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Review

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Review

AI for imaging evaluation in rheumatology: applications of radiomics and computer vision—current status, future prospects and potential challenges

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Abstract

Inflammatory rheumatic diseases, a diverse group of immune-mediated conditions, are characterized by chronic inflammation that can lead to irreversible damage to joints, bones and organs, posing a significant global health challenge. If left untreated, these conditions can severely deteriorate patients' quality of life, underscoring the importance of timely and accurate diagnosis and appropriate management. Artificial intelligence (AI), including radiomics and computer vision, presents promising advancements in improving the early diagnosis and monitoring of these diseases through the analysis of various imaging modalities such as X-rays, CT scans, MRIs and ultrasounds. This review examines the current state of AI applications in the imaging analysis of inflammatory rheumatic diseases, including RA, SpA, SS, SSc and GCA. AI has demonstrated encouraging results, achieving high sensitivity, specificity and accuracy, often on par with or exceeding expert performance. The review also highlights future opportunities for improving the diagnosis and management of rheumatic diseases, as well as the challenges associated with their clinical implementation.

Lay Summary

What does this mean for patients?

Many people are affected by inflammatory rheumatic diseases that are characterized by chronic inflammation. If left untreated, they can lead to extensive damage to joints, bones and organs. Artificial intelligence (AI) is showing great promise in helping doctors diagnose and monitor these diseases earlier and more accurately by analysing medical images like X-rays and MRIs. This review looks at how AI is currently being used to help with the diagnosis of these diseases and highlights future opportunities for improving care. AI has shown results similar to those of expert doctors, but there are still challenges to overcome, such as making sure the technology is safe, understandable and well-integrated into medical care. This article presents the current status of AI applications in rheumatology imaging, explores potential future developments and discusses the challenges that need to be addressed for its successful use in clinical practice.

Keywords: artificial intelligence, imaging, radiomics, diagnostics, adult rheumatology.

Key messages

- Artificial intelligence (AI) presents promising advancements in diagnosing and monitoring of inflammatory rheumatic diseases.
- AI can aid in the early detection and monitoring of inflammatory rheumatic diseases through imaging analysis.
- Successful clinical AI implementation requires addressing challenges regarding data protection, interpretability, ethics and clinical validation.

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Introduction

Inflammatory rheumatic diseases (IRDs), a diverse group of immune-mediated conditions, are characterized by chronic inflammation that can lead to irreversible damage to joints, bones and organs, posing a significant global health challenge. If left untreated, these conditions can severely deteriorate patients' quality of life, underscoring the importance of timely and accurate diagnosis and appropriate management. Artificial intelligence (AI) applications in rheumatologic imaging, including radiomics and computer vision, present opportunities to enhance disease diagnosis, monitoring and management. These techniques enable a transition from qualitative assessments to quantitative and objective evaluations by analysing data embedded in medical images.

Rheumatologic imaging encompasses multiple modalities, e.g. conventional radiography (i.e. X-ray), MRI, ultrasound and CT. AI methods have been applied to various inflammatory rheumatic diseases, including RA, SpA, SS, SSc and GCA. By analysing X-rays and MRIs, AI models can assist in the early diagnosis of these conditions. Furthermore, they support the evaluation of salivary glands, arteries and joint sonography. AI enhances this process by providing quantitative assessments of disease markers such as joint space narrowing, bone erosions and synovitis across different imaging modalities, thereby contributing to accurate disease grading. This review examines AI applications in imaging of inflammatory rheumatic diseases, discussing potential benefits, current limitations, challenges and future directions.

Radiomics and computer vision

Radiomics treats medical images as sources of quantitative data, extracting features such as shape, texture, density and spatial relationships [1]. These features may reflect underlying genetic and biologic processes at the cellular level. Analysis of these features using machine learning can reveal patterns related to disease characteristics, treatment response and patient outcomes [2]. While initially developed for tumour imaging, radiomics is now being applied to enhance diagnosis, prognosis and treatment planning in various medical fields, including rheumatology.

Generative pretrained transformers (GPTs) are advanced language models trained on vast datasets of text to generate coherent and contextually relevant language [3]. Their application in radiomics is a growing area of research with the potential to transform the way complex radiomic data are interpreted and communicated. Radiomics studies often produce intricate datasets that require thorough analysis and summarization for clinical reports. GPT models can assist in automatically generating or summarizing these radiomic findings, providing physicians with clear and concise interpretations, significantly reducing the time needed for manual data analysis and reporting. Moreover, GPT models can support radiologists and clinicians by offering detailed information on radiological image analysis methodologies and techniques, streamlining the process of understanding complex imaging results [4]. As research advances, GPT models may play a key role in enhancing the efficiency and accuracy of radiomic reporting, ultimately improving patient care. However, there are important challenges and limitations to consider, such as ensuring the reliability and accuracy of AI-generated summaries, addressing biases in training data and maintaining interpretability for clinical decision-making. Additionally, integrating these models into clinical workflows while ensuring data privacy and meeting regulatory standards presents further hurdles. Despite these challenges, with continued refinement, GPT models hold promise in aiding radiologists by reducing workload and improving the quality of care.

Computer vision, a branch of AI, focuses on enabling machines to interpret visual information. Recent advances in computer vision have been driven by deep learning, particularly convolutional neural networks (CNNs). CNNs are algorithms that learn to recognize patterns in images by training on large datasets, mimicking the hierarchical processing of the human visual system [5]. Although there has been a recent shift in focus from CNNs towards transformer-based network architectures [6], CNNs remain the most widely used algorithms for computer vision.

CNNs consist of multiple layers that progressively extract higher-level features from input images. Initial layers recognize basic elements like edges and shapes, while deeper layers identify more complex patterns. This hierarchical learning allows CNNs to automatically discover relevant features for tasks like image classification, object detection and segmentation without manual feature engineering. In contrast to radiomics, where researchers specify the features to be extracted, CNNs learn features during the training process, potentially enabling the extraction of a more diverse range of features [7].

Although CNNs can have various architectures that researchers can design freely, in practice, a few established architectures are often used because they have been proven to perform well across a multitude of tasks in both medical and non-medical computer vision. Among the most frequently used CNNs are the ResNet [8] and DenseNet families [9] for classification tasks and U-Net type models [10] for segmentation tasks. Notably U-Nets can incorporate classification CNNs, such as ResNet or DenseNet.

A literature review was conducted to identify relevant studies on the applications of radiomics and computer vision in rheumatology (see Supplementary Data S1, available at *Rheumatology Advances in Practice* online). Table 1 categorizes the studies described in each section according to different AI applications, helping readers understand which category they fall into.

RA

RA is a chronic autoimmune disorder that predominantly affects the joints. Early diagnosis and intervention are crucial for preventing progressive joint destruction and disability. Since imaging of RA mainly focuses on cartilage loss, bone erosions, bone marrow oedema (BMO) and (teno-) synovitis, automated image analysis methods have been developed to detect and assess these manifestations [49].

To date, most efforts have been directed towards the automatic quantification of cartilage loss because plain radiographs are widely available and it is also relevant for OA. Since cartilage itself is not visible on X-ray-based images, cartilage loss can only be assessed indirectly by measuring the joint space. Examples therefore are the automated quantification of radiographic wrist joint space width of patients with RA [11] or the assessment of MCP and PIP joints [12]. Another key imaging feature in RA is bone erosions, which

Table 1. Original research articles on advanced automated techniques, with a focus on AI, applied to rheumatology image analysis

Type of disease	Modality	Reference	Methods
RA			
Wrist joint space	Radiograph	Huo *et al.* [11]	Quantification
Joint space in MCP and PIP joints	Radiograph	Schenk *et al.* [12]	Quantification
Joint space narrowing and erosions	Radiograph	Langs *et al.* [13]	Quantification
Cartilage lesions (knee)	MRI	Liu *et al.* [14]	Detection
Synovial activity	MRI	Kubassova *et al.* [15]	Detection and quantification
Synovitis	MRI	Czaplicka *et al.* [16]	Segmentation and quantification
BMO and tenosynovitis	MRI	Aizenberg *et al.* [17, 18]	Segmentation and quantification
Synovitis	Ultrasound	Hemalatha *et al.* [19]	Segmentation, quantification and classification
JIA			
Increased blood pool activity	Bone scintigraphy	Kian Ara *et al.* [20]	Detection and classification
Gout			
Presence of monosodium urate crystals	DECT	Faghani *et al.* [21]	Segmentation and quantification
Increased muscle density	DECT	Zeng *et al.* [22]	Segmentation and quantification
SpA			
Sacroiliitis	Radiograph	Bressem *et al.* [23]	Detection
Sacroiliitis	Radiograph	Üreten *et al.* [24]	Detection
Sacroiliitis	Radiograph	Dorfner *et al.* [25]	Detection
Erosions	CT	Castro-Zunti *et al.* [26]	Detection
Erosions and ankylosis	CT	Van Den Berghe *et al.* [27]	Segmentation and detection
Sacroiliitis	CT	Zhang *et al.* [28]	Segmentation and classification
Sacroiliitis	CT	Liu *et al.* [29]	Segmentation and detection
BMO	MRI	Faleiros *et al.* [30]	Classification
BMO	MRI	Lin *et al.* [31]	Detection
BMO	MRI	Lee et. al [32]	Detection and classification
AxSpA *vs* non-axSpA	MRI	Ye *et al.* [33]	Classification
Inflammatory and structural changes of the SI joint	MRI	Bressem *et al.* [34]	Classification
BMO and effusion/synovitis of the hip	MRI	Zheng *et al.* [35]	Segmentation
Hip BMO	MRI	Han *et al.* [36]	Segmentation, quantification and classification
Seropositive RA, seronegative RA and PsA	MRI	Folle *et al.* [37]	Classification
Erosion, synovitis and osteitis of the hand in patients with inflammatory arthritis	MRI	Schlereth *et al.* [38]	Classification
SS			
Pathological features of salivary glands	Ultrasound	Vukicevic *et al.* [39]	Segmentation
Pathological features of salivary glands	Ultrasound	Olivier *et al.* [40]	Segmentation and classification
Pathological features of salivary glands	Ultrasound	Kise *et al.* [41]	Classification
SSc			
Microvascular abnormalities	NFC	Bharathi *et al.* [42]	Quantification and classification
Microangiopathy	NFC	Garaiman *et al.* [43]	Classification
Extent of ILD	CT	Chassagnon *et al.* [44]	Segmentation and classification
Lung shrinkage	CT	Chassagnon *et al.* [45]	Classification
Extent of ILD	CT	Le Gall *et al.* [46]	Quantification and risk stratification
Pulmonary vascular changes	CT	Zhai *et al.* [47]	Detection and quantification
GCA			
Halo sign in temporal arteries	Ultrasound	Roncato *et al.* [48]	Segmentation and classification

can already be seen in plain radiographs and automatically identified by analysing the bone contour [13].

With the unique ability of visualize both bone and soft tissue changes, MRI provides much more detailed information about patients with RA, including precise quantification of cartilage thickness and volume. Due to this capability, it has been a focus of various AI research methods [50]. For instance, a fully automated cartilage lesion detection system has been developed using segmentation and classification CNNs. This system achieved a high diagnostic performance and good intra-observer agreement for two individual evaluations performed by AI in detecting cartilage degeneration and acute cartilage injury, based on fat-suppressed T2-weighted fast spin-echo MRI datasets of the knee [14].

Synovitis, a defining feature of RA, has been a focus of intensive research in the last few years. More than a decade ago, a computer-aided detection system was developed for MRI data interpretation and quantification of synovial activity in RA patients that enhanced the data quality significantly by eliminating motion artifacts and reducing the evaluation time. Moreover, it demonstrated benefits in estimating disease progression and evaluating therapy effects [15].

More recently, there has been an advancement in the automatic quantification of inflamed synovial membrane volume. This method involves analysing pre- and post-contrast MRI and segmenting wrist bones in contrast-enhanced MRI [16]. This study demonstrated a strong correlation between automatically quantified synovitis volumes and scores from the

Rheumatoid Arthritis MRI Scoring System (RAMRIS), comparable to correlations observed with manually quantified synovitis volumes. This underscores the significant potential of computer-assisted methods in clinical applications for assessing disease progression and therapy effects.

Furthermore, an automated quantitative measurement of BME and tenosynovitis in early arthritis patients has been created, achieving accuracy comparable to visual scoring by human clinicians. The method involved several steps: first, fusion of axial and coronal slices into a single high-resolution 3D image; next, localization of carpal bones and extensor/flexor tendon regions; and finally, quantification of BMO and tenosynovitis within each bone or tendon by analysing characteristic image intensity values and measuring the fraction of voxels exhibiting these intensities (Fig. 1). This approach enables precise quantitative assessment of BMO and tenosynovitis, demonstrating significant potential as a practical alternative to visual scoring methods [17, 18].

Regarding synovitis, ultrasound is a favoured imaging technique due to its low cost, lack of exposure to hazardous radiation and good availability. An automated quantification of synovial fluid was possible by training a CNN in a process that involved segmentation of the skin border and bone regions, detection of the joint, localization of the synovial region and finally categorization of fluid expansion in the synovial region [19].

Other inflammatory arthritis

Due to its prevalence, RA has been the primary focus of radiomics and computer vision research in inflammatory arthritis. However, there have also been notable advances in other types of inflammatory arthritis.

JIA

JIA is an autoimmune disease and the most common form of arthritis in children <16 years of age. It can affect not only the joints, but also other organs, including the eyes and skin, as well as impacting growth and development [51]. Given the critical role of angiogenesis in sustaining inflammatory and immune responses by increasing blood flow to affected areas, blood pool scintigraphy has demonstrated high sensitivity in detecting inflamed joints [52]. In this context, researchers compared four machine learning models and successfully developed an accurate CNN for distinguishing JIA-affected joints from healthy ones by analysing blood pool images from two-phase technetium 99m methylene diphosphonate bone scintigraphy, with a focus on the knee and ankle joints [20].

Gout

Gout is a common condition caused by the deposition of monosodium urate (MSU) crystals in both articular and non-articular structures, with elevated serum urate levels (hyperuricaemia) being the primary risk factor for its development [53]. Dual-energy CT (DECT) is a non-invasive and effective method for detecting MSU crystals in gout diagnosis [54]. Through colour-coding, DECT distinguishes MSU from calcium, typically displaying MSU as green and calcium as blue. Researchers trained two U-Net models to segment the green-encoded pixels of MSU crystals on DECT scans, creating a fast, consistent, highly sensitive and specific computer-aided diagnostic tool. This algorithm has the potential to enhance DECT workflow for radiologists and improve the accuracy of gout detection [21]. Another recent study identified significant differences in CT radiomics features of the soleus muscle between gout and non-gout cases, such as increased muscle density in gout patients due to urate crystal deposition in periarticular muscles [22].

SpA

The term SpA refers to a heterogeneous group of chronic inflammatory diseases driven by autoimmune processes, with its main types being axial SpA (axSpA) and PsA.

AxSpA is a chronic inflammatory disease that typically begins in young adulthood and is characterized by chronic back pain, often with inflammatory features. Beyond the axial skeleton (SI joints and spine), the disease can have peripheral manifestations, including arthritis (often asymmetric mono- or oligoarthritis, predominantly affecting the lower extremities), enthesitis and dactylitis. Additionally, extramusculoskeletal manifestations (EMMs), such as anterior uveitis, psoriasis and inflammatory bowel disease, are frequently associated with axSpA.

Axial SpA is further categorized into radiographic axSpA (r-axSpA), formerly known as AS, which shows definitive sacroiliitis according to the modified New York (mNY) criteria on X-rays, and non-radiographic axSpA (nr-axSpA), which lacks these radiographic changes but may show inflammation on MRI. Both r-axSpA and nr-axSpA are considered part of the axSpA spectrum, with nr-axSpA potentially progressing to r-axSpA over time in a significant number of patients. In this patient subgroup, structural changes in the

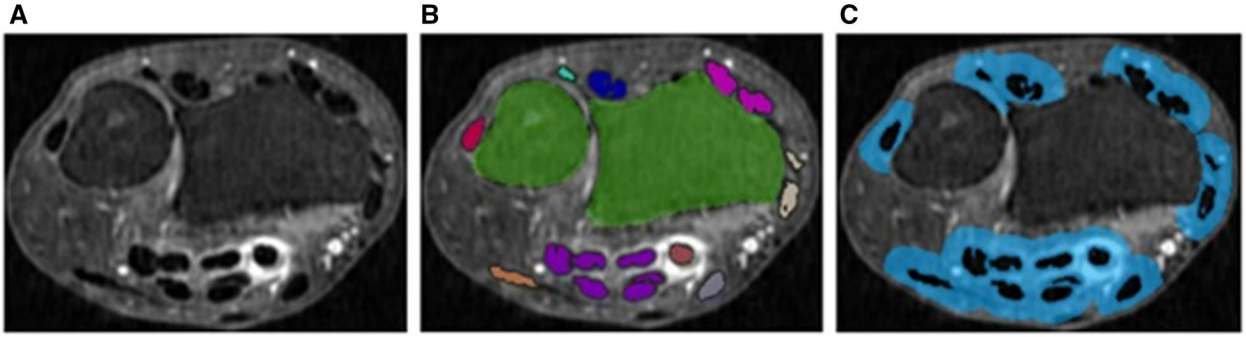

Figure 1. MRI scans of the wrist adapted from Aizenberg *et al.* [18]. This study is published under a CC-BY Creative Commons license. **(A)** A superresolution reconstruction (SRR) image of the wrist, **(B)** the segmented tendon regions and bones and **(C)** the area in which tenosynovitis is quantified

spine, such as new bone formations (syndesmophytes), can occur, ultimately leading to ankylosis. This progression results in limited spinal mobility and impaired physical function. Therefore, early diagnosis and intervention are crucial to managing axSpA and mitigating its long-term effects.

PsA is a complex and heterogeneous disease that affects multiple domains, including peripheral arthritis, psoriasis (skin and nail), enthesitis, dactylitis and the axial skeleton. Besides these physical manifestations, PsA impacts patients' lives through pain, fatigue, loss of function and diminished quality of life. Effective management of PsA requires regular monitoring of these diverse aspects to guide treatment decisions and improve patient outcomes. The significance of an early and correct diagnosis in PsA cannot be overstated, as diagnosing PsA in its initial stages allows for timely treatment that can significantly slow disease progression and preserve joint function.

Regular, non-invasive disease activity assessment plays a vital role in the ongoing management of PsA. Techniques such as ultrasound and MRI can detect early inflammatory changes, even before they become apparent on physical examination or traditional X-rays. These imaging modalities, along with clinical assessment tools, enable clinicians to monitor disease activity accurately and tailor treatment plans to the individual needs of patients.

AI in axSpA

Initial imaging in the diagnostic process for axSpA usually includes a plain radiograph of the SI joints to confirm the diagnosis in the presence of relevant structural changes indicative of sacroiliitis. According to the mNY criteria for AS, the presence of definite radiographic sacroiliitis (sacroiliitis of at least grade 2 bilaterally or at least grade 3 unilaterally) is a mandatory criterion for the diagnosis [55]. Although early signs of sacroiliitis cannot always be seen on plain radiographs, studies have shown that at the time of diagnosis, definite sacroiliitis can be detected on radiographs in one-third of patients with symptoms lasting up to 1 year and in ≈50% of patients with a symptom duration of 2–3 years [56].

By training a CNN with ResNet architecture on conventional radiographs of the SI joints, which were binarily assessed by experienced rheumatologists regarding the presence or absence of sacroiliitis, the model was able to achieve an expert-level performance [23]. Models that can clearly differentiate normal from pathological radiographs could assist clinicians in the diagnosis of sacroiliitis, provide an objective second interpretation and reduce the need for advanced imaging methods such as MRI [24].

Although axSpA primarily affects the SI joints, a pelvic X-ray encompasses the entire pelvic area and surrounding soft tissue, potentially diminishing the effectiveness of diagnostic algorithms. Inspired by the diagnostic process in which human readers assess radiographs by initially identifying the anatomical region of interest before assessing changes therein, a newer model that was first taught anatomical knowledge has demonstrated that incorporating anatomical awareness in such models can enhance the generalizability and progression prediction in deep learning–based radiographic sacroiliitis detection (Fig. 2) [25].

Nevertheless, conventional radiographs are not that sensitive in detecting early sacroiliitis [57, 58]. For detecting typical axSpA structural changes in the SI joints, CT scans offer better sensitivity and specificity. In recent years, deep learning–based models have advanced CT image analysis and demonstrated their ability to extract clinical information, potentially leading to more accurate and earlier diagnoses.

Some years ago, a research group used deep learning–based classifiers to detect bone erosions via CT imagery, outperforming an experienced musculoskeletal radiologist in terms of accuracy, sensitivity and specificity [26]. In addition to bone erosions, another model could identify sacroiliitis-related ankylosis on pelvic CT scans by using manual segmentations and combining a U-Net with two CNNs, achieving remarkable sensitivity and specificity. These results were further refined through patient-level optimization with a Grad-CAM++ explainability analysis, which highlighted the cortical edges as the focus for pipeline decisions [27].

Another study employed a fully automated approach using a U-Net and a 3D CNN for sacroiliitis segmentation and grading on CT images, ultimately achieving high accuracy and outperforming radiologist assessment in several cases [28]. More recently, by combining U-Net segmentations and radiomics, a state-of-the-art algorithm was developed for the diagnosis of sacroiliitis from CT scans, which also provided visually interpretable grading features to assist clinicians [29].

Similar to RA, MRI provides much more detailed information about patients with axSpA and as MRI quality continues to improve, MRI is often performed nowadays when X-ray results are negative or unclear, as it enables an earlier diagnosis [59].

The most common feature of patients with axSpA is BMO, which is diagnosed qualitatively and semi-quantitatively by expert radiologists and rheumatologists. However, this diagnosis is quite susceptible to significant intrapersonal and interpersonal variation [60]. Therefore, several machine learning methods have been developed for detecting active inflammatory sacroiliitis on different MRI sequences by identifying BMO. These methods have achieved promising results, for instance on short τ inversion recovery (STIR) sequences [30, 31] or gadolinium-enhanced fat-suppressed T1-weighted images (Fig. 2) [32]. However, due to the heterogeneity in axSpA, the image features of BMO are not always sufficient for the diagnosis since low-grade BMO on SI joint MRI is not specific and may contribute to overcalling a diagnosis of axSpA otherwise [61]. Therefore, structural lesions have become essential features for evaluating MRI scans due to their superior specificity, with erosions and subchondral lesions being the most common lesions. Nevertheless, identifying these image features can be challenging even for trained radiologists. Thus a method that evaluates quantitative features from all the subchondral or juxta-articular regions is quite beneficial. A model integrating radiomics features and clinical risk factors has demonstrated good discrimination and utility for separating axSpA from non-axSpA [33].

Furthermore, a model was created that combines inflammatory changes (BMO and enthesitis) with structural changes (erosions and sclerosis) and could help facilitate an earlier diagnosis, as non-inflammatory degenerative changes can mimic axSpA, potentially causing early signs to be missed. To address the heterogeneity of different MRI protocols, a U-Net architecture was employed for MRI denoising, artifact reduction and homogenization of intensity distribution between MRI scans [34].

Hip inflammation is a common complication in patients with SpA. Automated models have been developed that

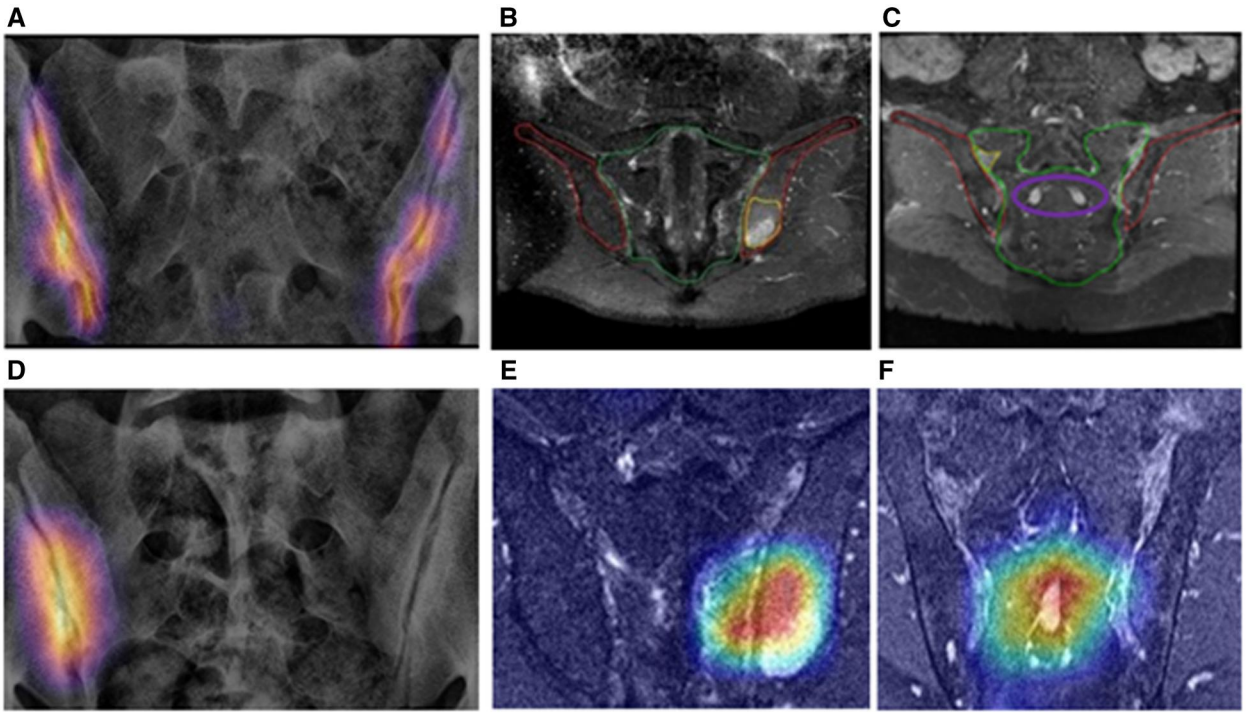

Figure 2. Examples of AI applications for detection of axSpA, adapted from Dorfner *et al.* (A and D) [25] and Lee *et al.* (B, C, E and F) [32]. Both studies are published under a CC-BY Creative Commons license. **(A, D)** Gradient-based class activation maps (grad-CAMs) of the anatomy-aware model for axSpA predictions on radiographs. (A) represents an image without radiographic axSpA, where the model focused equally on both sides and the full length of the SI joint. (D) represents an image with the presence of sacroiliitis at least grade 3, and the model based its decision for radiographic axSpA on only one joint and focused on the lesion. **(B, C)** Results of the class activation mapping (CAM) for MRI scans with BMO. **(E, F)** Grad-CAMs corresponding to B and C. The colour spectrum shows areas of highest activation, with activation intensity descending in the order of orange, yellow, green and blue

combine clinical information with features observed on hip MRI, such as BMO and effusion/synovitis and demonstrate quantification performance similar to that of expert radiologists. This approach has the potential to improve the accuracy and efficiency of clinical diagnosis for SpA patients with hip involvement [35], enabling earlier detection and automated grading of BMO in the hip [36].

AI in PsA

Although several studies have focused on machine learning for early diagnosis [62], disease activity tracking [63] and predictive analysis [64] of PsA, most have concentrated on laboratory work or health records. To date, only a few studies have delved into radiological imaging.

Given its impact on treatment decisions, a study aimed to differentiate between seropositive RA, seronegative RA and PsA. By analysing inflammatory patterns from various MRI sequences of the hand and employing a trained U-Net, promising results were achieved [37].

Another research group used similar MRI scans for the automated assessment of bone erosions, osteitis and synovitis in hand MRI of patients with inflammatory arthritis. Two expert rheumatologists evaluated the hand MRI scans using the OMERACT-validated RA and PsA MRI scoring system. These assessments were used to train, validate and test CNNs with the ultimately developed automated scoring system, enabling rapid grading of erosions, osteitis and synovitis with good diagnostic accuracy, using fewer MRI sequences compared with conventional scoring methods [38].

SS

SS is a complex and heterogeneous connective tissue disease primarily characterized by chronic inflammation of the exocrine glands, particularly the lacrimal and salivary glands, resulting typically in ocular and oral dryness [65]. Salivary gland ultrasonography (SGUS) is an effective tool for diagnosing various diseases associated with abnormalities in the salivary glands, including primary SS [66, 67].

The diagnosis of primary SS from SGUS involves visual assessment of the parotid and submandibular gland characteristics, along with a combined scoring system to establish a definitive diagnosis [68]. However, ultrasound imaging suffers from a weak signal:noise ratio and significant variation in the definition of ultrasound abnormalities, leading to high intra- and interrater variability. To address these challenges, different deep learning–based models have been created and compared for the automated segmentation of SGUS images, showing good promise in mitigating the aforementioned issues, suggesting their possibility for broader applications in clinical practice [39, 40].

Moreover, research has shown that a deep learning model capable of distinguishing between definite SS, probable SS, probable non-SS and definite non-SS can significantly aid inexperienced radiologists in interpreting ultrasound images.

This is especially beneficial because their sensitivity in detecting SS tends to be lower compared with the algorithmic performance [41].

SSc

SSc, also known as scleroderma, is a rare and complex autoimmune disease characterized by widespread vascular abnormalities, immune system dysregulation and progressive fibrosis of the skin and internal organs. The disease manifests in various forms, ranging from limited cutaneous involvement to diffuse systemic manifestations that can affect organs such as the lungs, heart, kidneys and gastrointestinal tract. Patients with SSc often experience symptoms like RP, skin thickening and joint stiffness, which can significantly impact their quality of life. Recent research advancements have significantly increased the understanding of its pathogenesis and expanded treatment options. Early diagnosis and a multidisciplinary approach to management are essential to address the diverse clinical features of SSc and to improve long-term outcomes [69].

The different manifestations mainly occur due to vasculopathy and fibrosis, prompting research into automated imaging biomarkers primarily focused on these issues. A valuable tool for evaluating vasculopathy in SSc patients is nailfold capillaroscopy (NFC). As interpreting NFC images can be challenging, a deep learning system for quantitative assessment of microvascular abnormalities was developed, combining U-Net and ResNet architectures to aid clinicians in analysis [42]. However, while automated tools for assessing microangiopathy patterns on NFC images may assist rheumatologists in generating consistent and high-quality NFC reports, the definitive diagnosis of a scleroderma pattern in any individual case still requires the judgment of an experienced observer [43].

Common complications of SSc include interstitial lung diseases (ILDs) such as lung fibrosis. Therefore, a multicomponent deep neural network for the automatic assessment of the extent of ILD related to SSc on chest CT images was created, performing comparably to radiologists [44].

Traditionally, the longitudinal follow-up of lung fibrosis relies primarily on evaluating the extent of ILD. However, as SSc progresses, problematic lung shrinkage can occur, which is often overlooked despite interstitial changes. To address this issue, a CNN was developed to detect the worsening of ILD by quantifying lung shrinkage through elastic registration of chest CT scans in patients with SSc [45].

Beyond their high diagnostic value, computer vision–aided algorithms can have prognostic significance by quantifying the extent of ILD. They provide an effective tool for risk stratification in SSc, which can even help identify patients at short-term risk of death [46].

Even in SSc patients without detectable pulmonary fibrosis, vasculopathy can still impair gas exchange and consequently reduce lung function. A recent discovery revealed that differences in the occurrence of small and large vessels are correlated with functional lung impairment, as alterations in pulmonary vascular morphology are associated with reduced gas exchange [47]. Researchers followed a multistep procedure in this process, beginning with the AI-based detection of pulmonary vessels resolvable by CT (down to 0.5 mm in diameter). They then quantified vessel morphology to produce imaging biomarkers by analysing the number of small and large vessels. Finally, these imaging biomarkers were correlated with gas transfer measurements, specifically the single-breath diffusion capacity for carbon monoxide corrected for haemoglobin concentration [47]. This is a good example where a method is intended to be complementary to visual scoring, as it is impossible to measure all vessels in the lungs visually or by hand.

GCA

GCA is an inflammatory autoimmune disease affecting large blood vessels, commonly the arteries in the head, particularly the temporal arteries. If left untreated, it can lead to severe complications, including artery blockage to the eye, resulting in blindness, as well as aortic dissection and aneurysm, underscoring the critical importance of early diagnosis.

Temporal artery ultrasound has emerged as a valuable non-invasive tool for diagnosing GCA and is recommended as the first-line imaging modality in the EULAR guidelines for evaluating this condition [70].

The most common feature observed in positive temporal artery ultrasounds is the halo sign (Fig. 3) [71, 72]. Researchers have utilized a U-Net model to automatically analyse ultrasound images for this characteristic [48]. The algorithm development began with semantic segmentation of transverse and longitudinal colour Doppler/power Doppler images of temporal arteries. This involved drawing boxes around the arteries and adjacent tissue, with individual pixels within these boxes classified as either halo sign positive or halo sign negative. The final classification of each image was determined by the percentage of pixels within the bounding box classified as halo sign positive. Ultimately, this approach can facilitate computer-assisted image acquisition, aiding clinicians in diagnosis [48].

Opportunities and challenges

AI is transforming the field of imaging in rheumatology, offering numerous benefits that enhance diagnostic accuracy and patient care. First, AI algorithms can analyse medical images with remarkable precision, identifying subtle patterns and abnormalities that might be overlooked by the human eye. These algorithms can detect early signs of rheumatologic diseases, often before clinical symptoms emerge, allowing for timely intervention that can slow disease progression and prevent severe complications.

Additionally, AI systems can process and analyse large volumes of imaging data much faster than humans, significantly reducing the time required for image interpretation. This enables rheumatologists to make quicker clinical decisions and improves the efficiency of patient care. Moreover, AI provides consistent and objective analysis of imaging data, reducing the variability associated with human interpretation. This standardization ensures that patients receive consistent evaluations regardless of where or by whom the images are analysed.

Furthermore, AI can track changes in imaging over time, offering valuable insights into disease progression and treatment response. This capability supports the development of more personalized and adaptive treatment plans, ultimately improving patient outcomes. AI can also integrate imaging data with other clinical information, such as patient history and laboratory results, to provide comprehensive insights

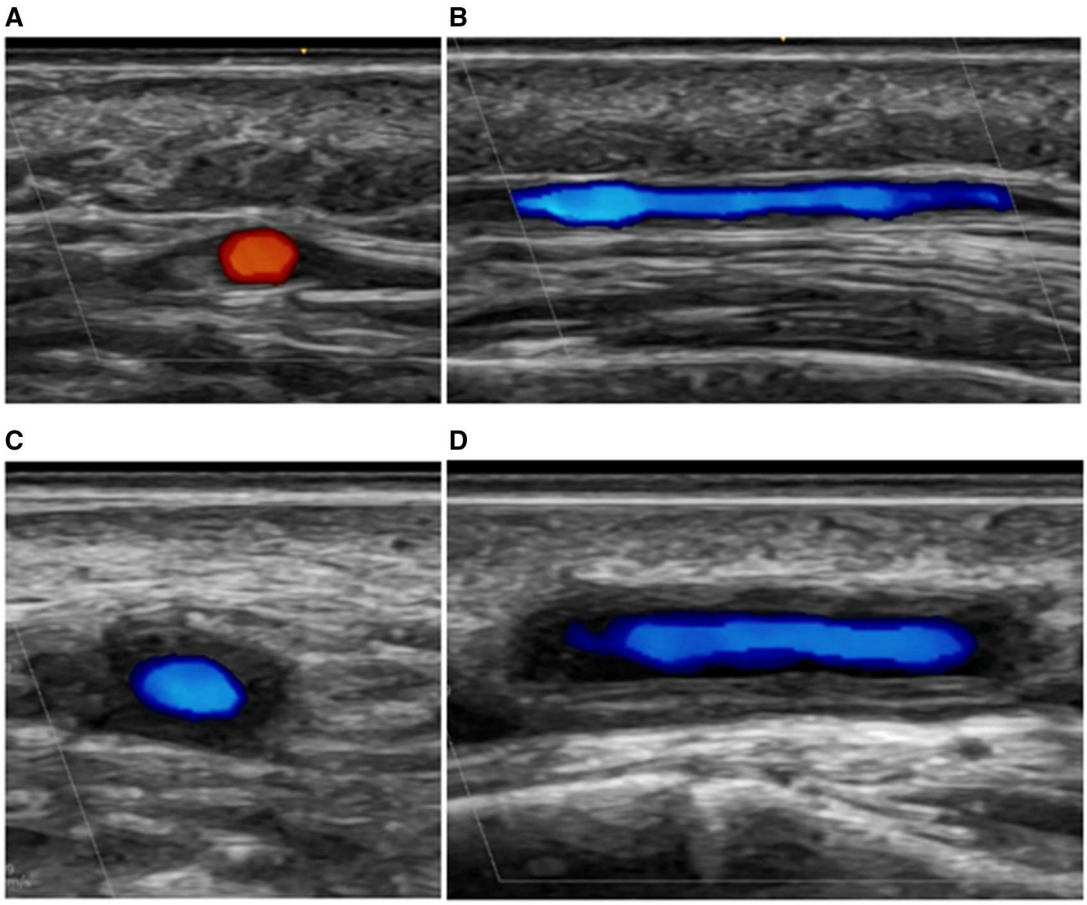

Figure 3. Ultrasound images of the temporal artery adapted from Hernández *et al.* [71]. This study is published under a CC-BY Creative Commons license. A normal superficial temporal artery in **(A)** transverse and **(B)** longitudinal view. A hypoechoic, homogeneous thickening of the superficial temporal artery—the halo sign—in **(C)** transverse and **(D)** longitudinal view

into a patient's condition, enabling more informed and effective clinical decision-making.

However, several challenges must be addressed. The success of AI in rheumatological imaging relies on the availability of high-quality data and radiological images. Due to the confidentiality of patient records, freely accessible datasets are limited, making it challenging to gather sufficient data to train accurate models. In particular, achieving optimal model performance requires a large number of annotated images, which necessitates a time-intensive labelling process by experts. Furthermore, variations in data quality, formats and interoperator variability present challenges in integrating data from electronic health records and imaging modalities.

Additionally, AI algorithms often operate as 'black boxes', meaning their decision-making processes are difficult for humans to interpret. This lack of transparency can make it challenging for clinicians but also society to trust AI-generated recommendations, particularly in critical healthcare decisions. Ensuring the explainability of AI models is crucial for building trust among clinicians and promoting widespread adoption.

Moreover, while AI shows great potential in research settings, transitioning from research to routine clinical practice remains a challenging and ongoing process. A common issue is overfitting, which occurs when AI models trained on limited or biased datasets become overly attuned to specific features of that data. This results in poor generalization to new, unseen cases, potentially leading to inaccurate diagnoses or predictions and compromising patient care. Therefore, real-world results may differ from those in research, making rigorous validation of AI algorithms across diverse datasets and among different readers necessary to confirm their robustness and applicability across various patient populations and clinical scenarios before they can be widely adopted in clinical practice.

Ethical considerations and regulatory approval related to AI, particularly concerning patient consent, data privacy and security, require thorough examination and resolution to maintain patient trust. Additionally, integrating AI tools into existing clinical workflows presents its own challenges, such as providing comprehensive education for healthcare professionals on AI use, developing user-friendly applications and establishing universal guidelines for their application. Finally, the risk of overreliance on AI systems, where humans may become too dependent on AI recommendations, must be addressed, as it can lead to a reduction in critical thinking. While radiomics and AI often complement each other in medical imaging, they serve distinct roles with their own strengths and limitations. Radiomics is more interpretable, easier to integrate into existing systems and requires fewer computational resources. However, its reliance on predefined features restricts its flexibility. In contrast, AI offers greater adaptability, the ability to process large and complex datasets and typically delivers higher predictive power. Despite these advantages, AI presents challenges related to interpretability, higher data requirements and increased computational demands.

Conclusion

The integration of AI holds great potential to advance rheumatology by enabling earlier, faster, more efficient and more accurate diagnoses, as well as predictive analysis. However, to fully unlock AI's potential in improving patient care and outcomes for rheumatic diseases, it is crucial to address challenges related to data quality, data protection, interpretability, traceability of decision-making processes, ethics and clinical validation, all while ensuring patient safety.

Supplementary material

Supplementary material is available at *Rheumatology Advances in Practice* online.

Data availability

All data relevant to the study are included in the article or uploaded as supplementary information.

Authors' contributions

Fabian Proft, Lina Xu, and Keno Bressem conceptualized the content and developed the initial idea. Lina Xu prepared the initial draft, which was subsequently revised based on feedback provided by Fabian Proft and Keno Bressem. The revised manuscript was then critically reviewed by all authors, with Lisa Adam and Denis Poddubnyy contributing their expert opinions. All authors have reviewed and approved the final version of the manuscript.

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