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REVIEW PAPER

Comparison of algorithms for detection of active inflammatory lesions in sacroiliitis

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ABSTRACT

Introduction. Artificial intelligence is increasingly being used in the medicine, particularly in radiological diagnosis of diseases such as an axial spondyloarthritis (axSpA). The aim of this study is to compare the available algorithms designed to detect active sacroiliitis in patients with axSpA.

Material and methods. Four algorithms, two semi-automated and two full-automated for the assessment of bone marrow edema (BME) on magnetic resonance imaging (MRI) of the sacroiliac joints (SIJs) were included in the study. They were described and compared in terms of specificity, sensitivity, and correlation of BME detection findings between AI and experts.

Analysis of the literature. Among all automated algorithms, the one created by Bressem et al. had the highest number of examinations analyzed in the study, involving 593 MRIs of SIJs. The sensitivity and specificity, as well as the correlation between the AI's detection of BME versus manual, were not calculated for each algorithm. Rzecki's algorithm had the greatest sensitivity and specificity for BME detection reaching 0.95 and 0.96, respectively. In addition, its Speraman's coefficient of correlation between manual and automated measurements was 0.866.

Conclusion. Each of described algorithms is certainly useful in assessing BME in the MRI examinations of SIJs.

Keywords. artificial intelligence, axial spondyloarthritis, bone marrow edema

Introduction

Artificial intelligence in medical imaging

Artificial intelligence (AI) can be loosely defined as the ability of a computer system to execute a task that typically or conventionally requires human intelligence.[1] AI encompasses systems that can perform tasks without the need for learning. In the field of medical imaging, for instance, AI can be employed to identify anatomical structures using predesigned algorithms that embody the concepts of software engineers. Conversely, a subset of AI techniques known as "machine learning" (ML) has the ability to automatically learn from presented data, often using ground truth data as training sets (i.e., supervised learning). This range of methods includes various algorithms for automatic pattern recognition, many of which have been developed over the past decades. "Deep learning" is a subcategory of machine learning that relies on artificial neural networks, mimicking human learning by employing mathematical representations of neurons and their connections. Within both of these AI categories, there is a wide spectrum of applications in the field of medical imaging diagnosis.[1]

Sacroiliitis

Sacroiliitis, which is characterized by inflammation of the sacroiliac joint (SI), typically results in pain. The sacroiliac joint, one of the largest joints in the body, frequently contributes to discomfort in the lower back

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and buttocks region. It connects the ilium bone to the sacrum. Diagnosing sacroiliitis can be challenging as its symptoms resemble those of other common causes of back pain, often leading to it being overlooked as a source of discomfort. Pain in this condition is often associated with chronic degenerative factors, although it is relatively uncommon. Sacroiliitis can be related to rheumatic, infectious, drug-related, or oncologic sources. Some specific nondegenerative conditions that can lead to sacroiliitis include ankylosing spondylitis, psoriatic arthropathy, Bechet disease, hyperparathyroidism, and various pyogenic sources.[2-4]

Axial spondyloarthritis

Axial spondyloarthritis (axSpA) results in persistent inflammation of the sacroiliac joints (SIJs), leading to chronic back pain, stiffness, and changes in skeletal structure and posture. This condition hampers the ability to carry out daily activities, contributing to a negative impact on the health-related quality of life (HRQoL) of individuals.[5] The development of new criteria for classifying and screening patients with axSpA has been crucial for early identification and treatment of such patients, with MRI being the most critical imaging method available.[6] This type of examination enables the assessment of various aspects, including bone marrow edema (BME), erosions, fat lesions, sclerosis, or ankylosis (bone formation).[7] While the utilization of magnetic resonance imaging and its integration into diagnostic standards has improved the recognition of initial axSpA, a consistent enhancement in early diagnosis has not been consistently documented in all research. Insufficient understanding of the full spectrum of axSpA symptoms and the failure to identify inflammatory back pain (IBP) in primary healthcare settings might be contributing factors to this issue.[8] The implementation of appropriate algorithms for recognizing axSpA through MRI imaging analysis may lead to earlier diagnoses, which in turn could be associated with the potential for improving patient treatment outcomes. According to the ASAS classification criteria, MRI is used to define active sacroiliitis through the following parameters:

1. Bone marrow edema, which is the accumulation of fluid within bone marrow cells due to inflammation, is observable in the "fluid-sensitive" STIR sequence (Short Tau Inversion Recovery) (also known as the T2-weighted sensitive to water sequence) as regions hyperintense to the sacral interforaminal bone marrow.
2. Bone marrow enhancement (osteitis), which can be detected in the T1-weighted sequence after contrast media administration.[9-11]

Algorithms for sacroiliitis diagnosis

It is possible to use algorithms for bone marrow edema. So far, only two algorithms for the semi-automated detection and measurement of sacroiliitis related to axSpA have been created. The first one, known as SCAISS, was developed by Zarco et al. in 2018, and the second one was introduced by Kucybała et al. in 2020.[12,7] In the research conducted by Rzecki et al., a fully automated algorithm for evaluating BME was outlined in 2021, and it was subsequently compared with alternative approaches in another study, affirming its potential for clinical application.[13,14] The subsequent year saw the development of another algorithm for analyzing MR images of sacroiliac joints in axial spondyloarthritis, as presented by Bressem et al.[15] Moreover, in 2023 in the study of Ożga et al. the algorithm created by Kucybala et al. and Rzecki et al. had been further developed and proven to handle a range of various conditions.[16] In contrast the one proposed by Bressem et al. is primarily focused on classifying entire MR images as either normal or abnormal.[15] Consequently, it does not determine the lesion's location or volume using the algorithm.[15]

Aim

In the following sections of this paper, each of the existing algorithms is described and compared in relation to one another.

Material and methods

The algorithms described in the following article were found in the PubMed database as those used to assess BME and thus detect active sacroiliitis.

Analysis of the literature

SCAISS algorithm by Zarco et al.

The method, known as SCAISS (Spanish abbreviation for "herramienta eSpañola para la Cuantificación semi-Automática de Inflamación de Sacroilíacas en resonancia magnética en eSpondiloartritis"), requires an MRI image in the STIR sequence saved in DICOM format.

It focuses only on two specific planes: semi-axial and semicoronal, which are oriented perpendicular to the sacroiliac joint, specifically within the periarticular region exhibiting hyperintense signals. Using the computer screen image, the physician identifies areas with visible bone marrow edema (BME) that appear hyperintense, one by one, with a mouse click. The software automatically selects adjacent areas with intensity falling within a predefined tolerance range centered around the pointer-click. Once the area is outlined, the software proceeds to calculate its size, perimeter length, and the mean signal intensity (brightness) within that region. It is essential to note that the lesions identified by mouse clicks should be situated in the periarticular area, as defined by the ASAS consensus regarding the anatomical characteristics of sacroiliitis.[12,17] The primary advantage of SCAISS compared to other methods is its simplicity – the reader only needs to choose ROI with a mouse click – supported by demonstrated validity and reliability. Additionally, the selected images can be saved (as ROI), not just the score, which implies improved tracking of the measurement process, allowing for reevaluation if necessary and easier monitoring of the same or new areas. Further benefits of the approach include the requirement of only STIR sequences and the capability to reliably interpret both coronal and axial slices, whereas other techniques can only be evaluated in coronal images. Nevertheless, it is important to consider certain limitations when interpreting these findings. It is crucial to note the small sample size, necessitating further confirmation in subsequent validation studies. Furthermore, the sensitivity to changes in the SCAISS scale has not yet been evaluated, which precludes recommending the use of this method in clinical trials.[12] On the other hand, the main disadvantage of this approach is its reliance on manual selection of lesions (as the software only identifies their outlines) and the inability to detect lesions overlooked by the observer.[7]

Algorithm by Kucybała et al.

This algorithm's development was grounded in the systematic approach outlined by Maksymowych et al. for evaluating active inflammatory changes in sacroiliac joints.[18] The semi-automated procedure for detecting bone marrow edema comprised the subsequent stages:

1. The sacral bone and visible portions of both iliac bones were manually delineated on T1-weighted sequence images using the Segmentation Editor plugin for ImageJ (National Institutes of Health, Bethesda, MD, USA). Each bone was assigned a distinct label.
2. Identification of the reference signal area: The algorithm determined the central axis of the sacral bone and identified all pixels within the sacrum that were closer to this central axis than a user-defined distance threshold, REFTH. Then these marked pixels were classified as part of the reference signal region.
3. Detecting central lines in the sacroiliac joint: Firstly, the algorithm calculated the distance from each non-bone pixel to both the iliac and sacral bones. Next, it assigned an absolute value representing the difference between these two distances to each non-bone pixel. Pixels positioned at the central line of the joint, where the distances to the sacral and iliac bones were equal, received zero values. Finally, the algorithm utilized Dijkstra's shortest path algorithm to identify the central joint lines.
4. Identifying regions of interest (ROIs): ROIs were defined as bone areas located near joint surfaces at a user-defined distance, where the algorithm aimed to detect inflammatory changes. Initially, the algorithm established the bony boundaries of the joint surfaces by projecting the central lines of the sacroiliac joints onto the surfaces of both the sacral and iliac bones. Following this, for each bone individually, the algorithm computed the distances from the pixels within the bone to its corresponding joint surface. Any pixel with a distance less than 10 mm was categorized as part of the ROI for that particular bone.
5. The partitioning of ROIs into quadrants: First, the central line of each sacroiliac joint was identified, and its midpoint was established. Then, a straight line, perpendicular to the central line and passing through its midpoint, was defined to separate the ROIs into upper and lower quadrants.
6. Identification of inflammatory changes: Since the patient's position remained consistent during the acquisition of both T1-weighted and STIR sequence images, the reference region and quadrants initially determined on T1-weighted sequence images were transferred to STIR sequence images to identify bone marrow edema.
7. within STIR sequence images, each pixel within the ROI was matched with a set of R reference pixels from the reference region. Subsequently, the mean and standard deviation of the signal intensity for this reference set were calculated. Following that, the test statistics were computed, which represented the difference in signal intensity between the tested pixel and the mean intensity of the reference set, divided by the standard deviation of the reference set. If these test statistics surpassed a user-defined threshold, it indicated the presence of bone marrow edema within the tested pixel.

The manual process was only required for the first step; steps 2 to 6 were completely automated.[7] The main advantage of this method is that by concentrating the detection on specific pixels, it becomes possible to identify and emphasize regions where the presence of bone marrow edema is suspected. Consequently, the radiologist can confirm the actual significance of the identified alterations and readily elucidate the findings of the examination. Nonetheless, the primary constraint of our approach is the prerequisite for manual preparation of bone segmentations forming the sacroiliac joints before the automated detection of inflammatory changes. This currently impedes the integration of this method into routine clinical practice.[7]

Algorithm by Rzecki et al.

Back then, only two algorithms had been developed for the semi-automated detection of sacroiliitis related to axSpA on MRI. The first one was created by Zarco et al., which allowed for the detection of inflammatory change boundaries as chosen by the observer, but it couldn't identify missed lesions.[12] On the other hand, the semi-automated algorithm by Kucybała, Rzecki et al. provided reliable identification of bone marrow edema lesions.[7] However, it required a labor-intensive manual segmentation of the sacroiliac joint bones before lesion detection. At that time, no fully automated method had been developed to aid in the diagnosis of axSpA through MRI. Subsequently, the study of Rzecki et al. significantly enhances the previously published algorithm with regard to bone and inflammatory change segmentation.[7] Firstly, Rzecki et al. replaced the manual bone segmentation, used in the algorithm by Kucybała et al. with a fully automated segmentation method based on deep learning. Secondly, Rzecki et al. substantially improved the precision of determining the volume of marrow edema lesions.

The automated algorithm developed by Rzecki et al. for bone marrow edema detection involved the following procedures:

1. Segmentation of the sacrum and the left and right iliac bones on 2D slices from a 3D T1-weighted sequence.
2. Identification and extraction of ROIs where the algorithm detects inflammatory changes.
3. Segmentation of the inflammatory lesions within the identified ROIs.

Subsequently, the algorithm was further tested on a larger number of MRI examinations by the team of Ożga et al.[16] The research team validated the algorithm's performance depending on the technical correctness of the MRI scan.

The project consisted of the following steps:

1. Assessment of the correctness of the alignment of the MRI section of the sacroiliac joints. The deviation angle of each examination was measured to validate the method of determining the technical correctness of the MRI examination.
2. Enhancement of the pre-existing algorithm in the form of post-processing adjustments. The algorithm by Rzecki et al. was updated by introducing the rule that BME is to be located up to 1 cm from the joint space.[7]
3. The following manual and automatic segmentation of the sacrum and iliac bones in T1-weighted images were performed at each examination.
4. Evaluation of inflammatory lesions present on the included examinations using the SPARCC scale.
5. Manual and automatic segmentation of bone marrow edema present on the sacrum and iliac bones in STIR images.[16]
6. The results of bone and BME segmentations performed by the algorithm and by experienced researchers were compared.

The results of the study revealed that the evaluated algorithm performs satisfactorily regardless of the angle of deviation and, consequently, the technical correctness of the examination. It is worth mentioning that the key advantage of this algorithm is its full automation, which eliminates the time-consuming manual segmentation, and has achieved significantly higher sensitivity and specificity compared to other algorithms. However, the sample size remains insufficient to take significant steps towards the implementation of this algorithm for routine use in clinics

Algorithm by Bressem et al.

A deep learning tool created by Bressem et al. was employed to identify signs of active inflammation and structural abnormalities associated with axSpA in sacroiliac joint MRI scans. Its primary function involves categorizing entire MR images as either normal or abnormal, without specifying the lesion's location or volume through the algorithm.[15] One of the strong points of this research is the incorporation of MRI scans obtained from various machines with diverse settings, the centralized standardized assessment of images by professionals, and the utilization of an external test set. This study has also several limitations. Firstly, the low axSpA prevalence in the test set might introduce performance uncertainty. Secondly, in GESPIC-Uveitis and OptiRef, MRI was conducted only in a subset of patients, potentially causing selection bias. Thirdly, the models were exclusively trained with semicoronal images, potentially leading to model failure with different orientations. Fourthly, the choice of global labels for model training and the absence of a quadrant analysis of the sacroiliac joints hindered a spatially accurate assessment of various joint regions. Finally, the variety of scanners and protocols used made it impossible to provide imaging parameters for all MRI scans, thus limiting the reproducibility of the data.[15]

Algorithm comparison

AI algorithms are a technological accomplishment enabling the development of many branches of science, including medicine.[19] Since the accurate diagnosis of axSpA depends on experience, the discussed algorithms could be particularly helpful for doctors without much experience in evaluating MRI of SIJs. The use of artificial intelligence in the clinical practice of doctors can contribute to reducing the time, increasing the accuracy and precision of their performance.[20] This results in reducing health care costs and a more efficient use of specialists' time, as well as enabling them to make the correct diagnosis in a larger number of patients, while recognizing a disease at an earlier advanced stage.[21]

It is crucial to choose the right algorithm to maximize the sensitivity and specificity of detecting inflammatory lesions in the sacroiliac joints using AI. Among the algorithms compared, Bressem et al. evaluated the largest number of images of patients (593), at the same time it is one of the two fully-automated algo-

Table 1. Comparison of algorithms created for the BME detection

	Zarco et al. (SCAISS)	Kucybała et al.	Rzecki et al.	Bressem et al.
Algorithm's automation	Semi-automated	Semi-automated	Fully-automated	Fully-automated
Algorithm's outcomes	The area, perimeter length, and mean of signal intensity (brightness) in bone marrow edema	The volume of marrow edema lesions	The volume of marrow edema lesions	Detection of active inflammatory changes (BME) or structural changes indicative of axSpA
Number of SIJs MRI included in the study	23	22	30	593
Number of patients with BME presence	23	22	30	222
Sensitivity in BME detection	Not calculated	Not calculated	0.95	0.88
Specificity in BME detection	Not calculated	Not calculated	0.96	0.71
Correlation between automatic and manual detection of BME	The three-phase Speraman's coefficient of correlation was 0.747, 0.729 and 0.74 compared to the Berlin method and to the SPARCC was 0.772, 0.840 and 0.793 for the first, second and third evaluators, respectively.	The correlation coefficient between semi-automated and manual detections was 0.87 for pixel-wise comparison and 0.83 for quadrant-wise analysis.	The Speraman's coefficient of correlation between verified ground truth and automated measurements was equal to 0.866 while the intraclass coefficient of correlation ICC (1,1) is equal to 0.947.	Not calculated
The time to analyze the whole MRI examination of one patient	28 s	Up to 10 s	Not mentioned	18.9 s

rithms described (the other was described by Rzecki et al.). Comparing the values achieved by these algorithms for sensitivity and specificity, significantly better results are obtained by the Rzecki's et al. algorithm than by the Bressem's one. Regrettably, in the case of semi-automated algorithms, these parameters were not calculated. Fully-automated algorithms provide a much broader range of actions carried out by AI than semi-automated algorithms, which makes them more widely used in clinical practice. The algorithm by Zarco et al. is the only one that requires a physician to manually mark the area with visible marrow edema to obtain its size, perimeter length, and the mean brightness calculated by software, which demonstrates its limited applicability in practice. However, none of the discussed algorithms considered the impact of the technical correctness of performing the MRI examination on its efficiency – only Ożga et al. evaluated the impact of this parameter on the performance of fully-automated algorithm previously created by Rzecki et al.

It is difficult to determine which algorithm is the best, because each of them performs in a slightly different manner. The algorithm by Bressem et al. additionally detects structural changes in axSpA, and the one by Zarco et al. measures more parameters, but it is semi-automated. The creation of algorithms by different research teams encourages each group to improve their algorithms. Possibly, with the cooperation of all researchers involved in the development of AI in diagnostic imaging of axSpA, an algorithm combining the advantages of all will be created in the future.

Conclusion

The development of artificial intelligence in diagnostic imaging axSpA is incredibly important and will help minimize costs and increase clinicians' productivity. Each of the algorithms presented in the paper has advantages and disadvantages. The algorithm created by Bressem et al. was trained on the largest number of examinations. The algorithm created by Rzecki et al. has the greatest sensitivity and specificity. The algorithm created by Kucybała et al. has the shortest time to analyze the whole MRI examination of one patient. However, it is impossible to determine the ultimate algorithm.

Declarations

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Author contributions

Conceptualization, I.G. and J.O.; Methodology, I.G.; Software, I.G.; Validation, J.O. and A.R.; Formal Analysis, I.G.; Investigation, I.G.; Resources, J.O.; Data Curation, I.G.; Project Preparation, I.G., A.R. and J.O.; Writing – Review and Editing, I.G.; Visualization, J.O.; Supervision, I.G.; Project Administration, I.G.

Conflicts of interest

The authors declare no conflict of interest.

References

1. Stoel B. Use of Artificial Intelligence in Imaging in Rheumatology-Current Status and Future. *Perspectives RMD Open*. 2020;6.
2. Slobodin G, Hussein H, Rosner I, Eshed I. Sacroiliitis – early diagnosis is key. *J Inflamm Res*. 2018;11:339-344. doi: 10.2147/jir.s149494
3. Chahal BS, Kwan ALC, Dhillon SS, et al. Radiation exposure to the sacroiliac joint from low-dose CT compared with radiography. *AJR Am J Roentgenol*. 2018;211(5):1058-1062. doi: 10.2214/ajr.18.19678

4. Gutierrez M, Rodriguez S, Soto-Fajardo C, et al. Ultrasound of sacroiliac joints in spondyloarthritis: a systematic review. *Rheumatol Int*. 2018;38(10):1791-1805. doi: 10.1007/s00296-018-4126-x
5. Rudwaleit M, van der Heijde D, Landewe R, et al. The development of Assessment of SpondyloArthritis international Society classification criteria for axial spondyloarthritis (part II): validation and final selection. *Ann Rheum Dis*. 2009;68(6):777-783. doi: 10.1136/ard.2009.108233
6. Sieper J, Poddubnyy D. Axial spondyloarthritis. *Lancet*. 2017; 390(10089):73-84. doi: 10.1016/s0140-6736(16)31591-4
7. Kucybała I, Tabor Z, Polak J, Urbanik A, Wojciechowski W. The semi-automated algorithm for the detection of bone marrow oedema lesions in patients with axial spondyloarthritis. *Rheumatol Int*. 2020;40(4):625-633. doi: 10.1007/s00296-020-04511-w
8. Kumthekar A, Bittar M, Dubreuil M. Educational needs and challenges in axial spondyloarthritis. *Curr Opin Rheumatol*. 2021;33(4):313-318. doi: 10.1097/BOR. 0000000000000806
9. Sieper J, Rudwaleit M, Baraliakos X, et al. The Assessment of SpondyloArthritis international Society (ASAS) handbook: a guide to assess spondyloarthritis. *Ann Rheum Dis*. 2009;68(2):ii1-ii44. doi: 10.1136/ard.2008.104018
10. Tsoi C, Griffith JF, Lee R, Wong P, Tam LS. Imaging of Sacroiliitis: Current Status, Limitations and Pitfalls. Quant. *Imaging Med Surg*. 2019;9:318-335.
11. Maksymowych WP, Lambert RG, Baraliakos X, et al. Data-driven definitions for active and structural MRI lesions in the sacroiliac joint in spondyloarthritis and their predictive utility. *Rheumatology (Oxford)*. 2021;60(10):4778-4789. doi: 10.1093/rheumatology/keab099
12. Zarco P, SCAISS Study Group, Almodóvar R, Bueno Á, Molinero LM. Development and validation of SCAISS, a tool for semi-automated quantification of sacroilitis by magnetic resonance in spondyloarthritis. *Rheumatol Int*. 2018;38(10):1919-1926. doi: 10.1007/s00296-018-4104-3
13. Rzecki K, Kucybała I, Gut D, et al. Fully Automated Algorithm for the Detection of Bone Marrow Oedema Lesions in Patients with Axial Spondyloarthritis-Feasibility Study. *Biocybern Biomed Eng*. 2021;41:833-853.
14. Garrido-González C, Pineda ML, Garrido-Castro JL, et al. Collantes Estevez POS0958 Responsiveness of Conventional, Semi-Automatic and Full-Automatic Methods to Quantify Marrow Bone Edema Lesions in MRI. *Ann Rheum Dis*. 2021;80:743-744.
15. Bressem KK, Adams LC, Proft F, et al. Deep learning detects changes indicative of axial spondyloarthritis at MRI of sacroiliac joints. *Radiology*. 2022;305(3):655-665. doi: 10.1148/radiol.212526
16. Ożga J, Wyka M, Raczko A, et al. Performance of fully automated algorithm detecting bone marrow edema in sacroiliac joints. *J Clin Med*. 2023;12(14):4852. doi: 10.3390/jcm12144852
17. Weber U, Ostergaard M, Lambert RG, et al. Candidate lesion-based criteria for defining a positive sacroiliac joint MRI in two cohorts of patients with axial spondyloarthritis. *Ann Rheum Dis*. 2015;74(11):1976-1982.
18. Maksymowych WP, Dhillon SS, Chiowchanwisawakit P, et al. Development and validation of web-based training modules for systematic evaluation of active inflammatory lesions in the spine and sacroiliac joints in spondyloarthritis. *J Rheumatol Suppl*. 2009;84(0):48-57. doi: 10.3899/jrheum.090620
19. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. *Nat Med*. 2022;28(1):31-38. doi: 10.1038/s41591-021-01614-0
20. Ahmed Z, Mohamed K, Zeeshan S, Dong X. Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. *Database (Oxford)*. 2020;2020. doi: 10.1093/database/baaa010
21. Matheny ME, Whicher D, Thadaney Israni S. Artificial intelligence in health care: A report from the national academy of medicine. *JAMA*. 2020;323(6):509. doi: 10.1001/jama.2019.21579