Joint Bone Spine 91 (2024) 105651

Contents lists available at ScienceDirect

Joint Bone Spine

journal homepage: www.elsevier.com

Review

Artificial intelligence to analyze magnetic resonance imaging in rheumatology

Lisa C. Adams[a,1,*], Keno K. Bressem[b,c,1], Katharina Ziegeler[e,f], Janis L. Vahldiek[b], Denis Poddubnyy[d]

[a] Department of Diagnostic and Interventional Radiology, Faculty of Medicine, Technical University of Munich, Ismaninger Str. 22, 81675 Munich, Germany
[b] Department of Radiology, Charité–Universitätsmedizin Berlin, Corporate Member of Freie Universität Berlin and Humboldt Universität zu Berlin, Hindenburgdamm 30, 12203 Berlin, Germany
[c] Berlin Institute of Health at Charité–Universitätsmedizin Berlin, Berlin, Germany
[d] Department of Gastroenterology, Infectious Diseases and Rheumatology (including Nutrition Medicine), Charité–Universitätsmedizin Berlin, Corporate Member of Freie Universität Berlin and Humboldt Universität zu Berlin, Hindenburgdamm 30, 12203 Berlin, Germany
[e] Department of Hematology, Oncology , and Cancer Immunology, Campus Charité Mitte, Charité Universitätsmedizin Berlin, Germany
[f] Evidia Radiologie am Rheumazentrum Ruhrgebiet, Germany

ARTICLE INFO

Article history:
Accepted 26 September 2023
Available online 4 October 2023

Keywords:
Rheumatology
Magnetic resonance imaging
Artificial intelligence
Disease diagnosis and management

ABSTRACT

Rheumatic disorders present a global health challenge, marked by inflammation and damage to joints, bones, and connective tissues. Accurate, timely diagnosis and appropriate management are crucial for favorable patient outcomes. Magnetic resonance imaging (MRI) has become indispensable in rheumatology, but interpretation remains laborious and variable. Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), offers a means to improve and advance MRI analysis. This review examines current AI applications in rheumatology MRI analysis, addressing diagnostic support, disease classification, activity assessment, and progression monitoring. AI demonstrates promise, with high sensitivity, specificity, and accuracy, achieving or surpassing expert performance. The review also discusses clinical implementation challenges and future research directions to enhance rheumatic disease diagnosis and management.

1. Introduction

Rheumatic disorders, a complex array of afflictions involving the musculoskeletal system, represent a considerable global health burden [1]. These diseases, characterized by inflammation and damage to the joints, bones, and other connective tissues, present significant diagnostic and therapeutic challenges for patients and healthcare providers alike. It is, therefore, of utmost importance to achieve accurate and prompt diagnosis, classification, and appropriate management, as these factors significantly influence patients' overall quality of life, functionality, and long-term prognosis.

MRI has surfaced as an invaluable, noninvasive imaging technique, offering unrivaled insights into the structural and pathological alterations concomitant with rheumatic diseases [2,3]. It plays a significant role in the diagnosis and management of rheumatoid arthritis (RA), spondyloarthritis (SpA) including ankylosing spondylitis (AS), osteoarthritis (OA), and others, and offers a noninvasive way to assess joint and soft tissue abnormalities, inflammation, and structural damage in patients with rheumatic conditions. Nevertheless, the interpretation of MRI is laborious, time-consuming, and subject to inter- and intra-observer variability. Further, the high cost and limited availability of MRI machines curtail their extensive implementation in rheumatology [4].

The remarkable advancements in AI furnish unparalleled prospects to redefine the realm of rheumatology by augmenting and automating diverse facets of MRI analysis. AI refers to the development of computer systems that can perform tasks typically requiring human intelligence, such as problem-solving, learning, and understanding complex patterns. ML is a subset of AI and pertains to the use of algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data without explicit programming. ML methodologies,

* Corresponding author.
E-mail address: lisa.adams@tum.de (L.C. Adams).
[1] These authors contributed equally.

https://doi.org/10.1016/j.jbspin.2023.105651
1297-319X/

Table 1
Original research articles on advanced automated techniques, with a focus on AI, applied to rheumatology MRI analysis. Non-AI-based approaches are highlighted in light gray color, AI approaches appear in white without color highlighting.

Type of disease	Reference	Number of subjects	Methods
Rheumatoid arthritis			
Joint space narrowing	Langs et al. [6], 2008	28 RA subjects	Quantification
Synovial activity	Kubassova et al. [7], 2010	135 active RA subjects and 5 healthy controls	Quantification
Bone erosion and edema	Crowley et al. [8], 2011	22 RA subjects	Segmentation
Tenosynovitis of the wrist	Czaplicka et al. [9], 2015	32 RA subjects	Segmentation
Tenosynovitis and bone marrow edema of the wrist	Aizenberg et al. [10,11], 2018 & 2019	485 RA subjects & 563 RA subjects	Segmentation
Kellgren–Lawrence grade assessment in knee RA	More et al. [12], 2021	193 subjects with knee RA	Segmentation and classification
Seropositive RA, seronegative RA, and PsA	Folle et al. [13], 2022	649 subjects (135 seronegative RA, 190 seropositive RA, 177 PsA, 147 psoriasis)	Classification
Spondyloarthritis			
Sacroiliac joint subchondral BME	Faleiros et al. [14], 2020	56 subjects	Classification
Sacroiliac joint bone marrow edema	Lee et al. [15], 2021	60 axSpA subjects & 19 healthy subjects	Classification
Structural lesions & incidental lesions	Jans et al. [16], 2021 & Morbée et al. [17], 2023	30 participants & 210 subjects	Detection
Hip bone marrow edema	Han et al. [18], 2022	141 SpA subjects	Segmentation and classification
AxSpA versus non-axSpA	Ye et al. [19], 2022	638 subjects	Classification (radiomics)
Inflammatory and structural changes of the sacroiliac joint	Bressem et al. [20], 2022	593 subjects	Classification
Hip inflammation	Zheng et al. [21], 2023	195 SpA subjects	Segmentation
Inflammatory and structural changes of the sacroiliac joint	Bordner et al. [22], 2023	256 subjects	Detection and classification
Osteoarthritis			
Cartilage changes	Prasoon et al. [23], 2013	139 knee MRI scans	Segmentation
Cartilage degeneration/injury	Liu et al. [24], 2018	175 subjects with knee pain	Detection
Radiographic OA	Pedoia et al. [25], 2019	4384 subjects (1937 OA; 2447 controls) Osteoarthritis Initiative (OAI) database	Classification
Structural features associated with knee pain	Chang et al. [26], 2020	1505 subjects OAI database	Classification
Bone shape features	Morales Martinez et al. [27], 2020	4796 subjects OAI database	Segmentation and classification
Total knee replacement	Tolpadi et al. [28], 2020	4796 subjects OAI database	Classification
Articular cartilage thickness	Desai et al. [29], 2021	88 subjects	Segmentation
Hip joint fluid volume	Jaremko et al. [30], 2021	93 OA subjects	Segmentation
Cartilage degradation	Schiratti et al. [31], 2021	3268 subjects OAI database	Classification
Radiographic joint space narrowing	Chang et al. [32], 2021	4796 subjects OAI database	Segmentation and detection
Cartilage thickness	Eckstein et al. [33], 2022	597 knees	Segmentation
Time to radiographic incidence	Lee et al. [34], 2023	2328 subjects OAI database	Classification
Incident symptomatic radiographic knee OA	Hirvasniemi et al. [35], 2023	242 subjects	Classification
Myopathy			
Type 1 facio-scapulo-humeral dystrophy versus myositis	Fabry et al. [36], 2022	40 subjects	Classification
Thigh muscles	Wang et al. [37], 2023	64 subjects	Segmentation
MRI acceleration and optimization			
Image quality, examination time	Herrmann et al. [38], 2023	21 subjects	DL reconstruction algorithm

MRI: magnetic resonance imaging; AI: artificial intelligence; RA: rheumatoid arthritis; SpA: spondyloarthritis; AS: ankylosing spondylitis; OA: osteoarthritis; DL: deep learning.

particularly DL algorithms, have exhibited capabilities in processing and analyzing vast quantities of intricate imaging data. DL is a subset of ML and specifically refers to the use of artificial neural networks with multiple layers to model high-level abstractions in data. By using DL algorithms, computers can extract pertinent features and patterns for precise diagnosis, assessment, and monitoring of rheumatic diseases. In summary, AI is the broader concept, ML is a subset of AI that focuses on learning from data, and DL is a subset of ML that employs deep artificial neural networks for more complex tasks [5]. AI includes various applications such as quantification, segmentation, classification, and detection. In this review, we categorize the studies described in each section according to these AI applications, to help readers understand which category they fall into (Table 1).

We aim to amalgamate the current state of knowledge and provides an overview of the applications of prior automated computer-based techniques and particularly AI in MRI analysis for rheumatology, encompassing various aspects such as diagnostic accuracy, disease classification, assessment of disease activity, prediction of therapeutic response, and monitoring of disease progression. In addition to highlighting the accomplishments and potential of AI in transforming rheumatology, the challenges and limitations of AI clinical implementation are outlined, and potential future research directions are envisioned. Please also refer to the Graphical abstract and Table 1 for an overview of advanced automated techniques, particularly AI, to analyze MRI in rheumatology.

2. Rheumatoid arthritis

RA is a chronic, systemic autoimmune disorder predominantly impacting the joints. Prompt diagnosis and intervention are indispensable for averting joint destruction and disability. Automated computer-based techniques have exhibited potential in various RA management aspects, including diagnosis [6,9,10,39] with disease activity evaluation [40], and predictive modeling.

2.1. Diagnosis with disease activity evaluation

Accurate diagnosis and subtyping of RA are vital for directing treatment strategies. AI algorithms can scrutinize a combination of imaging, genetic, and clinical data to distinguish between various RA subtypes, offering customized treatment approaches.

Several studies have demonstrated the capacity of ML and DL techniques in identifying RA based on clinical and imaging data. One way to measure the performance of an AI model is by calculating the area under the receiver operating characteristics curve (AUROC), which represents the model's ability to distinguish between classes. In a study using ResNet neural networks to analyze hand MRI scans from 649 patients, Folle et al. aimed to distinguish between seropositive RA, seronegative RA, and PsA based on inflammatory patterns [13]. AUROC results were 0.75 for seropositive RA vs. PsA, 0.74 for seronegative RA vs. PsA, and 0.67 for seropositive vs. seronegative RA, with the trained networks predominantly assigning psoriasis patients to PsA, suggesting a PsA-like MRI pattern may emerge early in the course of psoriatic disease [13].

For MRI applications, DL techniques have been utilized to recognize RA-related synovitis, bone erosions, bone marrow edema (BME), and cartilage loss, aiding both diagnosis and subtyping.

2.2. Detection and quantification of synovitis

Synovitis, a key pathological feature of RA, has been a subject of intense research in recent years. The advent of automated techniques has introduced promising tools for the assessment of synovitis, offering the potential to improve early diagnosis and treatment response evaluation in RA patients.

Over a decade ago, Kubassova et al. found that their developed automated system, Dynamika-RA, significantly enhances data quality by eliminating motion artifacts and reducing evaluation time for synovial inflammation on MRI in RA patients, further demonstrating the effectiveness and potential of automated techniques in clinical applications for objective disease progression estimation and therapy effect evaluation [7]. In a more recent study, dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) of the hand and wrist were employed to automatically quantify inflamed synovial membrane volume determination [9]. The study revealed a comparable correlation between the automatically and manually quantified synovitis volumes and Rheumatoid Arthritis MRI Scoring System (RAMRIS) scores, highlighting the substantial potential of computer-assisted methods in clinical applications for objective estimation of disease progress and therapy effects. Another study focusing on automatic quantification of tenosynovitis on MRI of the wrist in early arthritis patients reported a strong Pearson correlation of $r = 0.90$ ($P < 0.001$) between quantitative measurements and visual scores [11]. However, the presence of false detections due to blood vessels and synovitis led to a median offset from zero equivalent to 13.8% of the largest measurement value, underscoring the need for further improvements in segmentation and exclusion of false detections [11].

Gai et al.'s automatic segmentation algorithm for synovitis lesions in wrist MRIs of RA patients using DL-based conditional generative adversarial networks and U-Net demonstrated reasonable performance (Dice coefficient 0.78) with a small training dataset.

Overall, methods for automatic segmentation of synovitis have the potential for early diagnosis and treatment response evaluation in RA patients while addressing the challenges of manual segmentation [41].

2.3. Bone marrow edema and structural bony changes

Bone marrow edema and structural bony damage in RA are pivotal indicators of disease activity and joint destruction, warranting early detection and intervention.

Aizenberg et al. investigated the feasibility of automatic quantification of BME on wrist MRI in early arthritis patients. Using a three-stage process, a strong correlation ($r = 0.83$, $P < 0.001$) was found between quantitative and visual BME scores, indicating that automated measurement of BME could provide a feasible alternative to visual scoring [10].

Another pilot study by Crowley et al. examined the reliability, feasibility, and validity of a computer-assisted manual segmentation technique for measuring MRI bone erosion and BME at the wrist in RA patients compared to the RAMRIS scoring system [8]. The segmentation technique demonstrated similar reliability for quantifying erosions (intraclass correlation coefficient – ICC = 0.80) and high intra-observer reliability for both erosions (ICCs = 0.994) and edema (ICCs = 0.996) but showed lower interobserver reliability for BME (ICC = 0.46) and was more time-consuming (1–1.5 hours per patient), suggesting potential application in clinical trials but with current limitations in feasibility [8].

2.4. Disease activity and progression

Disease activity assessment is a critical aspect of RA management, as it guides treatment decisions and helps monitor treatment response. AI models can predict RA disease activity using various parameters, including laboratory data, clinical assessments, and imaging data. For instance, ML models have been utilized to analyze MRI data to assess joint inflammation and damage, providing valuable information on disease activity and progression.

In a preclinical study, researchers presented two methods for automatically quantifying changes in bone in in-vivo serial MR images of an experimental rat model of rheumatoid arthritis using rigid and nonrigid image registration. The results demonstrated significant temporal changes in local bone lesion volume in five out of eight identified candidate bone lesion regions, with significant differences between male and female subjects in three regions, highlighting the potential of these methods as sensitive biomarkers of disease progression [42].

2.5. Clinical predictive modeling

Predictive modeling using AI algorithms can help project the course of RA, enabling the development of personalized treatment plans for patients. By analyzing clinical, imaging, and genetic data,

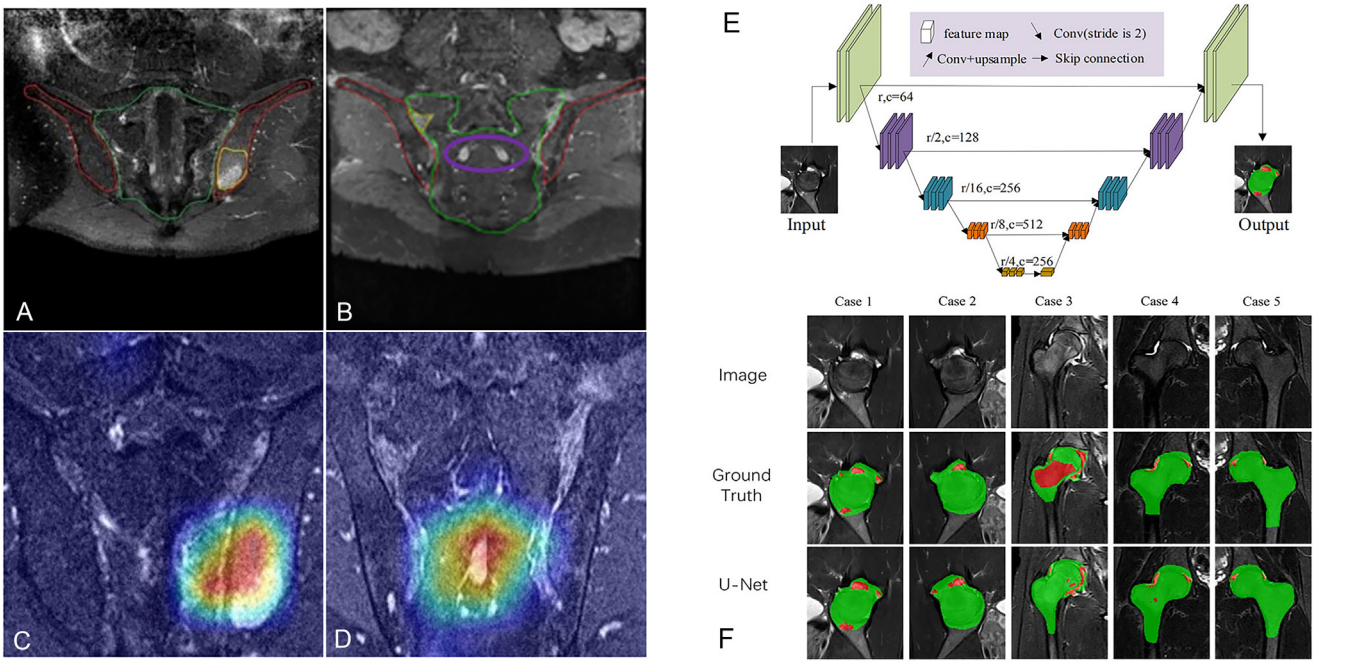

Fig. 1. Examples of artificial intelligence (AI) applications for axial spondyloarthritis (axSpA, A–D) and spondyloarthritis with hip involvement, adapted from Lee et al. (A–D) [15] and Zheng et al. (E–F) [21] (both studies published under a CC-BY Creative Commons license). A–D shows Grad-CAMs for diagnosis of bone marrow edema of the sacroiliac joint in axSpA patients and E–F indicates a U-Net network used for automatic magnetic resonance imaging (MRI) evaluation for SpA patients with hip involvement. A. Indicates class activation mapping outcome for a sample image with bone marrow edema. B. Additional instance of an image displaying indicators of bone marrow edema. C. Gradient-oriented class activation mapping corresponding to (A). D. Gradient-oriented class activation mapping corresponding to (B). The color spectrum denotes areas of highest activation, with activation intensity descending in the sequence of orange, yellow, green, and blue. E. Depiction of the network structure used by Zheng et al. [21]. This network served as the foundational network for preliminary segmentation and input. Data was initially fed into the U-Net network, followed by downsampling and upsampling processes. A three-stage point rendering refined the coarse prediction, producing pixel-level segmentation. F. This panel illustrates the U-Net network's segmentation outcomes and their visual representation.

AI models can predict factors such as disease progression, treatment response, and the likelihood of developing complications.

AI models have been developed to predict disease progression and treatment response in RA patients. For instance, ML techniques have been used to identify clinical and genetic factors associated with poor treatment response, helping clinicians select the most appropriate therapeutic strategy for each patient. Additionally, DL algorithms have been applied to analyze MRI data to predict joint damage progression, allowing for timely intervention to minimize joint damage and disability [43].

3. Spondyloarthritis

SpA encompasses a group of chronic inflammatory diseases that impact the axial skeleton and peripheral joints. Timely diagnosis, classification, and monitoring are essential to prevent irreversible joint damage and loss of mobility. Various AI models have shown potential in managing SpA, including early detection, classification, and disease tracking [44,45].

Zheng et al. employed a DL-based MRI evaluation model to detect irregular and multiple inflammatory hip lesions in SpA patients, achieving similar performance to expert radiologists [21]. For ankylosing spondylitis (AS), Han et al. used an automatic algorithm for quantifying and grading AS hip arthritis with MRI, showing potential for diagnosing and grading AS hip BME [18].

In axial SpA, Ye et al. developed a nomogram model that integrates radiomics features and clinical risk factors, demonstrating favorable discrimination and usefulness for axial SpA diagnosis [19]. Faleiros et al. utilized ML methods to identify sacroiliac joint (SIJ) subchondral BME in axial SpA patients, achieving promising results for detecting active inflammatory sacroiliitis on MRI short Tau inversion recovery (STIR) sequences [14].

Lin et al. created a DL algorithm using Attention U-Net for detecting active inflammatory sacroiliitis in STIR MRI, comparable to a radiologist's interpretation and outperforming that of a rheumatologist [29]. The algorithm was applied to a dataset of 326 axial SpA participants and 63 non-specific back pain participants [29].

Bressem et al. developed a DL model to detect MRI changes in sacroiliac joints indicative of axial SpA in a retrospective multicenter study of 593 patients, demonstrating potential in assisting clinicians in early inflammation detection and accurate diagnosis [20]. The network achieved an AUC of 0.94 for inflammatory changes, 0.88 for inflammatory changes fulfilling the Assessment of SpondyloArthritis international Society (ASAS) criteria, and 0.89 for structural changes indicative of axial SpA, with 88% sensitivity and 71% specificity for inflammatory changes, and 85% sensitivity and 78% specificity for structural changes, generalizing well to new data from different scanners and examination protocols [20].

Synthetic CT (sCT) is an emerging imaging technique that generates CT-like images from MRI data based on DL without exposing patients to ionizing radiation. While MRI is a valuable tool in assessing soft tissue and inflammatory changes, it often falls short in visualizing structural changes in bone. This limitation is particularly important when evaluating patients with suspected sacroiliitis, a key feature of spondyloarthritis. In this context, a DL–based image synthesis method for sCT has demonstrated higher accuracy than T1-weighted MRI for detecting structural lesions in patients with suspected sacroiliitis, with sCT being essential for diagnosis in a substantial number of cases [16,17].

In summary, AI models, especially deep neural networks, have demonstrated promise in various SpA management aspects [22], often achieving performance comparable to or exceeding expert radiologists and rheumatologists. Please also refer to Fig. 1.

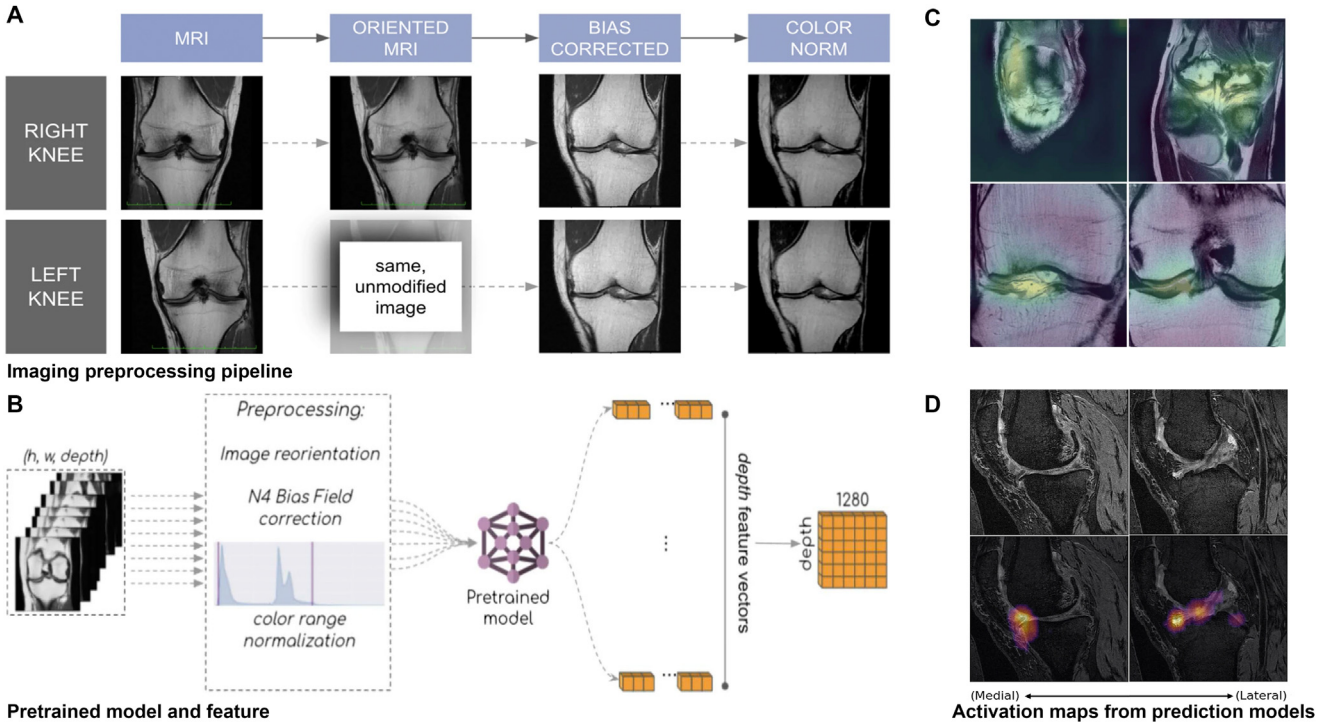

Fig. 2. Comprehensive visualization of the magnetic resonance imaging (MRI) image processing and feature extraction pipeline adapted from and used by Schiratti et al. as well as the Grad-CAMs from Schiratti et al. [31] and Tolpadi et al. [28] (both studies published under a CC-BY Creative Commons license). A. Schiratti et al. started image pre-processing with re-orienting raw MR images to ensure uniform orientation across the dataset by flipping left knee images and maintaining right knee images. Next, bias field correction and color normalization were applied. B. Preprocessed images (reorientation, N4 bias field correction, color normalization) were fed into a pre-trained EfficientNet-B0 network, generating 1280 features per slice and resulting in depth × 1280 features for the entire input volume. C. The resulting prediction models identified relevant zones, with yellow regions indicating high interest areas: intensity corresponds to contribution to prediction of joint space narrowing (bottom row) or severe pain classification (top row) in coronal views. D. Is adapted from Tolpadi et al. [28], who investigated prediction of total knee replacement with deep learning (DL). Occlusion map slices from true positive detections by the MRI pipeline were overlaid on corresponding MRI slices and analyzed for all 124 true positives and true negative controls within the integrated pipeline.

4. Osteoarthritis

OA is a degenerative joint disease characterized by cartilage loss and joint structural changes. AI has shown promise in various aspects of OA management (Fig. 2), particularly diagnosis and subtyping.

A previous proof-of-concept study demonstrated that a convolutional Siamese network could accurately assess knee pain from MRI scans in patients with unilateral knee pain, with an area under the curve (AUC) value of 0.808, increasing to 0.853 when non-discordant WOMAC pain scores were excluded [26]. Expert radiologist review revealed that effusion-synovitis was present in regions most associated with pain in approximately 86% of accurately predicted cases [26]. Pedoia et al. reported that a DenseNet trained on raw T2 data from 4384 OA subjects outperformed the best shallow model in differentiating knees with and without OA, highlighting the potential of feature learning from T2 maps for more effective radiographic OA diagnosis [25]. A recent study investigating volumetric quantitative measurement (VQM) of hip joint fluid volumes in OA patients demonstrated that VQM volumes could be reliably assessed manually and feasibly automated using AI, offering promising initial reliability [30]. This AI-based automation may enhance the precision of joint fluid measurements on MRI, improving correlations with clinical outcomes in rheumatology. Another study showed that a fully automated deep learning segmentation approach displayed similar sensitivity to longitudinal cartilage thickness loss in knee OA as manual expert segmentation and effectively differentiated rates of cartilage loss between cohorts with different progression profiles, suggesting potential for its application in clinical trials investigating knee OA structural progression [33]. Moreover, the integration of ML and DL techniques with MRI data has proven valuable in identifying additional OA-related features, such as cartilage degeneration and bone abnormalities.

4.1. Cartilage degeneration

CNNs have been applied to analyze MRI scans of the knee joint, showing promise for detecting cartilage lesions and predicting disease progression [46]. Furthermore, AI algorithms have been employed to analyze MRI data and segment articular cartilage, providing quantitative measurements that can help assess disease severity and monitor treatment response.

Prasoon et al. proposed a novel voxel classification system integrating three 2D convolutional neural networks (CNNs) for segmentation of anatomical structures in medical images. Applied to the segmentation of tibial cartilage in knee MRI scans, the method outperformed state-of-the-art approaches using 3D multi-scale features, demonstrating the potential of DL architectures to autonomously learn relevant features from images [23].

Liu et al. explored the feasibility of using a DL approach for detecting cartilage lesions within the knee joint on MR images. Results demonstrated that a fully automated DL-based cartilage lesion detection system could evaluate knee joint articular cartilage with high diagnostic performance (ROC curve 0.917), and good intra-observer agreement, showcasing its potential in detecting cartilage degeneration and acute cartilage injury [24].

A recent multi-institute knee MRI segmentation challenge organized to assess the semantic and clinical efficacy of automatic segmentation methods in monitoring osteoarthritis progression found high Dice coefficient scores (>0.85) between six assessed

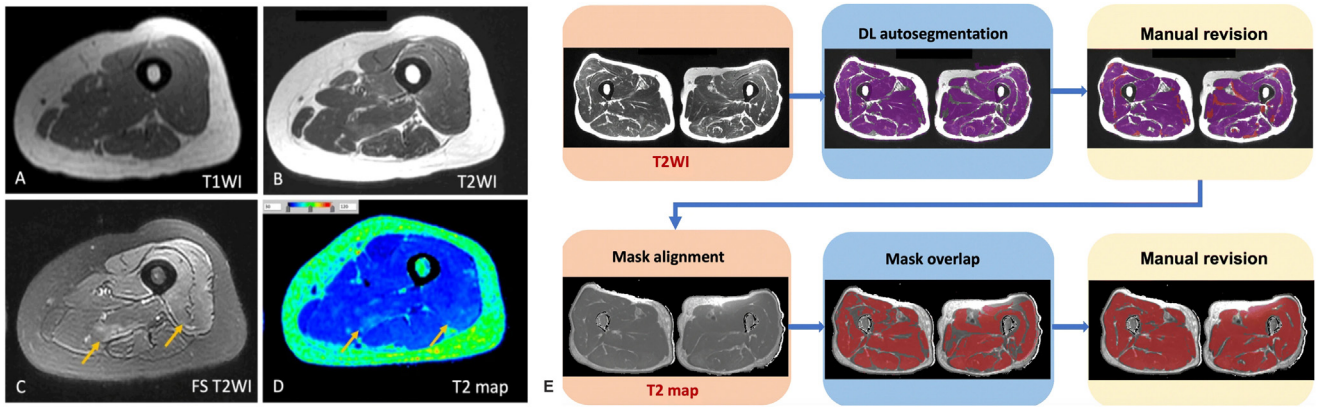

Fig. 3. Adapted from Wang et al. [37]. Their study demonstrated that an automatic deep learning (DL) method for segmentation of T2 maps could effectively differentiate idiopathic inflammatory myopathy (IIM) from healthy controls and quantitatively assess muscular inflammation through T2 mapping, with T2 values positively correlating with serum muscle enzymes. The left part of this figure shows the magnetic resonance imaging (MRI) of a 52-year-old female with dermatomyositis: (A–D) Axial T1-weighted image, T2-weighted image, fat-saturated T2-weighted image, and color-coded T2 map reveal slight hyperintensity in quadriceps and adductor magnus (yellow arrows); (E) Muscle T2 measurement segmented by DL and manually revised, displaying the final region of interest (dark red) and providing T2 values for bilateral thigh muscles.

networks, with comparable performance to the majority-vote ensemble [29]. The challenge demonstrated that diverse networks learned to segment the knee similarly and that high segmentation accuracy did not correlate with cartilage thickness accuracy in OA patients [29].

4.2. Bone marrow lesions

Detecting bone marrow lesions (BMLs) in knee OA patients using MRI can be challenging due to their small size, low contrast, and varying positions.

Morales Martinez et al. used convolutional neural networks (CNN) to learn bone shape features from spherical bone maps of knee MRI images, leading to an OA diagnosis model with an area under the curve (AUC) of 0.905, and sensitivity and specificity of 0.815 and 0.839, respectively [27]. The OA incidence models demonstrated AUCs ranging from 0.841 to 0.646 for predicting OA from healthy scans within 1 to 8 years, highlighting the potential of bone shape as a predictive imaging biomarker for osteoarthritis [27].

4.3. Predictive modeling

Leveraging DL and MRI data, predictive modeling has shown promise in enhancing early diagnosis and prognosis of OA, thereby enabling more effective interventions and improved patient outcomes. For instance, a DL pipeline utilizing MRI images, clinical, and demographic information was developed to predict total knee replacement (TKR) with high accuracy, particularly for patients without OA [28]. This approach not only helps identify higher-risk populations for TKR but also contributes to understanding OA progression and TKR onset by identifying imaging biomarkers [28].

In a study utilizing 9280 knee MR images from the Osteoarthritis Initiative database, a DL method was employed to predict further cartilage degradation measured by joint space narrowing at 12 months, considering MR images and clinical variables like body mass index [31]. The results revealed the model's ROC AUC score of 0.65, surpassing trained radiologists' score of 0.587, demonstrating the potential of DL in supporting radiologists in the challenging task of identifying patients at high risk of OA progression [31]. Another DL study showed that subchondral bone length (SBL) was associated with radiographic joint space narrowing, concurrent pain and disability, and future knee replacement, showing promise as an imaging marker in predicting clinical and structural OA outcomes [32].

A cohort study with 2328 participants utilized a DL model to automatically assess MRI-based structural phenotypes, finding that they were strongly associated with time to incident radiographic osteoarthritis, which suggests their potential use in personalized OA management and participant selection for future disease-modifying OA drug trials [34]. Besides, the recently published KNOAP2020 challenge objectively compared AI-based methods for predicting incident symptomatic radiographic knee osteoarthritis within 78 months using MRI and X-ray data, establishing a benchmark for future research while highlighting the complexity of accurately predicting the onset of this condition, which requires further investigation [35].

5. Myopathy

Myopathies in rheumatology represent a diverse group of inflammatory muscle diseases, often manifesting as progressive muscle weakness and associated with multisystem involvement. Accurate diagnosis and management of these conditions require a multidisciplinary approach, incorporating advanced imaging techniques and targeted therapies.

Using an automatic DL method, researchers analyzed T2 maps of thigh muscles in patients with idiopathic inflammatory myopathy (IIM) and healthy controls, finding significant differentiation between the two groups based on muscle T2 values ($P < 0.001$). Moreover, muscle T2 values in IIM patients positively correlated with serum muscle enzymes, suggesting that DL-based muscle segmentation could offer valuable insights into assessing muscular inflammation in IIM through T2 mapping [37]. Please also refer to Fig. 3.

In a study by Fabry et al., exploring the potential of DL for differentiating between type 1 facio-scapulo-humeral dystrophy (FSHD1) and myositis using whole-body muscle MRI, the DL tool demonstrated comparable diagnostic performance to two specialized musculoskeletal radiologists. This proof-of-concept investigation highlights the promise of DL approaches in accurately distinguishing between two distinct myopathies via MRI, even when working with a limited amount of data and without prior muscle signal changes grading [36].

6. Systemic sclerosis

In the realm of SSc, AI has previously been employed in analyzing anatomical sites to automate the detection of vasculopathy and fibrosis [4]. For instance, researchers have utilized ML techniques

for the analysis of nailfold capillaroscopy, chest CT scans for pulmonary vasculature, cardiac complications, and fibrosis in skin and lung tissues [47–51]. AI applications for MRI have been limited to cardiac assessment [49,50] and skin layer segmentation [52].

Despite these initial applications in anatomical sites associated with SSc, the potential of AI in providing valuable insights and complementing traditional scoring systems for better diagnosis and staging of SSc remains to be explored further.

7. AI-based acceleration of MR protocols

AI-based acceleration of MR protocols holds significant potential for enhancing efficiency in rheumatology practice. Advances in ML and DL techniques have led to the development of algorithms that expedite image acquisition and reconstruction, thereby reducing scan times without compromising diagnostic quality. Efforts to accelerate MR scans have incorporated physics-based fast imaging sequences, hardware-based parallel imaging, and signal processing-based MR image reconstruction from reduced samples, with DL techniques, such as CNNs, showing promise in reconstructing MR images from undersampled k-space data, potentially improving efficiency and effectiveness in imaging [53].

These accelerated protocols have been demonstrated to maintain or even improve image quality, enabling more precise visualization of musculoskeletal structures affected by rheumatic diseases [38], such as synovium, cartilage, and bone. Moreover, AI-driven acceleration can facilitate patient comfort and throughput, leading to increased accessibility and cost-effectiveness in rheumatology clinics.

8. Real-world application and challenges

Artificial intelligence (AI) carries a profound potential for shaping the future landscape of rheumatology. However, it is crucial to underscore that these promising advancements predominantly remain within the bounds of research and development. The transition from research to routine clinical practice is an ongoing process, a bridge that we are yet to fully cross.

AI algorithms demand rigorous validation and testing on substantial and diverse datasets. This is a fundamental step in confirming their robustness and applicability across a wide range of patient populations and clinical scenarios. Alongside, the integration of AI tools into pre-existing clinical workflows presents its own unique challenges. These include the development of user-friendly interfaces, extensive training programs for healthcare providers on AI usage, and the establishment of comprehensive guidelines for their application.

Adding to these challenges is the task of obtaining regulatory approval, a common hurdle when introducing any innovative medical technology. Furthermore, ethical considerations tied to the use of AI, particularly concerning patient consent and data privacy, are yet to be thoroughly explored and resolved.

To navigate these complexities and bridge the gap between research and practice, fostering multidisciplinary collaborations is of paramount importance. Partnerships that involve AI researchers, clinicians, patients, policymakers, and regulatory bodies can facilitate the creation of expansive, representative datasets for algorithm training and validation. They can also aid in the development of comprehensive guidelines for AI use in healthcare, and the creation of strategies to integrate AI effectively into clinical practice.

With the field of rheumatology standing to gain immensely from AI, concerted efforts are anticipated to eventually surmount these challenges. This would make these cutting-edge tools a regular part of our clinical armamentarium, fundamentally revolutionizing our approach to diagnosing, classifying, and managing rheumatic diseases.

In this context, it is worth noting that the majority of the current research on the application of MRI in rheumatology is retrospective. Hence, there is a clear need for additional prospective studies. These would validate the use of MRI in clinical practice and provide a more comprehensive understanding of the potential and limitations of AI in this area.

9. Future directions

As we look towards the future, the application of AI in MRI for rheumatology has shown promising results, but there is substantial room for growth and innovation. Enhanced AI algorithms, such as DL and reinforcement learning, can improve the accuracy and efficiency of MRI analysis, identifying subtle features and patterns associated with rheumatic diseases. The integration of multimodal data, coupling MRI data with genetic and clinical information, can result in improved diagnostic and treatment strategies. Longitudinal MRI data analysis can yield valuable insights into disease progression, enabling more accurate monitoring and timely interventions. Personalized treatment recommendations based on MRI data can enhance patient outcomes and optimize healthcare resource usage. Furthermore, addressing ethical considerations and mitigating biases in AI models for MRI analysis is essential for responsible use, and large-scale validation studies can build trust and support adoption in imaging-based rheumatology practice. Lastly, education and training for healthcare professionals in using and interpreting AI models for MRI analysis in rheumatology are vital for successful integration.

10. Conclusion

AI shows considerable promise in MRI in rheumatology, with potential uses in disease diagnosis, classification, and management. By harnessing the power of AI algorithms to analyze complex imaging data such as MRI, clinicians can make more informed decisions and provide personalized treatment plans for patients with rheumatic diseases. However, there are still challenges to overcome, such as the need for large, high-quality datasets, and the integration of AI into clinical workflows. Future research should focus on addressing these challenges and exploring new applications of AI in rheumatology, to improve patient outcomes and transform the field.

Disclosure of interest

The authors declare that they have no competing interest.

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