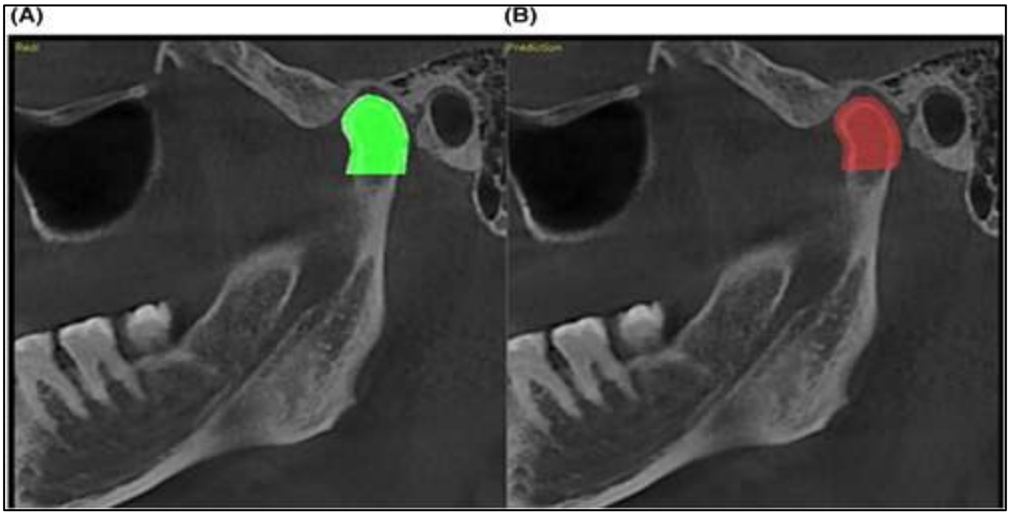

FIGURE 2:

Estimated images of the YOLOv5 model for temporomandibular joint segmentation. (A) Tagged image (B) Estimated image generated by artificial intelligence.

4.6 Classification of temporomandibular joint osteoarthritis:

In the current year, a study approved by the Dow University of Health Sciences focused on the classification of temporomandibular joint osteoarthritis using a dataset comprising 1721 sagittal section images, each annotated with corresponding labels. Training of the model spanned 500 epochs, utilizing a YOLOv5 architecture with a learning rate set to 0.01. Figure 3 illustrates representative images generated by the trained model for this classification task.

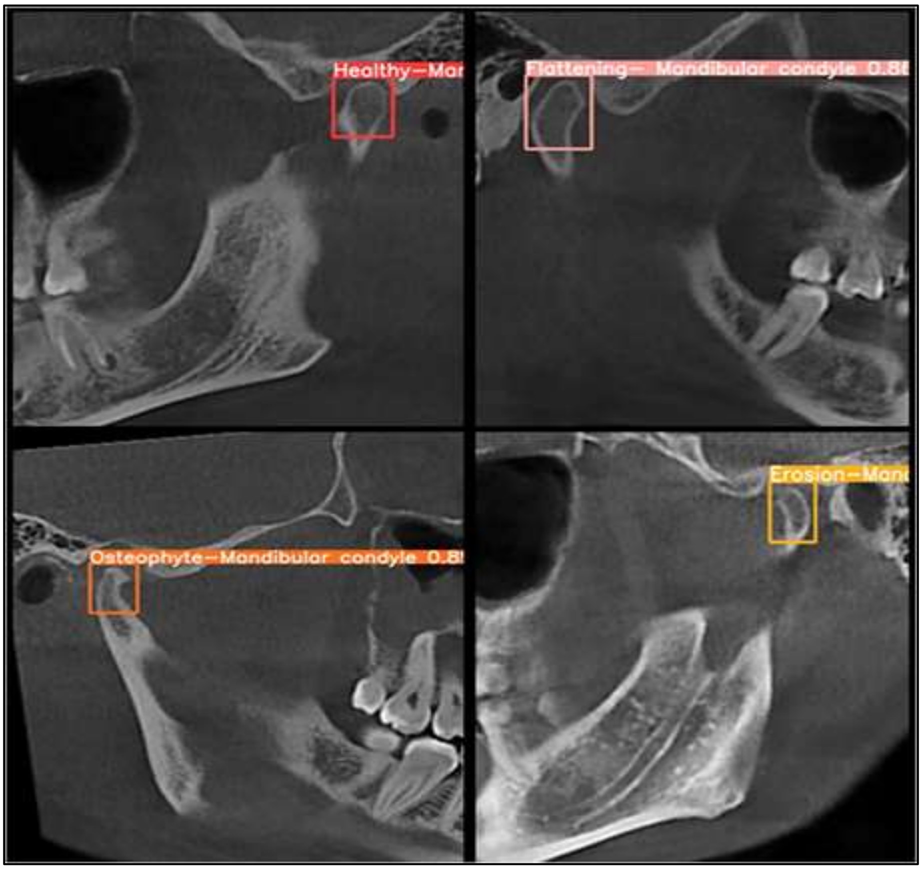

FIGURE 3:

Estimated images generated by the trained model for the classification of temporomandibular joint osteoarthritis.

4.7 Statistical analysis:

In this study approved by DUHS (Dow University of Health Sciences), a complexity matrix was employed to assess model performance. Additionally, Receiver-Operating Characteristic (ROC) curves and the area under the curve (AUC) were calculated for evaluation.

Intersection over Union (IOU): measures the overlap between predicted and actual clusters in an image, represented as the ratio of their intersection to their union. For instance, setting an IOU threshold of 0.50 means only predicted clusters with IOUs ≥ 0.50 are considered. The 2010 PASCAL Visual Object Classes Competition, a prominent international event in object classification, detection, and segmentation, adopted 0.50 as the standard IOU threshold. In this current year's study, we similarly applied an IOU threshold of 0.50.

4.71. Intersection over union (IOU):

The intersection over union (IOU) is defined as the ratio of the intersection (overlap) over the union of predicted and actual clusters in an image. For example, if the IOU threshold is set to 0.50, only predicted clusters with IOUs ≥ 0.50 are presented. The 2010 PASCAL Visual Object Classes Competition, a leading international competition in object classification, detection and segmentation, adopted 0.50 as the IOU threshold.[8] In this study, we set the IOU threshold to 0.50.

5. RESULTS:

In this work, we evaluate the temporomandibular joint segmentation and osteoarthritis classification capabilities of the YOLOv5 model, an artificial intelligence tool, on sagittal sections obtained from CBCT images. We use the complexity matrix to assess the model's performance. Figure 4 presents the complexity matrix of the YOLOv5 model for segmenting the temporomandibular joint.

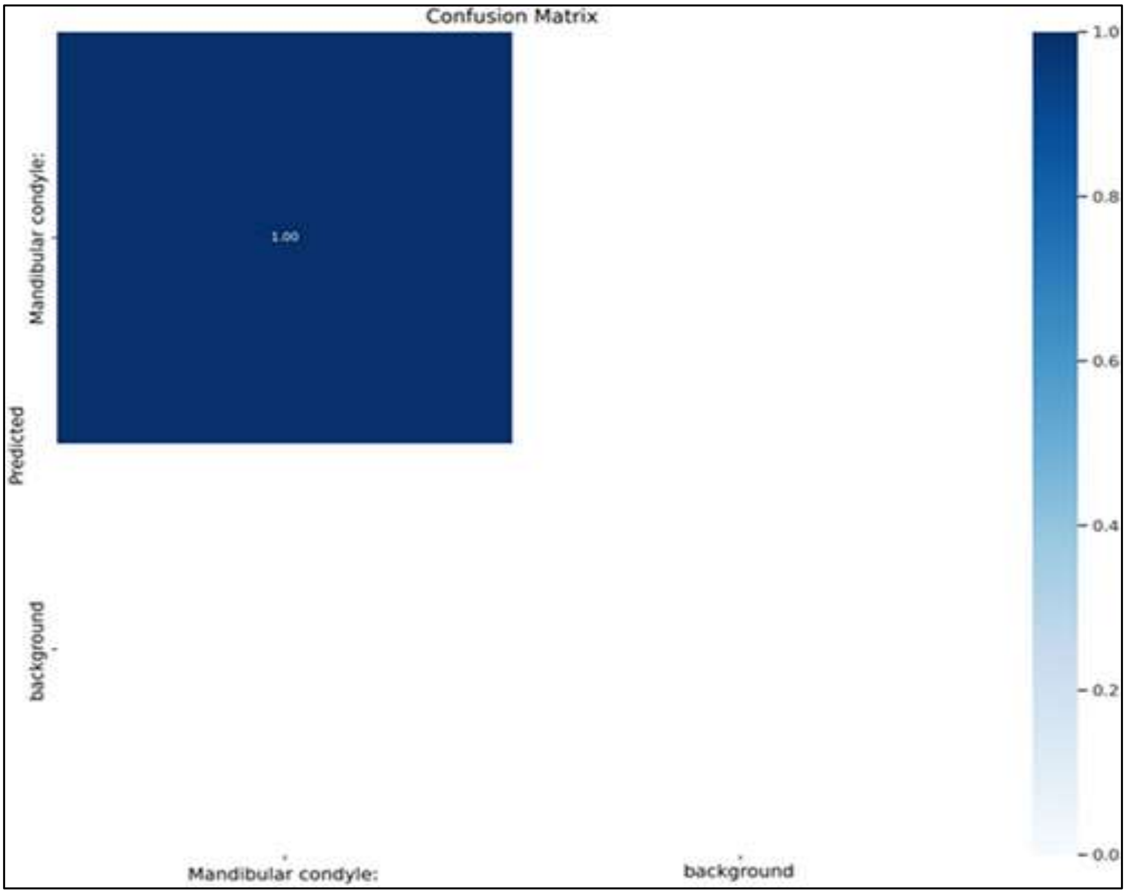

FIGURE 4: Confusion matrix plot of the YOLOv5 model for temporomandibular joint segmentation.

The YOLOv5 model demonstrates predictive values for classifying temporomandibular joint osteoarthritis as follows: 88% for healthy temporomandibular joints, 70% for flattened temporomandibular joints, 86% for joints with osteophytes, and 95% for joints with erosion. The complex matrix of the YOLOv5 model for this classification is illustrated in Figure 5 below.

In the current evaluation, the YOLOv5 model achieves the following metrics for temporomandibular joint segmentation:

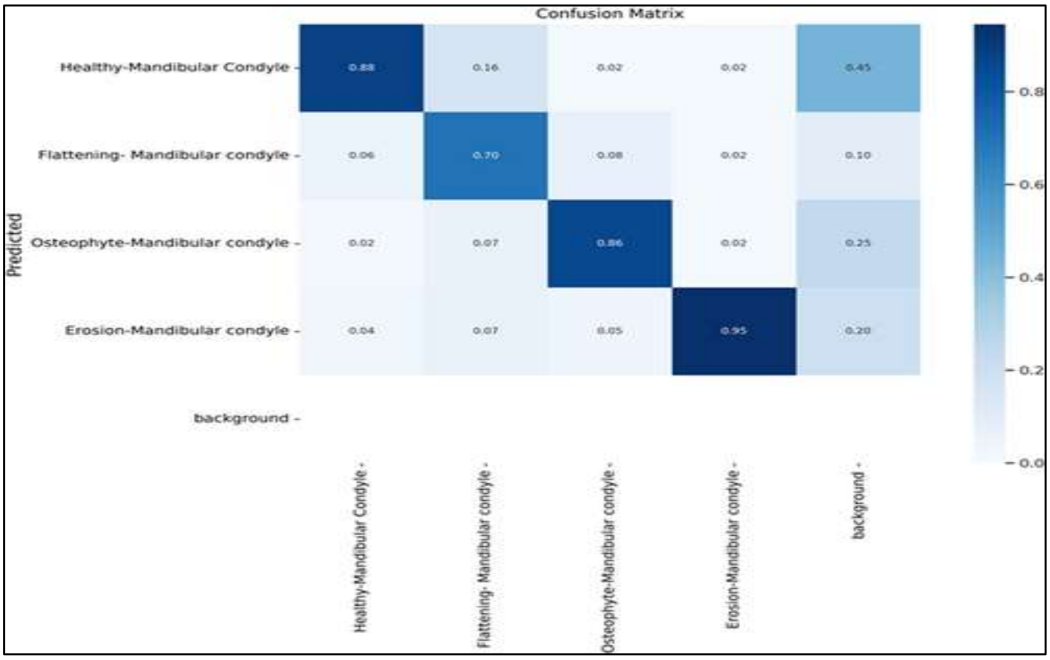

FIGURE 5: Confusion matrix plot of the YOLOv5 model for temporomandibular joint osteoarthritis classification.

True Positive (TP) is 215, False Positive (FP) is 1, and False Negative (FN) is 0. Based on these values, the sensitivity, precision, and F1 scores are calculated as 1, 0.9953, and 0.9976, respectively. For the classification of temporomandibular joint osteoarthritis using the YOLOv5 model, the metrics are as follows: TP is 172, FP is 52, and FN is 0. These values result in sensitivity, precision, and F1 scores of 1, 0.7678, and 0.8686, respectively.

5.1 ROC curve charts and AUC:

The performance of the YOLOv5 model in temporomandibular joint segmentation is evaluated using the ROC curve and AUC value[9].The false-positive rate (FPR) is divided by the true positive rate (TPR) to compute the ROC curve, which indicates the success of classification.The figure below (Figure 6) shows the ROC curves generated by the YOLOv5 model for both temporomandibular joint segmentation and osteoarthritis classification. The ROC curve for temporomandibular joint segmentation shows a TPR ratio that approaches the upper left corner and is near to 1.The AUC value for temporomandibular joint segmentation with the YOLOv5 model is 0.9723. For the classification of temporomandibular joint osteoarthritis, the AUC value is calculated as 0.4970.

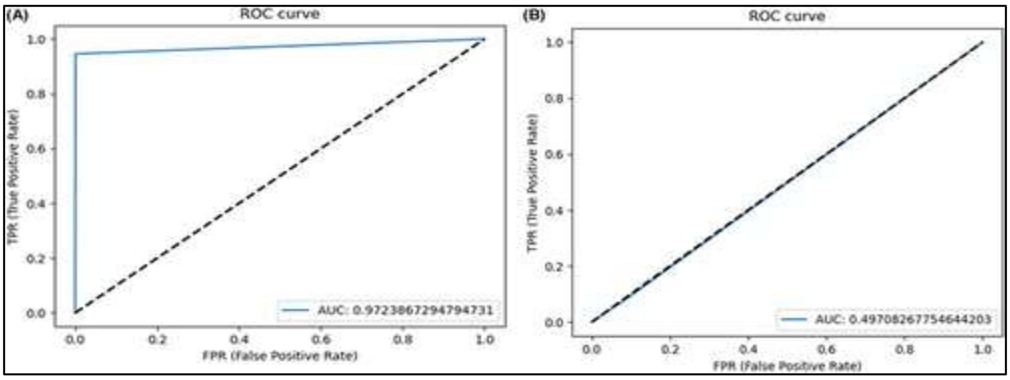

FIGURE 6: ROC curves generated by the YOLOv5 model for temporomandibular joint segmentation and osteoarthritis classification. (A) ROC curve generated for temporomandibular joint segmentation and (B) ROC curve generated for the classification of temporomandibular joint osteoarthritis.

5.2 Mean average precision (mAP):

The number, which is between 0 and 1, is used to assess detection techniques. A value is considered a true positive only if it exceeds 0.5.[10] The mean Average Precision (mAP) for temporomandibular joint segmentation is 0.995. The map values are 0.934 for a healthy joint, 0.856 for a flattened joint, 0.903 for a joint with osteophytes, 0.948 for a joint with erosion, and 0.910 for all classes in the categorization of temporomandibular joint osteoarthritis. The accuracy for temporomandibular joint segmentation is 0.9953, while the accuracy for classifying temporomandibular joint osteoarthritis is 0.7678.

6. DISCUSSION:

Recent advancements in technology have ushered in transformative changes in medicine and dentistry, with artificial intelligence (AI) standing out as a pivotal driver. AI is increasingly poised to revolutionize healthcare, offering unparalleled convenience to physicians and enhancing healthcare services. The evolution is marked by enhanced computing power, accelerated

PPV (95% confidence limits)	Sensitivity (95% confidence limits)	Test accuracy (95% confidence limits)	mAP50 %	IoU	Total training time
0.96 (0.93–0.98)	0.98 (0.96–1.00)	0.99 (0.98–0.99)	94%	0.9308	5 h

Table 1. The performance measures of the AI model. PPV positive predictive values, mAP mean average precision, IoU intersection over union.

Diagnostic performance

	Sensitivity (95% confidence limits)	Specificity (95% confidence limits)	PPV (95% confidence limits)	NPV (95% confidence limits)	Test accuracy (95% confidence limits)	Cohen's kappa	Kappa index	P value
Condylar fattening	**0.96 (0.91–1.00**	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00)**	**0.99 (0.98–1.00)**	**0.99 (0.98–1.00)**	**0.97**	**Near perfect agreement**	**0.0000****
Subcortical cyst	**0.99 (0.98–1.00)**	**0.98 (0.96–1.00)**	**0.96 (0.93–0.99)**	**0.99 (0.98–1.00)**	**0.98 (0.97–1.00)**	**0.96**	**Near perfect agreement**	**0.0000****
Surface erosion	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00)**	**1.00 (1.00–1.00) 1**	**0.99 (0.98–1.00)**	**1.00 (1.00–1.00)**	**1.00**	**Near perfect agreement**	**0.0000****
Osteophyte	**0.97 (0.92–1.00)**	**0.98 (0.97–1.00)**	**0.86 (0.76–0.96)**	**0.99 (0.98–1.00)**	**0.98 (0.97–0.99)**	**0.90**	**Near perfect agreement**	**0.0000****
All signs	**0.98 (0.96–1.00)**	**0.99 (0.98–1.00)**	**0.96 (0.93–0.98)**	**0.99 (0.98–1.00)**	**0.99 (0.98–0.99)**	**0.96**	**Near perfect agreement**	**0.0000****

Table 2. The diagnostic performance of the AI diagnosis against the golden reference. Statistically highly significant. PPV positive predictive values, NPV negative predictive values.

processing speeds, versatile task capabilities, advanced graphics processing units, and robust storage capacities, particularly in radiology. This era, extending to dentistry, promises significant strides in disease prevention and early detection.[11] In dentistry, oral radiology assumes a critical role in diagnosis and data management. Familiarity with AI is crucial for oral radiologists, as it empowers them with tools that expedite and refine diagnostic processes. The insights gleaned from AI promise faster and more precise diagnoses, heralding a new era of efficiency and accuracy in healthcare delivery. In the realm of dental radiology today, numerous studies are investigating the potential of artificial intelligence in diagnosing temporomandibular joint (TMJ) osteoarthritis, using Schiffman et al. 's[12] classification system. One recent study aimed to develop a diagnostic support tool using pre-trained models to categorize TMJ cases as normal or exhibiting osteoarthritis, using a dataset of 858 panoramic radiographs.[13] This study excluded cases showing only flattening or sclerosis as indeterminate for TMJ osteoarthritis. Another study

Diagnostic performance

	Sensitivity (95% confidence limits)	Specificity (95% confidence limits)	PPV (95% confidence limits)	NPV (95% confidence limits)	Test accuracy (95% confidence limits)	Cohen's kappa	Kappa index	P value
Condylar fattening	0.89 (0.82–0.96)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	0.97 (0.95–0.99)	0.98 (0.96–0.99)	0.93	Near perfect agreement	0.0000**
Subcortical cyst	0.93 (0.88–0.97)	0.98 (0.96–1.00)	0.96 (0.93–0.99)	0.95 (0.93–0.98)	0.96 (0.94–0.98)	0.91	Near perfect agreement	0.0000**
Surface erosion	0.91 (0.74–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00) 1	1.00 (0.99–1.00)	1.00 (0.99–1.00)	0.96	Near perfect agreement	0.0000**
Osteophyte	0.95 (0.88–1.00)	0.98 (0.97–1.00)	0.86 (0.76–0.96)	0.99 (0.98–1.00)	0.98 (0.96–0.99)	0.89	Near perfect agreement	0.0000**
All signs	0.92 (0.88–0.95)	0.99 (0.98–1.00)	0.96 (0.93–0.98)	0.98 (0.97–0.99)	0.98 (0.97–0.98)	0.92	Near perfect agreement	0.0000**

Table 3. The diagnostic performance of the oral radiologist against the golden reference. Statistically highly significant. PPV positive predictive values, NPV negative predictive values.

employed CBCT images to classify TMJ into healthy, flattening, erosion, and osteophyte categories, based on Koyama[6] et al.'s framework. It utilized 858 images from left and right condyles of 518 patients, with 395 normal and 463 osteoarthritic images, split randomly into training, validation, and test sets (6:2:2). Transfer learning models like Pre-trained ResNet-152 and EfficientNet-B7 achieved classification accuracies of 0.87 and 0.88,[13] respectively. In a recent study, 2000 CBCT images from 290 patients were used, applying the YOLOv5 architecture to classify TMJ OA with an accuracy of 0.76. This underscores the potential of AI as a screening tool for diagnosing TMJ osteoarthritis on panoramic radiographs.[13]

Another study focused on developing an AI model for diagnosing TMJ osteoarthritis on panoramic radiographs and compared it with expert diagnosis. Using Karas' ResNet model, the AI was trained to classify images into normal, uncertain osteoarthritis, and osteoarthritis categories. The study used 1189 panoramic radiographs confirmed by CBCT, showing that after excluding uncertain osteoarthritis, the AI's performance closely matched expert diagnosis and CBCT findings, achieving accuracy, sensitivity, and specificity values of 0.78, 0.73, and 0.82, respectively, after 700 epochs.[14]

In another study categorizing TMJ osteoarthritis into four classes using 2000 sagittal KIBT images, the AI model trained over 500 epochs and achieved accuracy and sensitivity of 0.7678 and 1, respectively. These findings underscore the evolving role of AI in enhancing diagnostic capabilities in dental radiology.

The purpose of this research is to use biomarkers and machine learning to diagnose temporomandibular joint osteoarthritis (TMJ OA) at an early stage. A total of 52 variables, including magnetic resonance and CBCT images, and biomolecular and clinical markers, are evaluated to identify the most relevant feature pools for detecting TMJ OA status. Four machine-learning models Logistic Regression, Random Forest, LightGBM, and XGBoost—are

	AI model	**Oral radiologist**	**z**	**P value**
Condylar fattening	**0.99**	**0.98**	**1.52**	**0.12863**
Subcortical cyst	**0.98**	**0.96**	**1.99**	**0.04614**
Surface erosion	**1.00**	**1.00**	**Equal values**	**Equal values**
Osteophyte	**0.98**	**0.98**	**0.26**	**0.79408**
All signs	**0.99**	**0.98**	**2.33**	**0.01984**

Table 4. Test accuracy of the AI model compared to the oral radiologist. *Statistically significant.

	Percentage of agreement (95% confidence limits) C		
Condylar fattening	**98.57% (97.33–99.81%)**	**0.95**	**0.0000****
Subcortical cyst	**97.43% (95.77–99.09%)**	**0.95**	**0.0000****
Surface erosion	**99.71% (99.16–100.00%)**	**0.96**	**0.0000****
Osteophyte	**99.71% (99.16–100.00%)**	**0.99**	**0.0000****
All signs	**98.86% (98.30–99.41%)**	**0.95**	**0.0000****

Table 5. The agreement between the AI model diagnosis and the oral radiologist diagnosis. Statistically highly significant

used to test diagnostic performance. The XGBoost and LightGBM models achieve an accuracy of 0.823, an AUC of 0.870, and an F1 score of 0.823.

In contrast, our study focuses on classifying TMJ OA using CBCT alone, without clinical examinations, blood, and saliva evaluations. TMJ OA is categorized into four classes by evaluating the performance of a single YOLOv5 model. Our results indicate an accuracy of 0.9953, an AUC of 0.9723, and an F1 score of 0.9976 for TMJ segmentation, whereas the accuracy and F1 score for TMJ OA classification are 0.7678 and 0.8686, respectively.

In the present condition, the study aims to develop an automatic diagnostic tool for temporomandibular joint osteoarthritis (TMJ OA) using CBCT images from 314 patients with temporomandibular joint disorders showing signs of TMJ OA. The participants included 230 females and 84 males, with a total of 3514 sagittal CBCT images evaluated. The study employs a single shot detection (SSD) model, an object detection model for disease detection, and trains it exclusively with CBCT images of patients exhibiting TMJ symptoms. The images are classified into two categories: TMJ OA and uncertain for TMJ OA, achieving accuracy, precision, sensitivity, and F1 scores of 0.86, 0.85, 0.84, and 0.84, respectively. These findings indicate that automatic detection of TMJ OA from sagittal CBCT images using a deep neural network model is feasible.[8]

In a current artificial intelligence study for diagnosing temporomandibular joint osteoarthritis (TMJ OA), the dataset comprises three-dimensional joint images obtained from CBCT scans. The training dataset includes 259 condyles, with 105 from control subjects and 154 from patients diagnosed with TMJ OA. For image analysis classification, the test dataset contains 34 right and left condyles from 17 patients who have exhibited signs and symptoms of the disease for less than five years. Clinical questionnaires, blood samples, and saliva samples were also collected from these patients.

The temporomandibular joint (TMJ) images were classified into five classes based on degeneration levels observed in the three-dimensional images. This classification was performed using an architecture called ShapeVariationAnalyzer (SVA). The study achieved a 91% agreement between the SVA classifier and clinicians regarding the five-stage structural degenerative changes in condyle morphology in the TMJ.[15]

In a similar study aiming to develop an artificial intelligence model for diagnosing TMJ OA, three-dimensional joint images obtained from CBCT scans, clinical markers (such as pain and mouth opening), and blood and saliva samples from patients were analyzed. As in the previous study, the TMJ was classified into five classes based on the severity of degeneration observed in the three-dimensional images. The study resulted in an accuracy of 0.823 in predicting TMJ OA using machine-learning models.

In a current study focusing on the automatic segmentation of the temporomandibular joint using artificial intelligence, a small subset of 40 CBCT images is used for training. The segmentation employs a 3D U-Net model, achieving an average dice coefficient of 0.976.[16] However, unlike our study, three-dimensional TMJ segmentation is not conducted. Our research uses the YOLOv5 model for segmentation with a significantly larger dataset of 2000 CBCT images from 290 patients. Another study aims to develop an automatic segmentation method for early osteoarthritis diagnosis in the temporomandibular joint, utilizing CBCT images from 95 patients. Three-dimensional images are generated, and automatic segmentation of the TMJ is compared with manual segmentation, resulting in a Dice coefficient of 0.9461 with a standard deviation of 0.0888. This fully automated condylar segmentation method is expected to enhance the accuracy of condylar degeneration classification in TMJ OA[18].

Since temporomandibular joint osteoarthritis involves bone surfaces, CBCT is currently considered the gold standard for diagnosis. Additionally, the use of artificial intelligence is increasing in areas such as magnetic resonance imaging (MRI) and ultrasound, which are used for diagnosing soft tissue diseases. In one study, artificial intelligence automatically detects anterior disc displacement on MRI. Sagittal MR images of 2520 TMJs from 861 male and 399 female patients are collected. The prediction performances of models and experts are compared based on areas under the curve (AUCs). The study finds that artificial intelligence is useful for detecting disk displacement, with the model exhibiting high specificity, aiding professionals in evaluating true negative diagnoses. Despite the MR images coming from a single center and containing a single sagittal plane, the model shows potential generalizability across multiple genders and ages.[19]

In 2024, a research project designs an artificial intelligence algorithm to monitor the temporomandibular joint using ultrasonography (USG) images. The study employs U-Net and 3D U-Net architectures, utilizing recorded USG video sequences. While the approach highlights the benefits of integrating distinct modules, the principal drawback is the small dataset size of only 10 videos. Despite this limitation, the investigation yields satisfactory outcomes, presenting a novel method for TMJ monitoring. The study concludes that larger datasets would yield more effective results[20].

This study has certain limitations, such as a relatively narrow patient population and the exclusion of some patients for various reasons. Additionally, the use of a single CBCT device and uniform imaging parameters further constrain the study. Future research could benefit from incorporating multiple observers and involving dentists with diverse experiences from various specialties to enable more robust comparisons of outcomes.

7. CONCLUSIONS:

In conclusion, this investigation represents the initial endeavor to execute TMJ segmentation and TMJ OA classification utilizing the YOLOv5x model. We expect that this study and its outcomes will serve as a valuable guide for clinicians regarding the early detection and diagnosis of TMJ osteoarthritis.

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