International Journal of Electrical and Data Communication 2024; 5(2): 33-36

International Journal of Electrical and Data Communication

E-ISSN: 2708-3977
P-ISSN: 2708-3969
IJEDC 2024; 5(2): 33-36

www.datacomjournal.com
Received: 06-08-2024
Accepted: 08-09-2024

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Artificial intelligence using YOLOv8 for the identification of elbow OCD in ultrasound images

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DOI: https://doi.org/10.22271/27083969.2024.v5.i2a.62

Abstract
When a pitcher uses their elbow over and over again, it might develop a condition known as baseball elbow. Baseball elbow diseases include osteochondritis dissecans (OCD), an intractable osteochondral lesion most often seen in middle and high school kids. Setting a period to cease playing baseball is the conservative therapy that may totally cure it if discovered in its early stages. Consultations are difficult to arrange due to the lack of discomfort during the early stages, and many patients experience a worsening of their illness. There is a scarcity of doctors who can diagnose baseball elbow, thus the number of modifications is several times each year, despite the fact that periodic medical checks are useful. For early identification and effective conservative treatment of elbow osteochondritis dissecans (OCD), ultrasonography (US) screening is necessary. Finding out how well YOLOv8, an AI model based on deep learning, can diagnose US photos of OCD or normal elbow-joint imaging is the main goal of the research. Methods: More than 2,430 photos were used. The YOLOv8 model was used for object identification and picture classification in order to identify OCD lesions or normal elbow joint images. End result: The confusion matrix values for the normal with OCD lesion binary categorization were: These metrics are as follows: F-measure = 0.9987, Accuracy = 0.998, Recall = 0.9975, and Precision = 1.000. Both the YOLOv8n and YOLOv8m models achieved mean average precision (mAP) values of 0.994 and 0.995, respectively, when comparing the trained model's bounding box detection to the true-label bounding box. In summary: Standard images of elbow joints while OCD lesions were used to train the YOLOv8 model for object identification and picture classification. The high degree of accuracy shown by both tasks suggests they might be valuable for baseball elbow screenings conducted as part of routine medical examinations.

Keywords: OCD, YOLOv8, ultrasound images, deep learning, object detection

Introduction

When a pitcher uses their elbow over and over again, it can develop a condition known as baseball elbow. Baseball elbow disorders include osteochondritis dissecans (OCD), an intractable osteochondral injury most commonly seen in pupils in junior high and elementary schools. If caught early, conservative treatment-which entails establishing a time limit for when the patient cannot play baseball-can be effective in curing the condition [1]. Dissecans osteoarthritis (OCD) of the humeral capitellum is a prevalent source of elbow pain, especially in young throwers. Managing Obsessive-Compulsive Disorder (OCD) is best accomplished through conservative treatment, and the likelihood of full disease resolution is greatly affected by early intervention [2]. The accuracy of an ultrasonography diagnosis of humeral osteochondritis dissecans (OCD) is dependent on the skill level of the examining physician. Recent medical research has reported high diagnostic accuracy using computer-aided diagnosis (CAD) applying deep learning [3]. Repetitive throwing in baseball can lead to a kinetic disorder known as baseball elbow. One of the most prevalent types of baseball elbow is osteochondritis dissecans (OCD), a condition affecting the humeral capitellum of the elbow. It is crucial to detect OCD early on [4]. In the field of musculoskeletal medicine, ultrasound imaging plays an essential role. There has been an upsurge in the number of publications discussing ultrasound-guided surgery, particularly in minimally invasive procedures pertaining to sports, foot and ankle, as well as hand surgery. The limitations of ultrasound imaging include the need for a skilled operator and the blurred quality of the images. These problems can be solved by AI and its subset, deep learning (DL) [5, 11, 12, 13, 16].

Related Work

The purpose of this study is to compare US images of normal elbow-joints and images of

OCD using YOLOv8, an AI model based on deep learning, in order to establish its diagnostic accuracy [6]. Methods: More than 2,430 images were utilized. The YOLOv8 model was used for object detection and image classification in order to identify OCD lesions or normal elbow joint views. End result: The confusion matrix values for the normal and OCD lesion binary classification were: These metrics are as follows: F-measure = 0.9987, Accuracy = 0.998, Recall = 0.9975, and Precision = 1.000. Both the YOLOv8n and YOLOv8m models achieved mean average precision (mAP) values of 0.994 and 0.995, respectively, when comparing the trained model's bounding box detection to the true-label bounding box. Results: The normalized perspectives of elbow joints along with OCD lesions were used to train the YOLOv8 model for object detection and image classification. The high degree of accuracy demonstrated by both tasks suggests they could be valuable for baseball elbow screenings conducted as part of routine medical examinations. The goal of this study is to create a classification model for ultrasound images using deep learning for computer-aided diagnosis, as stated in [7]. A method for OCD classification in ultrasound images based on deep learning is proposed in this paper. After detecting the humeral capitellum with YOLO, the suggested method uses VGG16 to estimate the OCD risk of the detected region. The removal of superfluous regions is our working hypothesis for an improvement in performance. We used five-fold-cross-validation to test the suggested method on 158 participants (OCD: 67, Normal: 91). While OCD chance estimation obtained an average F1 score of 0.894, precision of 0.888, accuracy of 0.890, recall of 0.927, and area under the curve (AUC) of 0.962, the study showed that humeral capitellum detection achieved a mean average precision (mAP) of over 0.95. hThe recall, F1 score, accuracy, precision, and AUC were 0.806, 0.932, 0.843, and 0.928, respectively, when the whole image classification model was built. The researchers in this study set out to determine how well DL performed in diagnosing OCD in US images [8]. We postulated that OCD prediction accuracy would be enhanced by employing DL for US imaging. Research Methods: Level 2 Evidence; Design of the Study: Cohort Study (Diagnosis) Participants in the study were 40 adults (mean age 12.1 years) whose suspicion of Obsessive-Compulsive Disorder (OCD) was initially raised during a routine medical examination and subsequently confirmed through the use of radiographs along with magnetic resonance imaging (MRI). As a control group, we utilized the non-affected elbows, and as an OCD group, we utilized the affected elbows. For each group, we prepared four thousand images of the elbows by capturing 100 images from various angles of each elbow from US videos. Around 80% of these were picked at random by DL models to serve as training data, while the rest were utilized as test data. Using three pretrained DL models, transfer learning was performed. In order to assess the model, we utilized the confusion matrix with the area under the receiver's operating characteristic curve (AUC). Additionally, we visualized the regions that the DL models considered important. Using ultrasound images, the authors of [9] set out to create a computer-aided detection (CAD) system that relies on deep learning to identify obsessive-compulsive disorder (OCD). The two-step CAD procedure begins with an object-detection algorithm for humeral capitellum detection and ends with an image classification system for OCD classification. For training and validation, we utilized four-directional ultrasound images of the throwing arm of 196 baseball players (mean age, 11.2 years). Of these, 104 had normal findings and 92 had OCD. To assess the CAD system's precision, an external dataset was utilized, consisting of 20 baseball players (10 having typical findings and 10 with OCD). In order to measure how well the system worked, it was compared using a confusion matrix and the AUC. AUCs were high in all four directions during clinical evaluation using the external dataset: 0.966 for the anterior short axis, 0.996 for the posterior long axis, 0.969 for the anterior long axis, and 0.993 for the posterior short axis. Thus, in all four directions, the accuracy of OCD detection was higher than 0.9. Finally, we offer a computer-aided design (CAD) system that uses deep learning to identify OCD lesions in ultrasound pictures. In order to determine its impact on medical ultrasound's capacity to identify OCD, researchers examined an updated Delay-Multiply-and-Sum (DMAS) reconstruction technique in [10]. Based on the DMAS reconstruction algorithm outlined by Matrone *et al*. (2015), we tweaked the filtering and envelope detection implementation steps. On both phantom and cadaveric model of capitellar OCD, the Delay-and-Sum (DAS), DMAS, and improved DMAS methods were evaluated. A histogram matching process was employed to compare the DMAS and revised DMAS images quantitatively to the DAS image. We compared the algorithms' outputs for lesion contrast and bone surface clarity by taking multiple profiles across the photos of the synthetic OCD lesions. After applying histogram matching, we discovered that the original DMAS algorithm still wasn't much better than the DAS algorithm. Comparing to the DMAS algorithm, the modified DMAS approach significantly improved the detection of OCD lesions.

Proposed Work

A. Database Description

Participants in the research were 40 adults (mean age 12.1 years) whose suspicion of Obsessive-Compulsive Disorder (OCD) was first raised during a routine medical examination and then validated by the use of radiography and magnetic resonance imaging (MRI). As a control group, we used the non-affected elbows, and as an OCD group, we utilized the afflicted elbows. For each group, we produced four thousand photos of the elbows by capturing 100 photographs from various angles of each elbow from US footage. Around 80% of these were picked at random by DL models to serve as training data, while the rest were employed as test information. Three pre-trained DL models were used to perform the transfer learning.

B. Preprocessing

With Python-3.9.13, we fine-tuned a data preparation approach for x-ray picture analysis. Because JPEG compression has a little effect on picture quality while lowering processing and storage needs, we converted the DICOM data from PNG to JPEG using the PIL library after reading the files using the pydicom library. The photos were then downsized to 640 × 640 and normalized using the in-built features of YOLOv8. Also, we made advantage of YOLOv8's built-in data augmentation library. Adjusting the brightness (hsv-v=0.4), translating (translate=0.1), scaling (scale=0.5), flipping (flipud=0.5), flipping (fliplr=0.5), and picture mosaicing (mosaic=1.0) were the parameters used for the image augmentation.

C. YoloV8 Model

For object recognition, we go with the YOLOv8n approach, which has 3.0 M parameters-the smallest of all the pre-trained YOLOv8 models-and the YOLOv8m approach, which has 25.8 M parameters-a reasonable amount. These models were contrasted with YOLOv5, a model from the previous generation that was introduced by the same team. The YOLOv5n and YOLOv5m models were used for the YOLOv5 models, with the former having a parameter size of 1.8 M and the latter of 20.8 M. The input data utilized for transfer learning was the pre-trained weights of YOLOv8, and the output data was US pictures with bounding-box label information. A total of five different types of object identification tasks were carried out: AL, AS, PL, PS, with OCD. Mean average precision (mAP), the Precision-Recall curve, while the F-measure Confidence curve are commonly used metrics in object identification tasks, therefore we tested them to see how well the trained models detected objects. At an intersection over the Union (IoU) criterion of 0.5, the mAP is computed as mAP (0.5), and at several IoU thresholds ranging from 0.5 to 0.95 using a step size of 0.05, the average of these mAPs is mAP (0.5-0.95). On one side of the Precision-Recall curve is the ratio of true bounding box detections, and on the other is the ratio of expected bounding box detections; this relationship is shown by the X- and Y-axes, respectively, of the curve. With its effective real-time target recognition and excellent adaptation to complicated settings, YOLOv8 is an algorithm for automatically identifying and removing artifacts in photoacoustic pictures. Typically, the object or surface that produces photoacoustic pictures has its own distinct form and texture. YOLOv8 can efficiently analyze photoacoustic pictures, find and identify their source, and clean them up by removing unwanted elements, all with the goal of improving the photos' quality and clarity. Photoacoustic image processing, which YOLOv8 excels at, provides trustworthy picture assistance for medical diagnosis due to its great efficiency and accuracy. Trustworthy picture assistance.

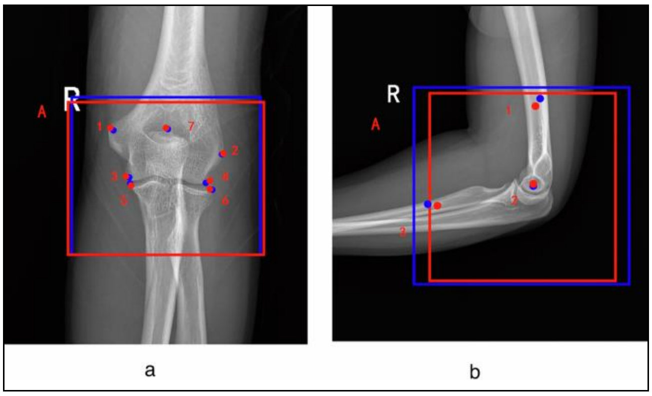

Fig 1: Predictions made by the AI models and annotated by the doctor

Figure 1 Predictions made by the AI models and annotated by the doctor. The blue boxes and red important points are created by the AI model, while the red ones come from the clinician's comments. One target recognition box with seven key points are shown in the anterior-posterior view; three critical points are shown in the lateral view.

Furthermore, we measured the model's computing performance on the computer by looking at its inference time per picture and the amount of floating-point calculations per second (FLOPs). Also, a local PC was used to develop a GUI program in the YOLOv8 as well as YOLOv5 environments its functionality was then tested by linking it to an imaging system in the US.

Results and Discussion

To train our key points detection techniques for both AP and LAT perspectives on the elbow joint, we utilized the YOLOv8 Large (YOLOv8L) variant, which is the most precise and extensive model in the YOLOv8 series with 43.61 million parameters (Figure shows the design of the YOLOv8 algorithm). Three main parts make up the architecture: A backbone that extracts features from x-ray images of the elbow, a neck that fuses those features, and a head that outputs the final predictions, such as the object detection box classification, the size and location of the detection box, while the location of important points. We used YOLOv8L pre-trained weights for transfer learning. The software configurations used in the training regimen included Python-3.9.13, PyTorch-1.13.1, and Ultralytics YOLOv8.0.62 on a GPU framework. A server-grade computer with an AMD Ryzen Threadripper 5975wx CPU with an NVIDIA GeForce RTX 3,090 GPU was part of the computing setup. The following were the main training parameters: trainer running for 100 epochs, optimizer set to stochastic gradient descent (SGD), and starting learning rate of 0.001. On the DR system's post-processing workstations, we implemented the GUI software. Radiologists were able to evaluate elbow joint pictures in real-time with the use of this YOLOv8-QC GUI. The radiologists had the ability to re-photograph these views if they found pictures that were not up to par.

Table 1: Performance in Yolo models

	Precision	Recall	mAP50	mAP50-95
YoloV3	0.988	0.984	0.995	0.814
YoloV7	0.995	0.996	0.994	0.992
YoloV8	0.993	0.994	0.991	0.987

Conclusion

For x-rays of the elbow joint, we presented a novel AI-driven automated QC model. For the purpose of locating specific targets and other important features in photos, this model makes use of the state-of-the-art YOLOv8 algorithm. This is the first instance of our using this technique to train a model for picture quality control. Since it is very difficult to compute QC findings directly from photos, the models use a string of exact geometric computations to convert these detecting boxes and critical locations into the five QC standards mentioned earlier.

All five of our quality control requirements were met by the AI-based models, according to our findings. Using typical view of the elbow joints while OCD lesions, the YOLOv8 system was trained to classify images and recognize objects. There was a high degree of accuracy in both tasks, which bodes well for the potential use of these tools in future mass screenings for baseball elbow during medical checkups. Finally, it seems like the results could have some good clinical applications. Using artificial intelligence (AI) to automate quality control for elbow x-ray pictures allows us to tackle problems like subjective assessment findings and heavy effort that come with human quality control. This technology allows for the continuous monitoring of image quality, which greatly decreases the chances of radiography technicians making mistakes during the imaging process. As a result, disagreements between patients and doctors are successfully avoided. By improving the medical process, automated quality evaluation may further guarantee diagnostic pictures are consistent and accurate, which in turn improves the quality of medical treatment offered to patients. As deep learning continues to revolutionize medical imaging, our algorithms might play a pivotal role in the development of future smart healthcare systems.

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