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Research Article

Anatomic Region Detection in MRI Using CycleGAN-Augmented Dataset with YOLOv8

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Abstract

Objectives: Proton Density (PD)-weighted MRI sequence is particularly effective for detecting shoulder pathologies but, limited in accurately delineating bone structures due to noise and trauma-induced signal blurring. To mitigate this limitation, this study employed a CycleGAN framework to generate synthetic PD-weighted images from T1-weighted MRI scans to enhance the dataset.

Methods: A CycleGAN framework was used to generate synthetic PD-weighted images from T1-weighted MRI scans. A total of 1,330 axial PD-weighted MR images, including both original and CycleGAN-augmented images, were employed to train a YOLOv8 model for detecting the humeral head and scapular regions.

Results: The YOLOv8 model achieved a detection accuracy of 98.70% 91.20 % for humeral head and for scapula, respectively, with an intersection over Union (IoU) threshold of 0.25.

Conclusion: This study demonstrates the potential of integrating CycleGAN and YOLOv8 for enhancing bone structure localization in PD-weighted MRI, particularly in challenging scenarios with noise and ill-defined borders.

Keywords: Shoulder MRI bone segmentation, YOLOv8, CycleGAN Data Augmentation

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Glenohumeral joint is primarily composed of two key bony structures: the humerus and scapula. Unlike many other ball-and-socket joints in the human body, the glenohumeral articulation exhibits limited bony congruency but is characterized by a remarkable soft tissue stabilization, providing stability through a wide range of motion. However, the architecture of the shoulder joint makes it susceptible to instability. The issue of shoulder instability is on the rise among athletic individuals engaged in high-demand physical activities.[1]. In cases of instability, evaluating the glenohumeral articulation often necessitates the use of advanced imaging techniques. This is due to the potential risk of soft tissue injuries and structural deformities in the bone resulting from initial trauma or instability. It is not uncommon to encounter concurrent soft tissue and bone-related issues in the humerus and scapular glenoid following such occurrences.[1,2]

MRI encompasses a variety of sequences, each endowed with unique capabilities for distinct tissues or pathologies. Among these, the PD weighted MRI sequence is particularly valuable for assessing extremities. PD weighted MR images excel in simultaneously localizing both bone and soft tissue pathologies, offering superior soft tissue details compared to T1 sequences. However, it is important to note that discriminating between soft tissue and bone can pose challenges in certain anatomical regions, such as bone-tendon interfaces.[3]

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In computer-based diagnostic systems, segmentation and detection of anatomical regions hold pivotal roles in defining various pathologies. Segmentation of humeral head bone and scapula regions is imperative for soft tissue and bone discrimination and ensuring precision in diagnostic procedures, facilitating effective treatment planning, and enabling the continuous monitoring of disease progression.[4, 5]

The use of variational methods, particularly in the field of medical image segmentation, offers a promising approach to improve the accuracy and robustness of diagnostic systems. Variational models often rely on energy minimization frameworks to model the underlying structures and boundaries within medical images. These techniques allow for the smooth and precise delineation of anatomical regions, even in the presence of noise or complex tissue boundaries, making them particularly useful in challenging imaging conditions like those of the shoulder joint. By modeling the segmentation process as an energy minimization problem, variational methods help to reduce errors and improve consistency in detecting soft tissue and bone regions.

A variety of deep learning algorithms have been employed for medical image segmentation, often categorized into instance-based and semantic-based methods. Among these, object detection algorithms can be divided into single-stage (e.g., YOLO,[6] SSD, RetinaNet) and two-stage methods (e.g., Mask R-CNN, Faster R-CNN, R-CNN). These methods, while effective in many applications, tend to focus more on the recognition and localization of objects in images rather than on the precise boundary delineation that variational models excel at. In the context of shoulder imaging, there has been limited focus on the detection and segmentation of the humeral bone and scapula regions. Liu et al. used a convolutional neural network (CNN) to segment and quantify bone mineral density in the humerus, achieving high accuracy with a dataset of X-ray images.[8] Similarly, He et al.[9] introduced a recursive learning framework combined with a deep end-to-end network to segment bones in shoulder joint images, improving segmentation accuracy on small datasets with significant parameter variations.

Variational methods have proven especially useful in addressing the challenges of boundary detection in such complex anatomical structures. These methods can enhance the precision of segmentation by focusing on the underlying geometric properties of tissues, thereby improving overall diagnostic accuracy. CycleGAN has been utilized in medical imaging to augment datasets and improve segmentation performance. Studies have shown that combining such techniques with variational models can result in better image quality and more accurate delineation of anatomical structures.[13-17]

In this study, while YOLOv8 was employed to delineate the humeral head and scapula regions in PD-weighted MR images. Via integration with variational methods a more accurate and robust segmentation process was achieved. Combination of YOLOv8's faster inference time enhancing real-time diagnostics and the precision provided by variational models made it more suitable for medical diagnostics, where both speed and accuracy are critical.

Methods

Dataset

A total of 665 axial Proton Density (PD)-weighted MRI scans were obtained from patients with shoulder instability. The dataset comprised 412 male and 253 female participants, with an average age of 27±5.2 years (range: 18–42 years). All scans were acquired using a 1.5 Tesla MRI scanner, with a slice thickness of 4 mm and an image resolution of 256×256 pixels in DICOM format. To address the limitations associated with small datasets in medical imaging, the dataset was augmented using a CycleGAN model. This approach involved generating synthetic PD-weighted MRI images from T1-weighted MRI scans, effectively increasing the dataset size to 1,330 images. The dataset was then divided

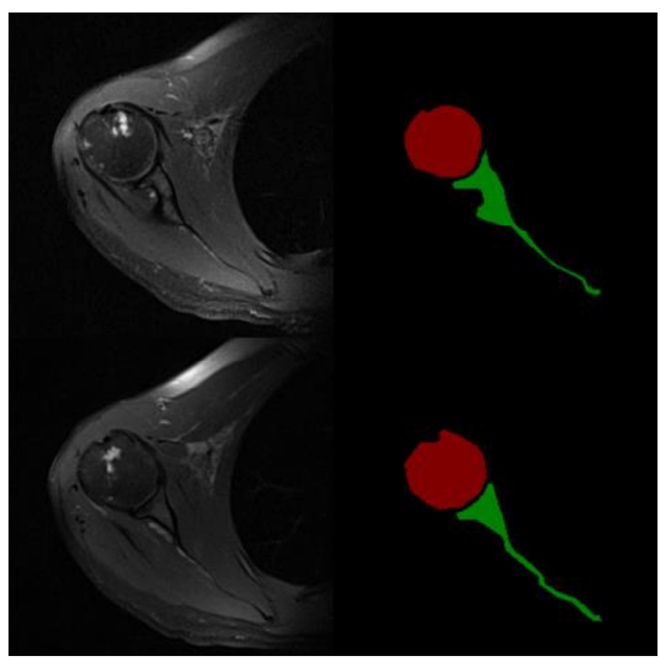

Figure 1. The first column represents the original PD-weighted axial MR image of the shoulder, while the second column shows the manual segmentation results performed by an expert.

into three subsets: 886 images for training, 200 images for validation, and 244 images for testing. Manual annotations of the humeral head and scapula regions were performed using the LabelMe tool as in Figure 1. The annotations were subsequently converted from COCO format to YOLOv8 format to ensure compatibility with the object detection algorithm.

Preprocessing

The CycleGAN model was employed to translate T1-weighted MRI images into synthetic PD-weighted MRI images using unpaired data. The model utilized cycle consistency loss to maintain anatomical accuracy and ensure the visual quality of the generated images. This augmentation step aimed to mitigate challenges posed by noise and the limited resolution of the original PD-weighted MRI scans, improving the detection accuracy for the humeral head and scapular regions. A visual representation of the CycleGAN workflow is provided in Figure 2.

YOLOv8 Model Configuration

The YOLOv8 model, a state-of-the-art single-stage object detection algorithm, was configured to detect humeral head and scapular regions. Its architecture features CSP-Darknet53 as the backbone, with 53 convolutional layers and cross-stage partial connections, and a self-attention-based detection head for dynamic feature prioritization.

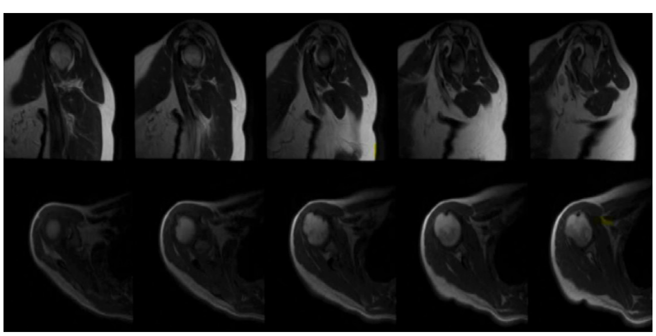

Figure 2. Illustration of CycleGAN generated synthetic PD-Weighted Images from T1- Weighted MRI Scans.

Training was conducted over 150 epochs using the Adam optimizer (learning rate: 0.001) on an NVIDIA V100 GPU. Model performance was evaluated using precision, recall, and mean Average Precision (mAP) at IoU thresholds of 0.5 and 0.5:0.90. These metrics provided comprehensive insights into the model's detection capabilities across different levels of overlap.

Results and Discussion

The YOLOv8 model demonstrated high accuracy in detecting the humeral head and scapula regions from PD-weighted MR images, with notable improvements following data augmentation using CycleGAN, as summarized in Table 1.

CycleGAN-based augmentation significantly enhanced model performance, addressing the limitations of a small dataset and improving detection accuracy for both the humeral head and scapula. For the humeral head, the mAP50 score showed a slight decrease from 99.00% to 98.70% after data augmentation. However, the mAP50:90 score improved notably from 90.40% to 94.40%, indicating that CycleGAN augmentation enhanced the model's ability to detect the humeral head across varying image qualities and sizes. Similarly, the scapula region saw an increase in mAP50 from 89.90% to 91.20%, with a corresponding improvement in mAP50:90 from 66.70% to 78.40%. This indicates that the CycleGAN-based augmentation was particularly beneficial for enhancing the model's performance in detecting the scapula, improving accuracy not only for more typical cases but also in challenging imaging scenarios. Overall, the combined effect of data augmentation led to an increase in the overall mAP50 score, from 94.50% to 94.95%, and in mAP50:90 from 80.10% to 86.40%, demonstrating a robust enhancement in the model's ability to detect and localize anatomical structures in the presence of noise and inconsistencies inherent in PD-weighted MRI scans.

Despite the improvements in detection accuracy, the model's performance was less robust in cases involving complex conditions, such as edema, Hill-Sachs lesions, and scapular wing discontinuities as demonstrated in Figure 3.

Table 1. Detection Performance of YOLOv8 Model for Humeral Head and Scapula Regions Before and After CycleGAN-Based Data

Augmentation	Before data augmentation		After data augmentation with CycleGAN	
Class	**mAP50 (%)**	**mAP50:90 (%)**	**mAP50 (%)**	**mAP50:90 (%)**
Humerus	99.00	90.40	98.70	94.40
Scapula	89.90	66.70	91.20	78.40
Overall	94.50	80.10	94.95	86.40

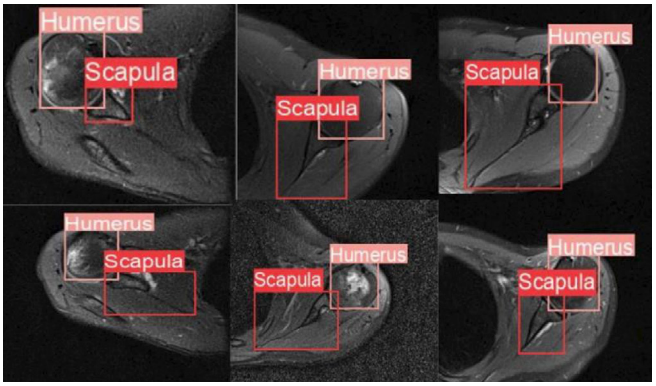

Figure 3. YOLOv8 Performance in Detecting the Humeral Head and Scapula, Highlighting the Impact of CycleGAN-Based Data Augmentation.

These pathological conditions introduced additional noise and intensity irregularities, which the model struggled to accurately detect. These challenges highlight the need for further refinement in both the augmentation techniques and the detection models. The presence of trauma-induced distortions, such as blurring and inconsistent signal intensities, affected the model's ability to maintain high detection accuracy in certain clinical scenarios.

High-quality data augmentation is crucial for improving the accuracy of these methods. While a limited number of studies in the literature employ CycleGAN for data augmentation and various versions of YOLO for object detection,[18,19] to the best of our knowledge, no published research has applied these methods to shoulder MRI images, particularly for detecting the humeral head and scapula regions. This demonstrates the originality of our approach in addressing the specific challenges of shoulder MRI analysis.This process enriched the dataset by introducing a greater variety of training samples, thereby enhancing the robustness of the object detection model.

YOLOv8's use of a feature pyramid network (FPN) proved effective in handling multi-scale detection, allowing for accurate localization across varying object sizes. The ability to detect smaller and larger structures across different image scales helped in improving the detection of both the humeral head and scapula. However, persistent issues related to noise and intensity irregularities in trauma-affected regions suggest that there is still room for further improvement in handling these complex conditions.

Conclusion

This study demonstrates the potential of combining CycleGAN-based data augmentation to improve YOLOv8 based detection of humeral head and scapula regions in PD-weighted MRI scans. The findings show that data augmentation can significantly enhance the model's ability to handle noise and dataset limitations. While high accuracy was achieved in detecting normal anatomy, performance challenges remain in more complex pathological conditions. Future work should focus on incorporating additional augmentation methods, such as more varied synthetic transformations, and exploring hybrid models that combine YOLOv8 with more specialized segmentation techniques to further improve detection accuracy in clinically challenging scenarios.

Disclosures

Ethics Committee Approval: The study protocol received approval from the University of Health Sciences Hamidiye Etfal Training and Research Hospital Clinical Research Ethics Committee (date: 13.12.2016, no: 1343) and adhered to the principles of the Declaration of Helsinki.

Peer-review: Externally peer-reviewed.

Conflict of Interest: None declared.

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