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AI-DRIVEN AND MULTIMODAL INNOVATIONS IN BIOMEDICAL IMAGING AND SENSING IN ARTHRITIS

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Abstract
Artificial intelligence (AI) especially deep learning is changing biomedical imaging and quantitative sensing for all types of arthritis such as osteoarthritis (OA), rheumatoid arthritis (RA), psoriatic arthritis and axial spondyloarthritis (axSpA). Recent advances include automated grading of structural damage on X-rays, three-dimensional (3D) segmentation and tissue characterization on MRI and CT, radiomics-based phenotyping and combining imaging with clinical, biomarker and multi-omics data to predict prognosis and treatment response. Deep learning models now match or exceed the performance of expert readers in detecting cartilage lesions, automating Kellgren–Lawrence grading, segmenting cartilage and menisci and predicting radiographic progression and the need for joint replacement from baseline MRI or radiographs in osteoarthritis. AI helps with automated radiographic scoring, MRI detection of inflammatory sacroiliitis and risk stratification for cardiovascular complications in RA and spondyloarthritis using imaging-derived radiomic biomarkers. AI pipelines are being used more and more to analyze multimodal workflows in musculoskeletal imaging that combine radiography, CT, DXA, MRI, ultrasound and clinical data. These pipelines help find quantitative, reproducible biomarkers of joint damage, inflammation and prognosis. This narrative review talks about new AI-driven and multimodal technologies for imaging and sensing arthritis. It also talks about new clinical uses that are coming up and the main problems that need to be solved such as generalizability, bias, interpretability and regulatory translation.

Keywords
Arthritis, Artificial intelligence, Deep learning, Multimodal imaging, Biosensor, Quantitative imaging

1. Introduction

Arthritic diseases are major causes of pain, disability and lower quality of life around the world. Osteoarthritis and inflammatory arthritides (RA, psoriatic arthritis, axial spondyloarthritis) are

two of the most important clinical and economic problems. Traditionally structural joint damage and inflammatory activity have been evaluated visually through radiographs, CT and MRI utilizing semi-quantitative scoring systems that are time-consuming, reader-dependent and relatively insensitive to early disease and subtle changes [1].

In the past ten years AI applications in rheumatologic and musculoskeletal imaging have grown quickly. This is because deep learning methods have improved, there are more large open imaging cohorts (like the Osteoarthritis Initiative and Multicenter Osteoarthritis Study) and computers are getting faster. Convolutional neural networks (CNNs) and similar architectures now do important jobs in image classification, lesion detection, segmentation and outcome prediction often with accuracy that is equal to or better than that of expert radiologists [2].

At the same time multimodal approaches that combine different imaging techniques (radiography, CT, DXA, MRI, ultrasound), different MRI sequences and non-imaging data (clinical, serologic, genomics and proteomics) make it possible to fully phenotype joint structure and inflammation and support precision medicine strategies. Radiomics pipelines take standard images and pull out high-dimensional texture, shape and intensity features. These features can then be used with AI models to make diagnoses and predictions [1,3].

This review concentrates on AI-driven and multimodal advancements in biomedical imaging and sensing pertaining to arthritic diseases, highlighting deep learning for osteoarthritis imaging via radiographs and MRI. AI applications in rheumatoid arthritis and spondyloarthritis imaging, quantitative radiomics and morphological phenotyping, multimodal integration with clinical and biomarker data as well as cross-cutting challenges and future directions pertinent to clinical translation.

2. Conventional imaging methods

2.1. Radiography

Radiographic imaging continues to be fundamental in the analytical assessment and differentiation of inflammatory arthritis by detecting disease-specific structural signatures and joint distribution patterns. A systematic evaluation of alignment, bone quality, cartilage degeneration, erosions and soft-tissue changes allows clinicians to differentiate between types of arthritis in the early stages of assessment. For example, rheumatoid arthritis [4] shows symmetrical marginal erosions and juxta-articular osteopenia mostly at MCP joints while psoriatic arthritis [5] is marked by periostitis, DIP involvement and pencil-in-cup deformities. Erosive osteoarthritis has central erosions that look like a classic gull wing shape. CPPD is known for chondrocalcinosis and hook osteophytes that show up in unusual joint distributions. Gout causes clear punched-out erosions with overhanging edges while systemic lupus erythematosus usually causes deformities without erosions. These different types of X-ray patterns work together to help doctors figure out what's wrong and keep an eye on the disease over time in people with arthritis [6,7].

2.2. Ultrasound

Musculoskeletal ultrasound has become an essential imaging technique in the diagnostic process of arthritis allowing for real-time observation of inflammatory and structural alterations that may not be apparent clinically or on standard radiographs. Ultrasound aids in the early identification of synovitis, tenosynovitis, enthesitis, bone erosions and crystal deposits. Thereby facilitating the distinction between inflammatory arthritis phenotypes including rheumatoid arthritis, spondyloarthritis and crystal-induced arthropathies. Its non-invasive and cost-effective characteristics facilitate dynamic, multiplanar evaluation of joints and peri-articular tissues while power doppler imaging offers supplementary insights into vascularity and active inflammation. Thereby enhancing diagnostic confidence in the initial stages of disease. Also ultrasound can predict the course of a disease or the return of symptoms by

finding subclinical inflammation and predicting the course of the disease especially in the case of rheumatoid arthritis. Although there are some problems with ultrasound such as operator dependence and limited bone penetration, combining it with clinical and radiographic evaluation improves early diagnosis, risk stratification and long-term monitoring in arthritis management [8–12], as shown in table 1.

2.3. Computed tomography

Computed tomography (CT) especially dual-energy CT (DECT) and high-resolution peripheral CT has become a useful additional tool for diagnosing arthritis by allowing for precise characterization of bone and crystal related pathology with high spatial resolution. CT is the best way to find cortical bone erosions and structural damage. It is more sensitive than radiography and gives a better picture of the anatomy than ultrasound. DECT is very important for crystal arthropathies because it can tell the difference between monosodium urate and calcium containing deposits. This makes it possible to diagnose gout and calcium pyrophosphate deposition disease without having to do a separate test [13]. Advanced methods like subtraction imaging and iodine mapping make it easier to look at synovial inflammation and tissue perfusion which helps doctors figure out how active a disease is and how well treatment is working. High-resolution peripheral CT also helps find erosive progression in rheumatoid arthritis by spotting structural changes that standard X-rays might miss and helping doctors figure out the best treatment plan early on [14]. Despite concerns about radiation exposure recent low-dose protocols and technological advancements continue to enhance the clinical utility of CT within multimodal arthritis imaging frameworks [15].

2.4. Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) has become a very sensitive way to find arthritis early and figure out how bad it is because it has better soft tissue contrast and can show synovitis, tenosynovitis, bone marrow edema, cartilage damage and early erosions before they show up on regular X-rays. MRI-based scoring systems like RAMRIS provide a consistent way to measure inflammatory activity and structural damage with high reliability between and within readers. This makes them useful for clinical trials and early arthritis monitoring [16]. MRI can find subclinical inflammation even when the disease is not active according to evidence. For example, synovitis and bone marrow edema are strong predictors of disease flare and joint deterioration which shows how useful MRI is for predicting the course of juvenile idiopathic arthritis and similar conditions [17]. Moreover, MRI is effective in detecting early inflammatory patterns such as tenosynovitis and marrow edema which may signify the advancement towards rheumatoid arthritis or immune-mediated inflammatory arthritis thus facilitating risk stratification and treatment planning [18]. Comparative imaging studies establish MRI as a benchmark for identifying early inflammatory and structural alterations underscoring its pivotal function in multimodal imaging approaches for arthritis diagnosis and disease surveillance [19].

Table 1: The primary benefits, constraints and standard diagnostic functions of traditional imaging modalities employed in arthritis

Modality	Advantages	Limitations	Typical roles by arthritis type	References
Radiography	Low cost, widely available, good overview of alignment and osseous features, established	Low sensitivity for early soft-tissue and bone-marrow	Initial assessment and routine monitoring in osteoarthritis; serial erosions and joint-	[20,21]

	scoring for RA joint damage (Sharp, Larsen)	changes; detects mostly late structural changes	space monitoring in RA; cervical spine assessment in severe RA	
Ultrasound (US)	Real-time, dynamic joint and soft-tissue evaluation; detects synovitis and tendon pathology; Power Doppler indicates synovial vascularity linked to activity	Operator dependent; limited penetration for bone marrow and deep structures; standardization issues	Early RA detection and therapy monitoring; focused assessment of symptomatic joints; guidance for arthrocentesis; alternative to MRI for erosions when MRI unavailable	[22]
Magnetic resonance imaging (MRI)	High sensitivity for bone marrow edema, synovitis, cartilage and early erosions; quantitative/compositional sequences add tissue characterization in OA	Higher cost, limited availability, contraindications (implants, claustrophobia) and longer scan times	Advanced evaluation in OA (cartilage, subchondral changes); early RA detection and prediction of future radiographic damage; atlanto-axial/occipital and extra-articular assessment	[23]
Computed tomography (CT)	Excellent depiction of osseous detail; detects destructive bone changes earlier than radiographs; specialized CT (CBCT, 4DCT) for weight-bearing or dynamic assessment	Ionizing radiation; inferior soft-tissue contrast compared with MRI	Complex bony anatomy, preoperative planning, detecting erosions or subchondral bone detail, and dynamic/weight-bearing evaluation in OA when indicated	[24]

3. Imaging Needs Across the Arthritis Spectrum

3.1 Osteoarthritis

In osteoarthritis (OA), structural imaging priorities encompass the early detection of alterations in cartilage, menisci and subchondral bone prior to evident radiographic joint space narrowing, sensitive quantitative evaluation of disease progression for clinical trials and the identification of imaging phenotypes that forecast rapid progression or the necessity for joint replacement. MRI shows cartilage, menisci, bone marrow lesions, synovitis and subchondral bone in three dimensions. However radiographs are still the most important tool for Kellgren-Lawrence (KL) grading in routine care and large epidemiologic cohorts. Compositional MRI (e.g. T2, T1p mapping) provides quantitative biomarkers of cartilage matrix integrity. However manual analysis is labor-intensive and inconsistent [1].

3.2 Rheumatoid arthritis and psoriatic arthritis

In RA and psoriatic arthritis imaging aims include finding synovitis, bone marrow edema and erosions early on to start aggressive treatment, accurately measuring structural damage for drug trials and automatically scoring joint damage to get around the problems with manual radiographic scoring systems [25]. MRI and ultrasound are very good at picking up

inflammatory and erosive changes, but radiographs are still widely used for structural scoring even though they aren't very good at picking up early disease. AI is being set up to make radiographic scoring more sensitive and to combine imaging with clinical and biomarker data to predict how active a disease is and how well a treatment will work [26].

3.3 Axial spondyloarthritis

In axial spondyloarthritis (axSpA) imaging is used to find active inflammatory sacroiliitis on MRI (bone marrow edema in sacroiliac joints), check for structural damage (erosions, fat metaplasia, backfill, ankylosis) on radiography and CT and keep track of how well biologic therapies are working. Bone marrow edema on short tau inversion recovery (STIR) MRI is fundamental to classification but lacks specificity. AI models are being developed to standardize and quantify these findings and to differentiate axSpA from mimics [27].

3.4 Temporomandibular joint (TMJ) osteoarthritis and other sites

Osteoarthritis of the temporomandibular joint, hands, hips and shoulders all need to be found early, graded automatically and tracked quantitatively. However they often use cheaper methods like panoramic radiography, orthopantomograms or DXA instead of high-end MRI. TMJ is a good fit for AI because its anatomy is complicated and needs expert interpretation. Deep learning systems can now find TMJ-OA on 2D images just as well as or better than dentists and oromaxillofacial radiologists [28].

4. AI in Osteoarthritis Imaging

4.1 Deep learning on MRI: lesion detection and diagnosis

MRI is the main way to do OA imaging research. AI is used to automatically find cartilage lesions, meniscal tears, bone marrow lesions and synovitis [29].

4.1.1. Cartilage lesion detection

VGG-based CNNs that look at T2-weighted or proton-density (PD) sequences can find cartilage lesions with an area under the curve (AUC) of about 0.9, a sensitivity and specificity of 80–90%, and an agreement level that is similar to that of expert musculoskeletal radiologists [29]. U-Net and similar architectures have been adapted for multi-class classification of cartilage integrity (intact, partial-thickness, full-thickness), demonstrating commendable performance across all categories [30].

4.1.2. Automated OA diagnosis and grading

Deep learning models that look at knee MRIs can tell if OA is present and how bad it is by combining different morphological features (like cartilage, meniscus, bone marrow lesions and osteophytes) and compositional biomarkers. This works as well as experienced radiologists [30]. Deep learning also supports large-scale MRI-based morphological phenotyping in which CNNs sort knees into phenotypes like bone-dominant, inflammatory or hypertrophic patterns. These patterns are linked to different risks of developing structural OA and needing a total knee replacement. This method goes beyond simple scalar scores to use rich phenotype-based stratification [31].

4.2 Automated segmentation and quantitative MRI biomarkers

Quantitative MRI assessment in OA has traditionally depended on manual or semi-automatic segmentation of cartilage, menisci and synovium which is labor-intensive and restricts scalability. This problem is solved by segmentation based on deep learning. U-Net and its variants have been employed to segment cartilage, bone and menisci achieving dice coefficients generally exceeding 0.8–0.9 along with sub-millimeter average surface distances

when compared to manual reference standards. Conditional generative adversarial networks can enhance segmentation and delineation of thin cartilage and diminutive structures [30]. Automated segmentation allows for high-throughput measurement of cartilage thickness, volume and T2/T1ρ relaxation times which are important markers for early cartilage degeneration and progression. AI is also helping more and more with quantitative imaging of bone marrow lesions, meniscus and synovitis. Software tools break up lesions and areas of interest so that volumetric and texture measures can be taken. These quantitative biomarkers exhibit correlations with pain and structural progression and are currently being assessed as outcome measures for disease-modifying osteoarthritis drug trials [1].

4.3 Deep learning on radiographs: automated KL grading and texture analysis

Radiography is still the most important way to diagnose and grade OA because it is cheap, easy to get and has a lot of historical trial data.

4.3.1. Automated KL grading

CNNs (e.g. VGG, ResNet, DenseNet, Siamese architectures) trained on extensive radiographic datasets attain multi-class accuracy for Kellgren-Lawrence grading that is comparable to or exceeds that of traditional image classifiers and approaches the inter-reader agreement observed among expert radiologists [30]. When compared to expert central readings the weighted kappa values between AI and human readers frequently resemble the inter-reader agreement among radiologists indicating their potential use as decision-support tools [32].

4.3.2. Trabecular bone texture analysis (radiomics)

AI models that look at the texture of radiographic trabecular bone using fractal or CNN-based methods show strong links to new and worsening radiographic OA especially in the tibiofemoral joint. Trabecular texture CNNs trained on one cohort (e.g. Osteoarthritis Initiative) can forecast the progression of joint space narrowing in another cohort (e.g. Multicenter Osteoarthritis Study) indicating a degree of cross-cohort generalizability [32]. These AI-generated texture and shape descriptors detect subtle microarchitectural alterations that are not easily discernible to human observers presenting potential early biomarkers of disease [30].

4.4 Risk prediction and precision medicine

One of the most important changes is the use of imaging-based AI models to predict future OA outcomes. This is a big step forward from descriptive imaging to actionable prognostics. Deep learning models trained on baseline radiographs or MRI have been utilized to forecast radiographic osteoarthritis incidence or progression (KL grade deterioration or joint space width reduction) over a span of 5-7 years, total knee replacement within 5-9 years, pain progression trajectories and the risk of chronic severe pain [29]. Imaging-based CNNs surpass conventional risk models derived solely from clinical and radiographic factors in various studies while integrated models that amalgamate deep imaging features with clinical data demonstrate optimal performance. This multimodal integration at the data-fusion level is an example of AI-driven precision medicine which is shown in figure 1.

5. Multimodal Imaging and Radiomics

5.1 Radiomics in CT and MRI of OA and related conditions

Radiomics changes regular images into sets of quantitative features (like texture, shape and intensity) that can be linked to clinical outcomes using machine learning. Radiomics was first created for cancer imaging but it is now being used more and more in imaging of the musculoskeletal and rheumatologic systems. Quantitative assessment of subchondral bone

texture via radiographs and MRI serves as biomarkers for osteoarthritis incidence and progression. Radiomic characterization of bone marrow lesions, meniscus morphology and synovitis correlate with pain and structural damage [1] and radiomics applied to parotid gland and temporomandibular joint imaging in osteoarthritis-like degenerative conditions identifies textural signatures associated with disease grade or prognosis [33]. In TMJ disorders CBCT and MRI radiomics measure bone volume, number and separation of trabecular bones, entropy and contrast. Entropy was found to be a stable marker across modalities and was linked to sclerosis while contrast was not as stable. Deep learning models utilizing these features can diagnose TMJ osteoarthritis with accuracy comparable to clinicians interpreting 2D/3D radiographs although their efficacy for disc disorders on MRI is comparatively limited [33].

5.2 Large-scale MRI-based phenotyping

Morphological phenotyping constitutes a robust multimodal radiomics framework in osteoarthritis. In a substantial Osteoarthritis Initiative study CNNs were trained to categorize knees into phenotypes indicative of predominant bone, meniscus/cartilage, inflammatory or hypertrophic alterations utilizing comprehensive 3D MRI datasets. Every phenotype classifier had a high AUC (0.89–0.96) and some phenotypes (bone-dominant and hypertrophic) were linked to a much higher chance of developing structural OA and symptomatic OA after 48 months. All phenotypes apart from the isolated meniscus/cartilage pattern were linked to an elevated risk of total knee replacement within an 8-year timeframe [31]. These findings demonstrate how AI can distill intricate high-dimensional MRI data into clinically relevant phenotypic labels thereby connecting detailed imaging with trial or clinical decision-making [34].

5.3 Multimodal fusion of imaging with clinical, biomarker and omics data

Multimodal AI models are now using more than just single modality radiomics. They are also using imaging features (like X-rays and MRIs), clinical variables (like age, sex, BMI and symptoms), laboratory and biomarker data and genomic and proteomic signatures [35]. In osteoarthritis joint training models that combine deep imaging features with clinical and radiographic factors yield substantially higher AUCs for predicting structural progression, total knee replacement or exacerbation of pain compared to either modality used in isolation [30]. In rheumatoid arthritis (RA) and spondyloarthritis scoping reviews indicate that supervised machine learning and deep learning models are progressively incorporating electronic medical records, imaging, clinical biomarkers and multi-omics data to forecast treatment responses to biologics and JAK inhibitors with AUCs ranging from 0.63 to 0.92. Similar multimodal frameworks have been suggested for cardiovascular and stroke risk stratification in rheumatoid arthritis (RA) integrating radiomic vascular biomarkers (e.g. plaque area and burden, carotid intima-media thickness) with genomic and serological markers in AI-driven risk engines [36,37]. These kinds of integrative models are examples of biomedical sensing that uses AI where imaging derived features stand in for tissue pathology and systemic risk when combined with molecular and clinical data [26].

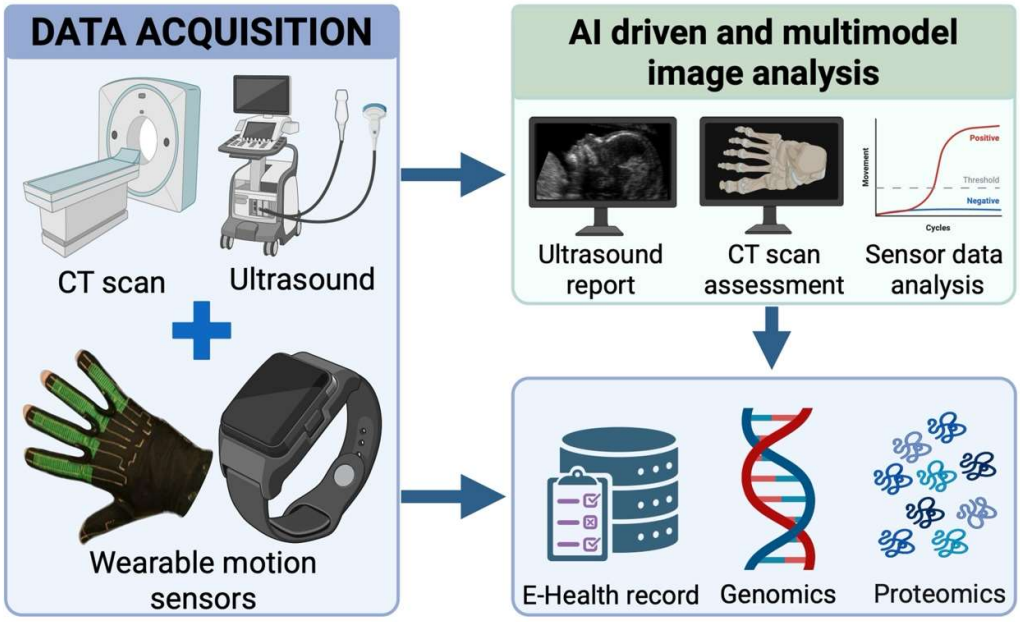

Figure 1: AI-Driven Multimodal Imaging and Sensing Framework in Arthritis

6. AI in Inflammatory Arthritis Imaging

6.1 Rheumatoid arthritis: radiographic scoring and beyond

Conventional radiographic scoring systems (e.g. Sharp, van der Heijde) are essential for evaluating structural damage in RA trials. However, they are time consuming and progressively less sensitive to the milder disease profiles associated with contemporary therapy [38]. AI is being used to automate the scoring of erosions and joint space narrowing on plain radiographs. Prototype systems have shown that this is possible and could make it easier to find subtle damage and detect joint erosions and halo signs on ultrasound and radiography using deep learning. This could help find and keep an eye on problems earlier [25]. Some people think that AI-based scoring could give us faster and more sensitive ways to measure damage, which could make imaging endpoints for RA drug development more useful again as long as methods are properly validated and standardized [38].

6.2 Axial spondyloarthritis: MRI of sacroiliitis

MRI of the sacroiliac joints is essential for axSpA diagnosis. However, the interpretation of STIR images for bone marrow edema is subjective and susceptible to inter-observer variability [39]. Deep learning algorithms utilizing attention U-Net have been developed to identify inflammatory sacroiliitis on STIR MRI, employing manually labeled bone marrow edema as reference masks. Models trained on fake color representations of edema achieved sensitivity around 0.90 and specificity around 0.93 with AUCs up to 0.96 comparable to expert radiologist performance and better than rheumatologists in some settings [27]. Narrative reviews underscore that AI in axSpA encompasses diagnostic support via X-ray, CT and MRI predictive modeling of disease progression and tailored treatment selection. However, generalizability is constrained by prevalence of small, retrospective, single-center studies thus far [39].

6.3 AI for treatment response prediction in RA and SpA

A recent scoping review found almost 90 studies that used AI to predict how well treatment would work (mostly in RA but also in SpA and psoriatic arthritis). These studies used random forests, support vector machines, clustering, and deep learning. Imaging (like X-rays,

ultrasound and MRI), clinical markers, serology, genetics and proteomics are all sources of data. Models based on multi-omics and imaging show the best performance, but they use different methods and often don't have outside validation [40]. These initiatives aspire to facilitate AI-guided therapy selection which is fundamental to precision rheumatology. However, significant standardization and prospective validation are requisite prior to widespread implementation [25].

7. AI and Multimodal Imaging in Musculoskeletal and Hip Disorders

Advancements in musculoskeletal AI are directly pertinent to arthritic joint imaging, although not exclusively confined to arthritis.

7.1 Cross-cutting MSK applications

Perspective and review articles delineate a comprehensive array of musculoskeletal AI applications, encompassing fracture detection and triage, estimation of pediatric bone age, automated alignment and angular measurements and grading of osteoarthritis on radiographs. Many of these applications are already on the market and are being used in radiology workflows. This shows that when performance and reliability are proven, regulatory and workflow barriers can be broken down [41].

7.2 Hip osteoarthritis and bone density

Deep learning is being used more and more to help diagnose OA, femoroacetabular impingement, labral tears, dysplasia and other problems with hip MRIs. The reported accuracies and AUCs are usually between 76% and 98%. Quantitative CT and DXA studies have investigated side-to-side variations in bone mineral density in unilateral hip osteoarthritis occasionally employing deep learning-based QCT methodologies thereby underscoring the significance of AI in automated BMD assessment and osteoporosis screening among arthritic individuals [41].

8. AI in Temporomandibular Joint Osteoarthritis

TMJ osteoarthritis illustrates how AI and multimodal imaging can tackle intricate anatomical structures and nuanced degenerative alterations.

8.1 Deep learning on panoramic radiography and orthopantomograms

Numerous entities have trained Convolutional Neural Networks (CNNs) such as ResNet and EfficientNet on panoramic and orthopantomogram images to differentiate between normal temporomandibular joint (TMJ) conditions and osteoarthritis. These models reach classification accuracies of about 0.87 to 0.88 and show grad-CAM attention focused on areas of erosion and osteophytes which suggests that they are focusing on the right anatomy [42]. In certain contexts deep learning systems either match or exceed the capabilities of temporomandibular disorder specialists and general dentists, demonstrating comparable sensitivity to cone-beam CT as a reference thereby endorsing their application as screening instruments in primary dental practice [28].

8.2 Radiomics and deep learning-based radiomics in TMJ

A systematic review of automation and deep learning in TMJ radiomics found that for TMJ OA. The radiographic parameters that matter are bone volume, trabecular number and separation and bone surface-to-volume ratio. For MRI-based parameters the important ones are disc shape, signal intensity, fluid collection, joint space narrowing and arthritic changes [33]. Entropy is a stable radiomic parameter that is the same in both CBCT and MRI and is linked to sclerosis. Contrast, on the other hand is not as stable across modalities. Deep learning models

can diagnose TMJ OA from 2D and 3D X-rays just as well as doctors can, but they don't do as well with MRI scans for disc displacement and inflammatory disorders. This is because of the difficulties in classifying and getting images [43]. These results highlight the necessity of standardized imaging protocols rigorous radiomic feature selection and meticulous clinical labeling in the application of AI to multimodal TMJ sensing [44].

9. Smart Biosensing and Wearable Technologies in Arthritis

9.1. Wearable Motion Sensors

Wearable motion sensors are a reliable, objective and dynamic way to keep an eye on joint movement in arthritis. They get around the problems with traditional goniometry which can vary from person to person and even within the same person [45]. In rheumatoid arthritis sensor-integrated gloves and inertial measurement units (IMUs) make it possible to constantly check the range of motion (ROM), joint stiffness and dexterity of the MCP, PIP, DIP and CMC joints. Dynamic kinematic analysis with electromagnetic motion sensors has shown that people with carpometacarpal arthritis have less thumb circumduction and peak motion angles which shows that this method can be used in real life [46]. In knee osteoarthritis wearable sensors that measure acceleration and jerk are strongly linked to self-reported instability which shows that they are biomechanically relevant [47]. Also combining wearable activity trackers with patient-reported outcomes and clinical indices makes it possible to monitor RA patients from a distance and track the progress of their disease over time [48]. Overall wearable motion sensors provide precise, continuous and clinically meaningful joint movement analysis which improves early detection, functional monitoring and personalized arthritis management.

9.2. Biochemical Biosensors

Biochemical biosensors for arthritis are made to find biomarkers of inflammation and cartilage breakdown that are specific to the disease with high sensitivity and a quick turnaround time. In osteoarthritis (OA), CTX-II (uCTX-II and sCTX-II), COMP, MMP-1, MMP-3, CRP, TNF-α and interleukins are often used as biomarkers because they show cartilage breakdown and inflammation [49]. Researchers have made electrochemical nanobiosensors that can find rheumatoid factor (RF), anti-cyclic citrullinated peptide (anti-CCP), anti-mutated citrullinated vimentin (anti-MCV), 14-3-3 eta protein and CRP in people with rheumatoid arthritis (RA). These sensors can help doctors make a diagnosis earlier than traditional lab tests [50]. These biosensors mainly use electrochemical, optical, quartz crystal microbalance (QCM) and molecular sensing platforms to turn interactions between antigens and antibodies or peptides and antibodies into electrical or optical signals that can be measured. Peptide-based electrochemical biosensors utilizing screen-printed carbon electrodes have exhibited selective detection of juvenile idiopathic arthritis (JIA) antibodies, demonstrating commendable stability and the ability to differentiate between diseased and healthy samples [51]. Biochemical biosensors are better than ELISA and radioimmunoassay because they are cheaper, easier to carry, faster to find, need less sample and can be used at the point of care but they still need to be tested on a large scale [49].

9.3. Remote Patient Monitoring Systems

Remote Patient Monitoring (RPM) allows for real-time tracking of arthritis by combining electronic patient-reported outcomes (ePROMs), digital biomarkers from wearables and hybrid care models. This lets doctors check on the disease activity all the time even when they are not in the same room. Smartphone-based platforms enable patients to consistently report validated metrics such as RAPID-3, HAQ-DI and self-reported DAS28-CRP. Thereby facilitating virtual evaluations and minimizing superfluous in-person consultations while ensuring safety [52,53]. Wearable devices also passively collect biometric and activity data that can be analyzed by AI

to find patterns related to pain, fatigue and functional impairment. This makes personalized disease management better. Complementary systems like home-based capillary blood sampling and AI-assisted image analysis make remote monitoring even better. Together they make a scalable and data-driven framework for managing arthritis in real time [54].

10. AI-Enhanced Biomedical Sensing Beyond Joints

Most of the literature retrieved pertains to joint-level imaging. However, analogous AI and multimodal sensing approaches are being investigated in the context of systemic complications of arthritis.

10.1. Cardiovascular and stroke risk in rheumatoid arthritis and autoimmune diseases

Rheumatoid arthritis (RA) and associated autoimmune disorders present an elevated risk for cardiovascular events and strokes that is inadequately reflected in conventional risk assessment tools. Proposed AI frameworks amalgamate radiomic vascular biomarkers (carotid plaque area, plaque burden, intima–media thickness) obtained from ultrasound with genomic, proteomic and serologic markers to develop AI-based risk engines [26]. Utilize deep learning within extensive preventive, personalized and precision medicine frameworks (e.g. aiP3 models) to enhance the accuracy of cardiovascular risk classification in rheumatoid arthritis patients compared to conventional methods. These multimodal sensing systems conceptually resemble joint-focused AI models broadening the application of AI in arthritis from localized structural evaluation to systemic risk stratification [55,56].

11. Future Directions

Several future directions can be anticipated based on current trends in OA, RA, axSpA and TMJ disorders. End-to-end multimodal models that look at images (like X-rays, MRIs, CT scans and ultrasounds), clinical data and multi-omics all at once to give integrated diagnostic and prognostic results right at the point of care. Standardized quantitative imaging biomarkers (e.g., automated cartilage thickness, bone marrow lesion volume, synovial volume, trabecular texture metrics) have been validated as endpoints for clinical trials in osteoarthritis and inflammatory arthritis. Future multi-center trials will look at how AI tools affect diagnostic accuracy, treatment decisions, patient outcomes and workflow efficiency in rheumatology and musculoskeletal radiology. Adaptive and self-supervised learning that can keep models up to date as new data comes in while still following safety and regulatory rules. For example, combining joint imaging phenotypes with cardiovascular risk imaging and systemic biomarkers to manage both articular and extra-articular risks in RA and related diseases is an example of how this can be used in precision medicine frameworks.

12. Conclusions

AI-driven and multimodal innovations are changing how biomedical imaging and sensing work for arthritis across the whole disease spectrum. Deep learning and radiomics have given us strong tools for automatically finding, segmenting, grading, and predicting long-term risk from radiographs and MRIs in OA. This has made it possible to do large-scale phenotyping and helped with precision trial design. In inflammatory arthritis AI is enhancing radiographic scoring MRI identification of sacroiliitis and treatment response forecasting from multimodal data. TMJ osteoarthritis shows that AI-enabled screening can work on 2D dental images that are easy to find. Cardiovascular risk models in RA show that imaging radiomics can help us sense arthritis-related things that are not just in the joints. However, for this to become standard practice in medicine it will need to be rigorously tested by outside experts and have standardized imaging and labeling protocols makes easier to understand and show clear clinical

benefits across a wide range of patients. AI-enhanced imaging is a powerful link between mechanistic understanding, quantitative biomarkers and therapeutic development. This puts rheumatology at the forefront of data-driven precision medicine.

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Nitish Sengar: Writing the original manuscript; Avijit Mazumder: Validation of the data; Saumya Das: Analysis of results.

References

[1] Smith SE, Bahouth SM, Duryea J. Quantitative bone marrow lesion, meniscus, and synovitis measurement: current status. Skeletal Radiol 2023;52:2123–35. https://doi.org/10.1007/s00256-023-04311-w.

[2] Ruitenbeek HC, Oei EHG, Visser JJ, Kijowski R. Artificial intelligence in musculoskeletal imaging: realistic clinical applications in the next decade. Skeletal Radiol 2024;53:1849–68. https://doi.org/10.1007/s00256-024-04684-6.

[3] Stoel B. Use of artificial intelligence in imaging in rheumatology - current status and future perspectives. RMD Open 2020;6. https://doi.org/10.1136/rmdopen-2019-001063.

[4] Martínez de Vega L, Baker J, Suevos-Ballesteros C, Ferre-Sanfrancisco M, Acosta-Hernández R, Fernández-Rodríguez A, Vera-Carmona AM, Acosta-Batlle J. A Radiologic Walk through Rheumatoid Arthritis. RadioGraphics 2026;46. https://doi.org/10.1148/rg.250059.

[5] Żelnio E, Taljanovic M, Mańczak M, Sudoł-Szopińska I. Hand and Wrist Involvement in Seropositive Rheumatoid Arthritis, Seronegative Rheumatoid Arthritis, and Psoriatic Arthritis—The Value of Classic Radiography. J Clin Med 2023;12:2622. https://doi.org/10.3390/jcm12072622.

[6] Ezzati F, Pezeshk P. Radiographic Findings of Inflammatory Arthritis and Mimics in the Hands. Diagnostics 2022;12:2134. https://doi.org/10.3390/diagnostics12092134.

[7] Gessl I, Hana CA, Deimel T, Durechova M, Hucke M, Konzett V, Popescu M, Studenic P, Supp G, Zauner M, Smolen JS, Aletaha D, Mandl P. Tenderness and radiographic progression in rheumatoid arthritis and psoriatic arthritis. Ann Rheum Dis 2023;82:344–50. https://doi.org/10.1136/ard-2022-222787.

[8] Tan YK, Hong C, Li H, Allen JC, Thumboo J. A novel use of combined thermal and ultrasound imaging in detecting joint inflammation in rheumatoid arthritis. Eur J Radiol 2021;134:109421. https://doi.org/10.1016/j.ejrad.2020.109421.

[9] Molina Collada J, López Gloria K, Castrejón I, Nieto-González JC, Rivera J, Montero F, González C, Álvaro-Gracia JM. Ultrasound in clinically suspect arthralgia: the role of power Doppler to predict rheumatoid arthritis development. Arthritis Res Ther 2021;23:299.

https://doi.org/10.1186/s13075-021-02685-7.
[10] Silvagni E, Zandonella Callegher S, Mauric E, Chiricolo S, Schreiber N, Tullio A, Zabotti A, Scirè CA, Dejaco C, Sakellariou G. Musculoskeletal ultrasound for treating rheumatoid arthritis to target—a systematic literature review. Rheumatology 2022;61:4590–602. https://doi.org/10.1093/rheumatology/keac261.
[11] Di Matteo A, Mankia K, Azukizawa M, Wakefield RJ. The Role of Musculoskeletal Ultrasound in the Rheumatoid Arthritis Continuum. Curr Rheumatol Rep 2020;22:41. https://doi.org/10.1007/s11926-020-00911-w.
[12] Kaeley GS, Bakewell C, Deodhar A. The importance of ultrasound in identifying and differentiating patients with early inflammatory arthritis: a narrative review. Arthritis Res Ther 2020;22:1. https://doi.org/10.1186/s13075-019-2050-4.
[13] Kravchenko D, Karakostas P, Kuetting D, Meyer C, Brossart P, Behning C, Schäfer VS. The role of dual energy computed tomography in the differentiation of acute gout flares and acute calcium pyrophosphate crystal arthritis. Clin Rheumatol 2022;41:223–33. https://doi.org/10.1007/s10067-021-05949-4.
[14] Therkildsen J, Klose-Jensen R, Hänel M, Langdahl BL, Thygesen J, Thomsen JS, Manske SL, Keller KK, Hauge E-M. Erosive progression by high-resolution peripheral quantitative computed tomography and conventional radiography in rheumatoid arthritis. Rheumatology 2025;64:1092–101. https://doi.org/10.1093/rheumatology/keae281.
[15] Ulas ST, Diekhoff T. Computed tomography—current status and future directions for arthritis imaging. Ther Adv Musculoskelet Dis 2024;16. https://doi.org/10.1177/1759720X241287373.
[16] Dakkak YJ, Matthijssen XME, van der Heijde D, Reijnierse M, van der Helm-van Mil AHM. Reliability of Magnetic Resonance Imaging (MRI) Scoring of the Metatarsophalangeal Joints of the Foot according to the Rheumatoid Arthritis MRI Score. J Rheumatol 2020;47:1165–73. https://doi.org/10.3899/jrheum.190258.
[17] Mazzoni M, Pistorio A, Magnaguagno F, Viola S, Urru A, Magnano GM, Ravelli A, Malattia C. Predictive Value of Magnetic Resonance Imaging in Patients With Juvenile Idiopathic Arthritis in Clinical Remission. Arthritis Care Res (Hoboken) 2023;75:198–205. https://doi.org/10.1002/acr.24757.
[18] Malla S, Vyas S, Bhalla AS, Kumar U, Kumar S, Gupta AK. Ultrasonography in Early Rheumatoid Arthritis of Hand and Wrist Joints: Comparison with Magnetic Resonance Imaging. Indian J Orthop 2020;54:695–703. https://doi.org/10.1007/s43465-020-00178-4.
[19] Subedi A, Williams SG, Yao L, Maharjan S, Strauss J, Sharon E, Thomas A, Apolo AB, Gourh P, Hasni SA, Gulley JL, Kaplan MJ, Katz JD, Gupta S. Use of Magnetic Resonance Imaging to Identify Immune Checkpoint Inhibitor–Induced Inflammatory Arthritis. JAMA Netw Open 2020;3:e200032. https://doi.org/10.1001/jamanetworkopen.2020.0032.
[20] Demehri S, Hafezi-Nejad N, Carrino JA. Conventional and novel imaging modalities in osteoarthritis. Curr Opin Rheumatol 2015;27:295–303. https://doi.org/10.1097/BOR.0000000000000163.
[21] Kellner H, Schmidt W, Rau R. [Imaging procedures in rheumatology. Differential diagnosis using various imaging procedures in rheumatoid arthritis (RA)]. Z Rheumatol 2005;64:553–6. https://doi.org/10.1007/s00393-005-0720-x.
[22] OSTERGAARD M, EJBJERG B, SZKUDLAREK M. Imaging in early rheumatoid arthritis: roles of magnetic resonance imaging, ultrasonography, conventional radiography and computed tomography. Best Pract Res Clin Rheumatol 2005;19:91–116. https://doi.org/10.1016/j.berh.2004.08.006.
[23] Grassi W, Okano T, Di Geso L, Filippucci E. Imaging in rheumatoid arthritis: options, uses and optimization. Expert Rev Clin Immunol 2015;11:1131–46. https://doi.org/10.1586/1744666X.2015.1075395.
[24] da Mota LMH, Laurindo IMM, dos Santos Neto LL, Lima FAC, Viana SL, Mendlovitz PS,

Fernandes JL. Imaging diagnosis of early rheumatoid arthritis. Rev Bras Reumatol 2012;52:757–66.

[25] McMaster C, Bird A, Liew DFL, Buchanan RR, Owen CE, Chapman WW, Pires DE V. Artificial Intelligence and Deep Learning for Rheumatologists. Arthritis Rheumatol 2022;74:1893–905. https://doi.org/10.1002/art.42296.

[26] Al-Maini M, Maindarkar M, Kitas GD, Khanna NN, Misra DP, Johri AM, Mantella L, Agarwal V, Sharma A, Singh IM, Tsoulfas G, Laird JR, Faa G, Teji J, Turk M, Viskovic K, Ruzsa Z, Mavrogeni S, Rathore V, Miner M, Kalra MK, Isenovic ER, Saba L, Fouda MM, Suri JS. Artificial intelligence-based preventive, personalized and precision medicine for cardiovascular disease/stroke risk assessment in rheumatoid arthritis patients: a narrative review. Rheumatol Int 2023;43:1965–82. https://doi.org/10.1007/s00296-023-05415-1.

[27] Lin KYY, Peng C, Lee KH, Chan SCW, Chung HY. Deep learning algorithms for magnetic resonance imaging of inflammatory sacroiliitis in axial spondyloarthritis. Rheumatology (Oxford) 2022;61:4198–206. https://doi.org/10.1093/rheumatology/keac059.

[28] Choi E, Kim D, Lee J-Y, Park H-K. Artificial intelligence in detecting temporomandibular joint osteoarthritis on orthopantomogram. Sci Rep 2021;11:10246. https://doi.org/10.1038/s41598-021-89742-y.

[29] Kijowski R, Fritz J, Deniz CM. Deep learning applications in osteoarthritis imaging. Skeletal Radiol 2023;52:2225–38. https://doi.org/10.1007/s00256-023-04296-6.

[30] Joseph GB, McCulloch CE, Sohn JH, Pedoia V, Majumdar S, Link TM. AI MSK clinical applications: cartilage and osteoarthritis. Skeletal Radiol 2022;51:331–43. https://doi.org/10.1007/s00256-021-03909-2.

[31] Namiri NK, Lee J, Astuto B, Liu F, Shah R, Majumdar S, Pedoia V. Deep learning for large scale MRI-based morphological phenotyping of osteoarthritis. Sci Rep 2021;11:10915. https://doi.org/10.1038/s41598-021-90292-6.

[32] Demehri S, Kasaeian A, Roemer FW, Guermazi A. Osteoarthritis year in review 2022: imaging. Osteoarthritis Cartilage 2023;31:1003–11. https://doi.org/10.1016/j.joca.2023.03.005.

[33] Farook TH, Dudley J. Automation and deep (machine) learning in temporomandibular joint disorder radiomics: A systematic review. J Oral Rehabil 2023;50:501–21. https://doi.org/10.1111/joor.13440.

[34] Calivà F, Namiri NK, Dubreuil M, Pedoia V, Ozhinsky E, Majumdar S. Studying osteoarthritis with artificial intelligence applied to magnetic resonance imaging. Nat Rev Rheumatol 2022;18:112–21. https://doi.org/10.1038/s41584-021-00719-7.

[35] Tse JJ, Brunet SC, Salat P, Hazlewood GS, Barnabe C, Manske SL. Multi-Modal Imaging to Assess the Interaction Between Inflammation and Bone Damage Progression in Inflammatory Arthritis. Front Med (Lausanne) 2020;7. https://doi.org/10.3389/fmed.2020.545097.

[36] Gong X, Su L, Huang J, Liu J, Wang Q, Luo X, Yang G, Chi H. An overview of multi-omics technologies in rheumatoid arthritis: applications in biomarker and pathway discovery. Front Immunol 2024;15:1381272. https://doi.org/10.3389/fimmu.2024.1381272.

[37] Mendoza-Pinto C, Sánchez-Tecuatl M, Berra-Romani R, Maya-Castro ID, Etchegaray-Morales I, Munguía-Realpozo P, Cárdenas-García M, Arellano-Avendaño FJ, García-Carrasco M. Machine learning in the prediction of treatment response in rheumatoid arthritis: A systematic review. Semin Arthritis Rheum 2024;68:152501. https://doi.org/10.1016/j.semarthrit.2024.152501.

[38] Bird A, Oakden-Rayner L, McMaster C, Smith LA, Zeng M, Wechalekar MD, Ray S, Proudman S, Palmer LJ. Artificial intelligence and the future of radiographic scoring in rheumatoid arthritis: a viewpoint. Arthritis Res Ther 2022;24:268. https://doi.org/10.1186/s13075-022-02972-x.

[39] Adams LC, Bressem KK, Poddubnyy D. Artificial intelligence and machine learning in axial

spondyloarthritis. Curr Opin Rheumatol 2024;36:267–73. https://doi.org/10.1097/BOR.0000000000001015.

[40] Benavent D, Carmona L, García Llorente JF, Montoro M, Ramirez S, Otón T, Loza E, Gómez-Centeno A. Artificial intelligence to predict treatment response in rheumatoid arthritis and spondyloarthritis: a scoping review. Rheumatol Int 2025;45:91. https://doi.org/10.1007/s00296-025-05825-3.

[41] Gorelik N, Gyftopoulos S. Applications of Artificial Intelligence in Musculoskeletal Imaging: From the Request to the Report. Can Assoc Radiol J 2021;72:45–59. https://doi.org/10.1177/0846537120947148.

[42] Jung W, Lee K-E, Suh B-J, Seok H, Lee D-W. Deep learning for osteoarthritis classification in temporomandibular joint. Oral Dis 2023;29:1050–9. https://doi.org/10.1111/odi.14056.

[43] Yoon K, Kim J-Y, Kim S-J, Huh J-K, Kim J-W, Choi J. Explainable deep learning-based clinical decision support engine for MRI-based automated diagnosis of temporomandibular joint anterior disk displacement. Comput Methods Programs Biomed 2023;233:107465. https://doi.org/10.1016/j.cmpb.2023.107465.

[44] Bayrakdar IS, Kuran A, Celik O, Orhan K. AI in Temporomandibular Joint Imaging. Neuroimaging Clin N Am 2025;35:527–37. https://doi.org/10.1016/j.nic.2025.06.001.

[45] Henderson J, Condell J, Connolly J, Kelly D, Curran K. Review of Wearable Sensor-Based Health Monitoring Glove Devices for Rheumatoid Arthritis. Sensors 2021;21:1576. https://doi.org/10.3390/s21051576.

[46] Serra López VM, Gandhi RA, Falk DP, Baxter JR, Lien JR, Gray BL. Dynamic Thumb Circumduction Measured With a Wearable Motion Sensor: A Prospective Comparison of Patients With Basal Joint Arthritis to Controls. J Hand Surg Glob Online 2021;3:190–4. https://doi.org/10.1016/j.jhsg.2021.05.002.

[47] Na A, Buchanan TS. Validating Wearable Sensors Using Self-Reported Instability among Patients with Knee Osteoarthritis. PM&R 2021;13:119–27. https://doi.org/10.1002/pmrj.12393.

[48] Stradford L, Curtis JR, Zueger P, Xie F, Curtis D, Gavigan K, Clinton C, Venkatachalam S, Rivera E, Nowell WB. Wearable activity tracker study exploring rheumatoid arthritis patients' disease activity using patient-reported outcome measures, clinical measures, and biometric sensor data (the wear study). Contemp Clin Trials Commun 2024;38:101272. https://doi.org/10.1016/j.conctc.2024.101272.

[49] Longo UG, Candela V, Berton A, De Salvatore S, Fioravanti S, Giannone L, Marchetti A, De Marinis MG, Denaro V. Biosensors for Detection of Biochemical Markers Relevant to Osteoarthritis. Biosensors (Basel) 2021;11:31. https://doi.org/10.3390/bios11020031.

[50] Ram RK, Dutta N, Shukla J, Dutta G. Lab-On-Chip Electrochemical Biosensor for Rheumatoid Arthritis, 2023, p. 157–81. https://doi.org/10.1007/978-981-19-8714-4_8.

[51] Rodovalho VR, Araujo GR, Vaz ER, Ueira-Vieira C, Goulart LR, Madurro JM, Brito-Madurro AG. Peptide-based electrochemical biosensor for juvenile idiopathic arthritis detection. Biosens Bioelectron 2018;100:577–82. https://doi.org/10.1016/j.bios.2017.10.012.

[52] Seppen B, Wiegel J, ter Wee MM, van Schaardenburg D, Roorda LD, Nurmohamed MT, Boers M, Bos WH. Smartphone-Assisted Patient-Initiated Care Versus Usual Care in Patients With Rheumatoid Arthritis and Low Disease Activity: A Randomized Controlled Trial. Arthritis & Rheumatology 2022;74:1737–45. https://doi.org/10.1002/art.42292.

[53] Hamann PDH, Minaur N, Tobias JH, Clark EM. Capturing remote disease activity – results of a 12-month clinical pilot of a smartphone app in NHS rheumatology clinics in Bristol. Rheumatology 2020;59:2158–61. https://doi.org/10.1093/rheumatology/keaa015.

[54] Hamann P, Knitza J, Kuhn S, Knevel R. Recommendation to implementation of remote patient monitoring in rheumatology: lessons learned and barriers to take. RMD Open 2023;9. https://doi.org/10.1136/rmdopen-2023-003363.

[55] Tiwari E, Shrimankar D, Maindarkar M, Bhagawati M, Kaur J, Singh IM, Mantella L, Johri AM, Khanna NN, Singh R, Chaudhary S, Saba L, Al-Maini M, Anand V, Kitas G, Suri JS. Artificial intelligence-based cardiovascular/stroke risk stratification in women affected by autoimmune disorders: a narrative survey. Rheumatol Int 2025;45:14. https://doi.org/10.1007/s00296-024-05756-5.

[56] Jamthikar AD, Gupta D, Puvvula A, Johri AM, Khanna NN, Saba L, Mavrogeni S, Laird JR, Pareek G, Miner M, Sfikakis PP, Protogerou A, Kitas GD, Kolluri R, Sharma AM, Viswanathan V, Rathore VS, Suri JS. Cardiovascular risk assessment in patients with rheumatoid arthritis using carotid ultrasound B-mode imaging. Rheumatol Int 2020;40:1921–39. https://doi.org/10.1007/s00296-020-04691-5.