

ARTIFICIAL INTELLIGENCE AND RADIOMICS IN JOINT AND SPINE PAIN IMAGING: CURRENT CLINICAL APPLICATIONS, QUANTITATIVE BIOMARKERS, AND FUTURE PERSPECTIVES

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ABSTRACT

Background: Joint and spine pain are major contributors to global disability and healthcare burden. Although conventional imaging modalities, including radiography, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound, remain central to diagnosis, they rely predominantly on qualitative assessment and often demonstrate limited correlation with clinical symptoms. Artificial intelligence (AI) and radiomics have emerged as transformative technologies that enable automated image analysis and extraction of quantitative imaging biomarkers.

Objective: This review summarizes the current applications of AI and radiomics in joint and spine pain imaging, highlighting quantitative biomarkers, clinical applications, evidence from recent studies, challenges, and future directions.

Methods: A comprehensive narrative review of recent literature was performed, focusing on machine learning, deep learning, radiomics, and quantitative imaging biomarkers in musculoskeletal imaging. Studies involving degenerative, inflammatory, and traumatic disorders of the joints and spine were critically evaluated.

Results: AI has demonstrated high diagnostic performance in automated detection, disease classification, severity grading, and outcome prediction for conditions such as osteoarthritis, degenerative disc disease, lumbar spinal stenosis, sacroiliitis, meniscal injuries, and rotator cuff disorders. Radiomics provides objective characterization of cartilage, bone, intervertebral discs, bone marrow, muscles, and synovium, facilitating early disease detection, risk stratification, and personalized treatment planning. However, widespread clinical implementation is limited by small datasets, variability in imaging protocols, lack of standardization, segmentation challenges, limited external validation, reproducibility concerns, and regulatory issues.

Conclusion: AI and radiomics are transforming musculoskeletal imaging by enabling quantitative, data-driven assessment and precision medicine. Future advances in multicenter validation, standardized radiomics workflows, explainable AI, federated learning, and integration of imaging biomarkers with clinical and molecular data are expected to accelerate clinical translation and improve diagnosis, prognostication, and individualized management of patients with joint and spine pain.

KEYWORDS: Artificial intelligence; Radiomics; Musculoskeletal imaging; Joint pain; Spine pain; MRI; CT; Quantitative imaging biomarkers; Machine learning; Deep learning.

1. INTRODUCTION

1.1 Burden of Joint and Spine Pain

Joint and spine pain are major causes of disability, imposing substantial clinical, social, and economic burdens. Conditions including osteoarthritis (OA), degenerative disc disease (DDD), lumbar spinal stenosis, inflammatory arthropathies, tendon disorders, and sports-related injuries impair quality of life, mobility, and work productivity [1,2]. Their increasing prevalence, driven by population aging, obesity, sedentary lifestyles, and sports participation, has increased the demand for accurate diagnosis and individualized treatment [1,2]. Imaging is

essential for diagnosis, severity assessment, monitoring progression, intervention guidance, and evaluation of treatment response, making advances in musculoskeletal imaging important for precision medicine [1-4].

1.2 Current Imaging Approaches

Radiography remains the first-line modality because of its availability, low cost, and ability to demonstrate fractures, alignment abnormalities, osteophytes, joint-space narrowing, and advanced degeneration [1,2]. However, it has limited sensitivity for early cartilage degeneration, bone marrow abnormalities, ligament injuries, and soft-tissue pathology.

Computed tomography (CT) provides excellent spatial resolution for cortical bone and is particularly useful for fractures, complex osseous anatomy, postoperative assessment, and spinal canal stenosis. Advances in multidetector and quantitative CT have expanded its applications to bone-quality assessment and radiomic analysis of vertebral and joint structures [1,2,5,6].

Magnetic resonance imaging (MRI) provides superior soft-tissue contrast and multiplanar imaging, enabling detailed assessment of cartilage, intervertebral discs, bone marrow, ligaments, tendons, muscles, synovium, and neural structures. It is therefore central to evaluating OA, inflammatory arthropathies, spinal degeneration, and sports injuries [1-3,7]. Quantitative techniques such as T2 mapping, T1ρ imaging, diffusion imaging, and compositional MRI can provide objective tissue biomarkers before morphological abnormalities become evident [7].

Ultrasound (US) is a dynamic, inexpensive, radiation-free modality used for superficial tendons, ligaments, muscles, bursae, peripheral nerves, and joint effusions, as well as real-time image-guided procedures. Its limitations include operator dependence and restricted assessment of deep structures and complex spinal pathology [1,2].

Table 1. Comparison of Conventional Imaging Modalities for Joint and Spine Pain

Imaging Modality	Strengths	Limitations	Common Clinical Applications	Role of AI/Radiomics
Radiography (X-ray)	Widely available, inexpensive, rapid examination, excellent for bony alignment	Limited soft tissue contrast, poor sensitivity for early disease	Osteoarthritis, fractures, spinal alignment, degenerative changes	Automated fracture detection, osteoarthritis grading, abnormality detection, disease progression prediction
Computed Tomography (CT)	Excellent spatial resolution, superior cortical bone visualization, fast acquisition	Ionizing radiation, limited soft tissue characterization	Complex fractures, spinal canal assessment, osteoporosis, vertebral lesions	Quantitative bone analysis, vertebral radiomics, spinal stenosis prediction, opportunistic osteoporosis screening
Magnetic Resonance Imaging (MRI)	Superior soft tissue contrast, multiplanar imaging, no ionizing radiation	Higher cost, longer acquisition time, motion sensitivity	Cartilage, intervertebral discs, ligaments, menisci, spinal cord, inflammatory disorders	Deep learning, radiomics, automated segmentation, disease classification, quantitative biomarkers, outcome prediction
Ultrasound (US)	Real-time imaging, dynamic assessment, inexpensive, radiation-free	Operator dependent, limited evaluation of deep structures	Tendons, muscles, ligaments, bursae, synovitis, guided interventions	Automated tendon assessment, inflammatory activity quantification, image-guided procedures

1.3 Limitations of Conventional Imaging

Despite technological advances, conventional musculoskeletal imaging remains predominantly qualitative and dependent on visual interpretation, with subjective grading susceptible to interobserver variability and limited ability to detect subtle microstructural changes [3,8,9]. Imaging findings may also correlate poorly with clinical symptoms, particularly in osteoarthritis and chronic low back pain, where structural abnormalities alone may not explain pain severity or functional impairment [4,10]. These limitations have driven interest in computational methods that provide quantitative imaging biomarkers beyond visual assessment.

1.4 Emergence of Artificial Intelligence

Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), has emerged as a transformative approach in musculoskeletal imaging. AI can support image optimization, segmentation, lesion detection, disease classification, severity grading, workflow prioritization, and outcome prediction with high accuracy and reproducibility [1,2,8,11-19]. Landmark models such as MURA for musculoskeletal radiographs

and MRNet for knee MRI demonstrated diagnostic performance approaching that of expert radiologists in selected tasks [20,21]. Applications have subsequently expanded to lumbar spinal stenosis, disc degeneration, osteoarthritis progression, sacroiliitis, and postoperative outcome prediction [5,22-26].

1.5 Evolution of Radiomics

Radiomics converts medical images into high-dimensional quantitative data by extracting features describing intensity, texture, shape, spatial relationships, and tissue heterogeneity [9,27,28]. Initially developed mainly in oncology, radiomics is increasingly applied to musculoskeletal conditions including osteoarthritis, degenerative spine disorders, osteoporosis, sacroiliitis, and chronic low back pain [6,10,29-34]. These imaging biomarkers can identify subtle microstructural changes beyond routine visual assessment and support early diagnosis, risk stratification, prognosis, and treatment-response prediction [9,10,27,31].

1.6 Why AI and Radiomics are Complementary

AI and radiomics offer complementary capabilities. Radiomics generates quantitative descriptors of disease-related tissue characteristics, while AI identifies complex patterns within these data to develop predictive and clinically actionable models [9,27]. Their integration can facilitate automated feature selection, disease classification, prognostic modeling, and personalized decision support. Promising applications include prediction of osteoarthritis progression, lumbar disc degeneration, Modic changes, spinal stenosis, and postoperative outcomes [5,22,29-31,35].

1.7 Scope and Objectives of This Review

This review summarizes current developments in AI and radiomics for joint and spine pain imaging, including their principles, quantitative imaging biomarkers, and clinical applications across degenerative, inflammatory, and traumatic disorders. It also examines evidence for clinical implementation, challenges involving data quality, interpretability, standardization, and validation, and future directions toward precision musculoskeletal imaging and personalized patient care [1,2,8,9,11-19,27,34,36-38].

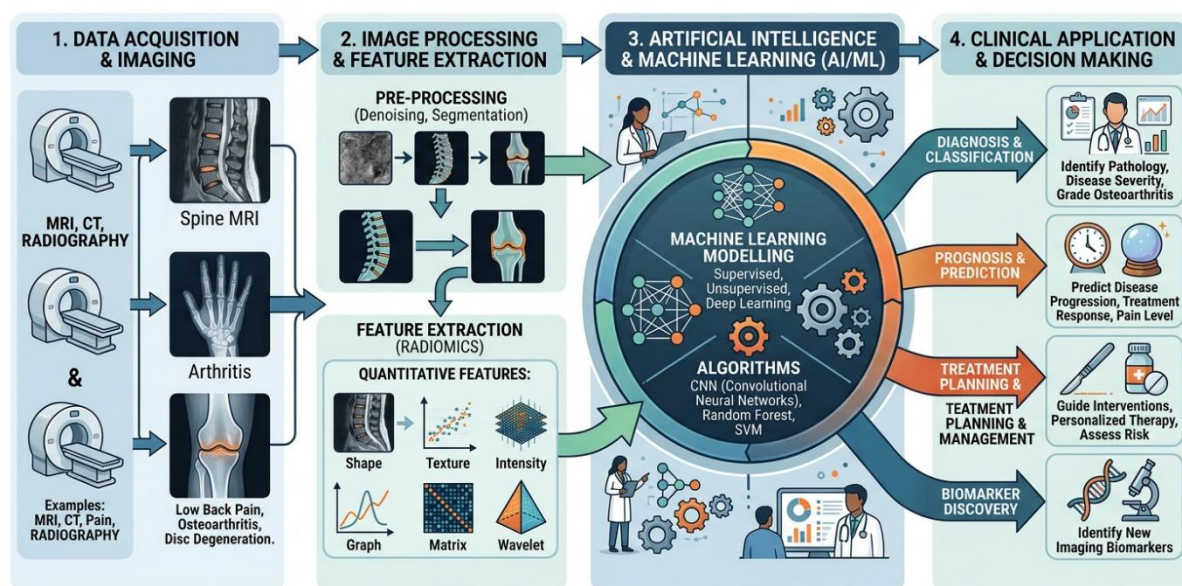


Figure 1. Overview of AI and Radiomics in Joint and Spine Pain Imaging

2. Artificial Intelligence in Musculoskeletal Imaging

Artificial intelligence (AI) has become an important tool in musculoskeletal imaging, supporting image interpretation, automation, diagnostic accuracy, and precision medicine. Advances in computational power, large imaging datasets, and machine learning have enabled AI applications across the imaging workflow, including image acquisition, segmentation, lesion detection, disease classification, prognosis, and clinical decision support [1,2,8,11-15].

Artificial intelligence (AI) refers to computer systems capable of performing tasks requiring human-like learning, reasoning, pattern recognition, and decision-making. In medical imaging, AI can analyze radiological images, identify abnormalities, quantify disease burden, and generate predictions. Rather than replacing radiologists, it primarily functions as an assistive technology that improves efficiency, reproducibility, and diagnostic consistency [1,8,11-15,38].

Machine learning (ML) is a subset of AI in which algorithms learn relationships from labelled or unlabelled data to make predictions. Supervised learning uses expert-annotated datasets, whereas unsupervised learning identifies patterns without predefined labels [12,13,15]. ML has been applied to osteoarthritis detection, lumbar spinal

stenosis classification, decompression-level prediction, osteoporosis risk assessment, and identification of imaging biomarkers associated with chronic low back pain [5,6,10,31].

Deep learning (DL) uses multilayered neural networks to automatically learn hierarchical features directly from imaging data, reducing dependence on handcrafted feature extraction [11-14]. Landmark datasets and models such as **MURA** and **MRNet** demonstrated strong performance in musculoskeletal radiographs and knee MRI, respectively [20,21]. Subsequent applications include disc degeneration grading, spinal stenosis detection, osteoarthritis progression prediction, and MRI-based sacroiliitis assessment [23-26,33,39-42].

Convolutional neural networks (CNNs) are widely used for medical image analysis. Through convolutional filters, pooling, and nonlinear activation functions, CNNs progressively learn features ranging from edges and textures to complex anatomical and pathological patterns [11-14]. They have been applied to fracture detection, cartilage and bone segmentation, knee osteoarthritis grading, meniscal injury detection, lumbar degenerative disease classification, and spinal MRI assessment [20,21,23-26,43-48].

Despite their performance, many DL models have limited interpretability. **Explainable artificial intelligence (XAI)** addresses this issue by identifying image regions or features contributing to model predictions. Methods such as SHapley Additive exPlanations (SHAP) and Gradient-weighted Class Activation Mapping (Grad-CAM) can improve transparency and help radiologists assess AI outputs [49-51]. XAI is therefore important for trustworthy clinical implementation and aligns with recommendations for ethical AI deployment [36,37].

The **AI workflow** generally includes image acquisition, preprocessing and quality assessment, expert annotation, feature extraction or automated feature learning, model training, validation, and clinical integration. Following internal and external validation, AI can support image triage, segmentation, abnormality detection, quantitative assessment, reporting, prognostic prediction, and decision-making. Continuous monitoring is required to maintain model accuracy and generalizability [9,11-15,27,28,37,38].

3. Radiomics: Principles and Workflow

Radiomics is a quantitative imaging approach that converts conventional medical images into high-dimensional data describing tissue morphology, intensity, texture, and spatial heterogeneity. Initially developed in oncology, it has expanded to musculoskeletal applications including osteoarthritis, degenerative spine disorders, osteoporosis, inflammatory arthropathies, and chronic low back pain [6,9,10,27,28,31,34]. Radiomic biomarkers can provide information beyond visual assessment and support disease detection, classification, prognosis, and treatment decision-making [9,10,27,31].

Radiomics is defined as the high-throughput extraction and analysis of quantitative imaging features to characterize tissue phenotype objectively and reproducibly [9]. It has been described as a bridge between medical imaging and personalized medicine by converting routine images into quantitative biomarkers [27]. In musculoskeletal imaging, radiomics has shown potential for detecting early cartilage degeneration, disc degeneration, Modic changes, paraspinal muscle alterations, chronic low back pain, and osteoporosis [6,10,22,29-32,35,52-55].

The **radiomics pipeline** comprises several sequential stages [9,27,28]. **Image acquisition** requires standardized, high-quality imaging, most commonly MRI and CT. Parameters such as slice thickness, voxel size, field strength, reconstruction kernel, and sequence can influence radiomic features, making protocol standardization important [9,27,28].

Image reconstruction and preprocessing include resampling, interpolation, denoising, intensity normalization, and harmonization. These processes can alter image texture and signal distribution and therefore influence feature reproducibility [9,28].

Segmentation identifies the region or volume of interest for analysis. It may be manual, semi-automatic, or fully automated using AI. Accurate segmentation is essential because all subsequent features are derived from the selected region. Common musculoskeletal targets include cartilage, intervertebral discs, vertebrae, subchondral bone, paraspinal muscles, menisci, synovium, ligaments, and bone marrow lesions [6,10,22,29,30,34,35,53-55].

Feature extraction generates hundreds or thousands of quantitative descriptors representing morphology, intensity, heterogeneity, and spatial organization [9,27,28]. Because many features may be redundant or correlated, **feature selection** identifies informative and reproducible variables while reducing dimensionality and overfitting. Methods include LASSO, recursive feature elimination, principal component analysis, and mutual information [9,27,28].

During **model development**, selected features are combined with ML or DL algorithms to establish relationships with clinical outcomes. Common approaches include logistic regression, support vector machines, random forests, gradient boosting, and artificial neural networks [9,27,28]. Finally, **validation** determines model reliability and generalizability. Internal validation assesses performance within the development dataset, whereas external validation uses independent cohorts. Common metrics include sensitivity, specificity, accuracy, ROC analysis, AUC, calibration, and decision-curve analysis [9,27,28].

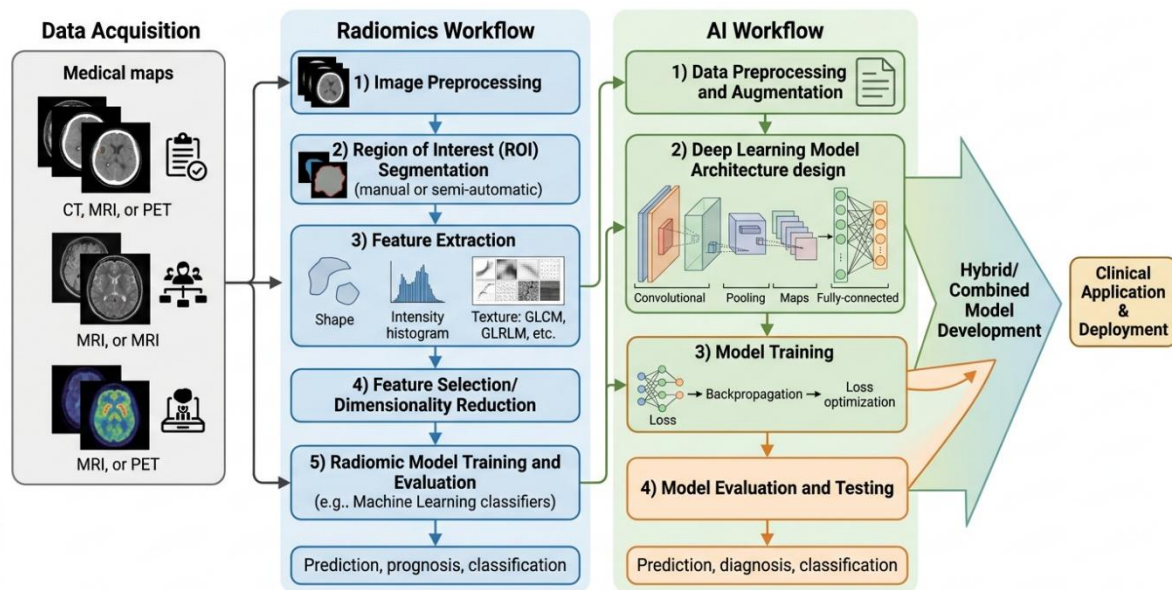


Figure 2. AI and Radiomics Workflow

Radiomic features are categorized into complementary groups based on the information they capture. **Shape features** quantify three-dimensional morphology, including volume, surface area, compactness, elongation, maximum diameter, and sphericity, providing objective measures of structural alterations [9,28]. **First-order features** describe voxel-intensity distributions without considering spatial relationships and include mean, median, variance, skewness, kurtosis, entropy, energy, and percentile values [9,27,28].

Texture features assess spatial relationships between neighboring voxels and quantify tissue heterogeneity. They are commonly derived from the Gray-Level Co-occurrence Matrix (GLCM), Gray-Level Run Length Matrix (GLRLM), Gray-Level Size Zone Matrix (GLSZM), Gray-Level Dependence Matrix (GLDM), and Neighboring Gray Tone Difference Matrix (NGTDM). These features can identify subtle microstructural changes in cartilage degeneration, disc degeneration, Modic changes, osteoporosis, and chronic low back pain [10,22,29-32,35,52-53]. **Wavelet features** use wavelet transformations to decompose images into multiple frequency components, enhancing subtle patterns and expanding quantitative feature extraction [9,27,28]. **Higher-order features** apply advanced filters, including Laplacian-of-Gaussian, Gabor, fractal, and local binary pattern transformations, to characterize complex tissue architecture [9,28].

Radiomics can be broadly classified into **handcrafted** and **deep radiomics**. Handcrafted radiomics uses predefined mathematical algorithms to extract quantitative features from segmented structures, offering relatively greater interpretability and reproducibility but depending heavily on segmentation quality and feature engineering [9,27,28]. **Deep radiomics**, in contrast, uses convolutional neural networks to automatically learn hierarchical features directly from images, capturing complex patterns and often providing stronger predictive performance, although with lower interpretability [11-14,22,34].

Delta radiomics extends conventional radiomics by assessing changes in radiomic features across serial examinations rather than at a single time point. It can provide quantitative measures of disease progression, treatment response, and postoperative recovery and is increasingly investigated in osteoarthritis and degenerative spine disorders [10,27,31,35]. **Radiogenomics** integrates radiomic biomarkers with genomic, transcriptomic, proteomic, and metabolomic information to associate imaging phenotypes with underlying molecular mechanisms. Although primarily studied in oncology, its application in musculoskeletal diseases may support non-invasive prediction of disease susceptibility, progression, and treatment response [27,31,34]. Together, these approaches strengthen radiomics as a quantitative complement to AI in personalized musculoskeletal imaging.

Table 2. Categories of Radiomic Features

Feature Category	Representative Features	Information Provided	Musculoskeletal Applications
Shape Features	Volume, surface area, sphericity, compactness, elongation	Lesion geometry and morphology	Bone lesions, cartilage defects, vertebral morphology [9,27,28]
First-order Statistics	Mean, median, standard deviation, entropy, skewness, kurtosis	Distribution of voxel intensities without spatial information	Tissue composition, cartilage degeneration, bone marrow assessment [9,27,28]

Texture Features	GLCM, GLRLM, GLSZM, GLDM, NGTDM	Tissue heterogeneity and spatial relationships	Osteoarthritis, disc degeneration, Modic changes, chronic low back pain [10,22,29-32,35,52-53]
Wavelet Features	High- and low-frequency transformed features	Multi-scale image information and hidden image patterns	Early disease detection and prediction models [9,27,28]
Higher-order Features	Laplacian of Gaussian, Gabor filters, Local Binary Pattern, fractal features	Complex tissue architecture following image filtering	Advanced radiomics models and AI-assisted disease prediction [9,28]

4. Quantitative Imaging Biomarkers in Joint and Spine Disorders

Quantitative imaging biomarkers provide objective measures of tissue composition, structural integrity, and disease activity, enabling detection of subtle changes that may precede morphological abnormalities. Their integration with advanced imaging, radiomics, and AI is increasingly supporting diagnosis, staging, prognosis, and treatment monitoring in osteoarthritis, degenerative spine disease, osteoporosis, inflammatory arthropathies, and chronic low back pain [1-4,9,10,27,31,34].

4.1 Cartilage Biomarkers

Articular cartilage is an early target in osteoarthritis. MRI provides direct assessment of cartilage morphology and composition, while techniques such as T2 mapping, T1ρ, dGEMRIC, sodium MRI, and compositional MRI provide biomarkers of collagen integrity, proteoglycan concentration, and water content before evident cartilage loss [7]. Radiomics further evaluates cartilage heterogeneity, with studies demonstrating potential for detecting early OA and predicting structural progression [3,7,31,32,39-42,48].

4.2 Bone Biomarkers

CT, HR-pQCT, and MRI provide quantitative measures of trabecular microarchitecture, cortical thickness, bone geometry, and mineralization. Opportunistic CT and radiomics can assess vertebral and subchondral bone quality and may improve osteoporosis and fracture-risk stratification without dedicated examinations [6]. Radiomic features can capture subtle changes in bone texture and structural heterogeneity associated with disease severity and mechanical strength [3-5,31].

4.3 Disc Biomarkers

Quantitative MRI techniques, including T2 mapping, T1ρ, diffusion imaging, and ADC measurements, provide objective information on disc hydration, collagen organization, and proteoglycan content [10,30]. Radiomics further characterizes disc texture and heterogeneity, with studies reporting applications in disc degeneration classification, symptomatic status, progression prediction, and automated grading [10,22,30,52,55].

4.4 Bone Marrow Biomarkers

MRI is sensitive to bone marrow lesions, edema-like changes, and Modic changes associated with degenerative and inflammatory disorders. These findings may correlate with pain more closely than conventional structural abnormalities [3,4]. Radiomic analysis can characterize bone marrow and Modic changes and identify features associated with pain, progression, and symptomatic disease [29,31,34].

4.5 Muscle Biomarkers

Quantitative MRI can assess muscle cross-sectional area, volume, fat infiltration, and tissue composition. Fatty degeneration of paraspinal muscles is associated with chronic low back pain, spinal instability, and postoperative outcomes (24). Radiomics provides additional information on intramuscular texture and heterogeneity, with paraspinal muscle features showing potential for predicting postoperative recovery in lumbar degenerative spondylolisthesis [35,53].

4.6 Synovial Biomarkers

MRI and ultrasound can assess synovial hypertrophy, vascularity, effusion, and inflammatory activity. Dynamic contrast-enhanced MRI and power Doppler ultrasound provide quantitative measures of synovial perfusion, while radiomics can characterize synovial texture and signal variation [3,4]. Emerging applications include differentiation of inflammatory and degenerative disease, treatment-response prediction, and disease monitoring, although further multicenter validation is required [31,34].

4.7 Imaging Phenotypes

Quantitative biomarkers enable identification of distinct **imaging phenotypes**, reflecting variations in cartilage, bone, marrow, synovium, muscle, and disc involvement [3,4,27,31,48]. AI and radiomics can integrate these multidimensional features to stratify patients according to disease progression, pain, treatment response, and prognosis, supporting individualized management and precision musculoskeletal medicine [10,31,34].

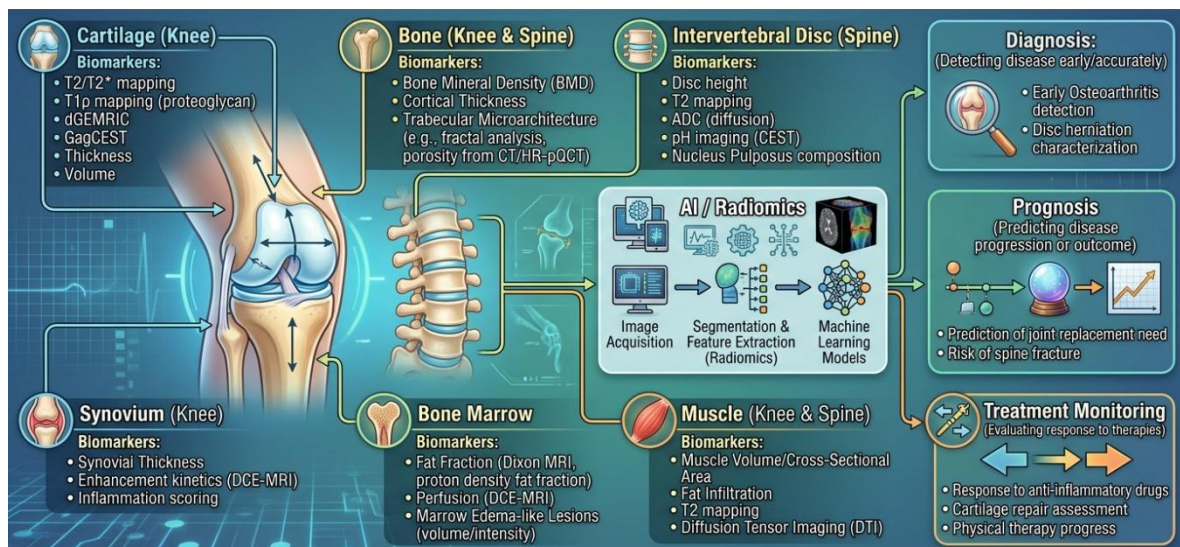


Figure 3. Quantitative Imaging Biomarkers in Joint and Spine Disorders

5. Clinical Applications in Spine Pain Imaging

Artificial intelligence (AI) and radiomics are increasingly transforming spine imaging by enabling quantitative assessment of degenerative, inflammatory, and metabolic disorders beyond conventional visual interpretation. MRI and CT remain central to spine evaluation, but their findings may show limited correlation with symptoms and functional impairment. AI and radiomic biomarkers provide additional information on tissue heterogeneity, structural integrity, disease progression, and treatment outcomes [1,2,8,10-15,34].

5.1 Degenerative Disc Disease

Degenerative disc disease (DDD) involves progressive disc dehydration, proteoglycan loss, annular fissuring, and structural collapse. Conventional MRI grading, including the Pfirrmann classification, is subjective and may miss early biochemical changes. Radiomics quantifies disc texture, intensity, and morphology, enabling detection and classification of degenerative changes [10,30,52]. Deep learning models have also demonstrated automated classification of lumbar disc degeneration, supporting standardized and reproducible assessment [22,43,55].

5.2 Lumbar Disc Herniation

MRI is the preferred modality for assessing lumbar disc herniation, neural compression, and associated inflammatory changes. However, distinguishing symptomatic from incidental disc abnormalities remains challenging. AI can automate detection, segmentation, and classification of herniation, while radiomics provides quantitative information on disc and surrounding tissue heterogeneity that may assist in assessing pain severity and treatment response [10-14,22,34].

5.3 Cervical Spondylosis

Cervical spondylosis involves degeneration of discs, facet and uncovertebral joints, and supporting ligaments, potentially causing neck pain, radiculopathy, or myelopathy. AI facilitates automated detection, segmentation, and quantification of degenerative changes and spinal canal narrowing [1,2,11-15]. Radiomics may additionally characterize disc degeneration, vertebral bone quality, and spinal cord features, supporting more objective assessment and treatment planning [10,34].

5.4 Spinal Canal Stenosis

Lumbar spinal stenosis involves narrowing of the central canal, lateral recesses, or neural foramina. Conventional grading is subject to interobserver variability. Deep learning models can automatically detect and grade central, lateral recess, and foraminal stenosis [23-25]. Radiomic analysis of CT myelography and MRI can quantify canal morphology and assist preoperative planning. Fan et al. demonstrated that CT myelography radiomic features could predict surgical decompression levels [5].

5.5 Vertebral Endplate Changes

Endplate abnormalities contribute to spinal degeneration and chronic low back pain. Although MRI can identify these changes, subtle morphological and microstructural alterations may be difficult to assess visually. Radiomics provides quantitative measures of endplate morphology, signal heterogeneity, and structural complexity, potentially improving detection of degenerative changes and assessment of disease progression [10,34].

5.6 Modic Changes

Modic changes are vertebral marrow signal abnormalities adjacent to degenerating discs and are associated with chronic low back pain. Types I, II, and III represent predominantly inflammatory, fatty, and sclerotic changes, respectively. Radiomic texture analysis can provide objective characterization of these lesions and identify biomarkers associated with pain severity and symptomatic disease [10,29].

5.7 Facet Joint Arthropathy

Facet arthropathy is an important cause of axial low back pain. CT and MRI demonstrate joint-space narrowing, osteophytes, sclerosis, cysts, and hypertrophic changes. Deep learning has shown accurate automated classification of facet arthropathy and associated spinal stenosis, improving consistency and workflow efficiency [24]. Radiomic assessment may further quantify degenerative severity and symptomatic disease [10,34].

5.8 Osteoporotic Compression Fractures

Osteoporotic vertebral compression fractures are major causes of pain and disability in older adults. Radiography and CT assess fracture morphology, while MRI helps distinguish acute from chronic fractures through marrow edema. AI supports automated vertebral segmentation, fracture detection, and opportunistic osteoporosis screening [6]. Vertebral radiomics may provide additional information on trabecular structure and bone quality for fracture-risk assessment [6,34].

5.9 Sacroiliitis

MRI is particularly valuable for detecting active sacroiliitis through visualization of bone marrow edema, erosions, fat metaplasia, sclerosis, and ankylosis. AI and deep learning radiomics have demonstrated promising performance in detecting sacroiliitis and differentiating inflammatory lesions from other sacroiliac abnormalities [33,56]. These approaches may improve diagnostic consistency and reduce observer variability.

5.10 Prediction of Surgical Outcomes

AI and radiomics are increasingly being investigated for predicting postoperative outcomes using imaging biomarkers from discs, vertebral marrow, spinal canals, and paraspinal muscles. MRI radiomics of paraspinal muscles has shown predictive value for postoperative outcomes in lumbar degenerative spondylolisthesis [35]. Radiomic features have also been associated with low back pain severity and functional disability, while canal radiomics has been used to predict decompression requirements in spinal stenosis [5]. These applications could support individualized surgical planning and patient selection, although broader clinical implementation requires multicenter datasets, standardized protocols, external validation, and explainable models [1,2,8,11-15,34,36-38].

6. Clinical Applications in Joint Pain Imaging

Artificial intelligence (AI) and radiomics have advanced joint pain imaging by enabling quantitative assessment beyond conventional visual interpretation. Although radiography, CT, MRI, and ultrasound remain the principal modalities, observer variability and imperfect correlation between imaging findings and symptoms remain important limitations. AI and radiomics support automated detection, classification, severity grading, prognostication, and treatment monitoring across degenerative, inflammatory, and sports-related disorders [1,2,8,11-19,31,34,48].

6.1 Knee Osteoarthritis

Knee osteoarthritis (KOA) is the most extensively studied joint application of AI and radiomics. Radiography remains first-line, while MRI provides detailed assessment of cartilage, menisci, subchondral bone, ligaments, and synovium [3,4,7]. Deep learning models have demonstrated accurate automated diagnosis and grading of KOA, with studies reporting performance comparable to expert interpretation [44-46]. Radiomics further quantifies cartilage texture and subchondral bone heterogeneity, supporting early diagnosis, progression prediction, and identification of clinically relevant imaging phenotypes [31,32,39-42,48].

6.2 Hip Osteoarthritis

Radiographs remain important for assessing hip joint-space narrowing, osteophytes, and sclerosis, while MRI evaluates cartilage, marrow lesions, labral pathology, and synovitis. Although AI applications are less developed than in KOA, quantitative MRI and CT biomarkers show potential for detecting early cartilage degeneration and predicting progression [3,4,31]. Radiomics may further characterize cartilage and subchondral bone heterogeneity for improved patient stratification.

6.3 Shoulder Disorders

Shoulder pain commonly results from degenerative, traumatic, or inflammatory pathology involving the rotator cuff, labrum, cartilage, and surrounding soft tissues. MRI and ultrasound are particularly useful because of their soft-tissue and dynamic capabilities. AI supports automated segmentation, lesion detection, and classification, improving diagnostic consistency and efficiency [1,2,8,11-15]. Radiomics may provide additional quantitative assessment of tendon, cartilage, and muscle abnormalities [34].

6.4 Rotator Cuff Disease

Rotator cuff disease includes tendinopathy and partial- or full-thickness tears. MRI evaluates tendon integrity, muscle atrophy, and fatty infiltration, while ultrasound provides dynamic assessment. AI-assisted analysis can automate tear detection and classification while improving reproducibility [1,2,11-15]. Radiomic features from tendons and muscles may further characterize degeneration, progression, and postoperative recovery [34].

6.5 Meniscal Injury

MRI is the reference standard for meniscal injuries. Deep learning has improved automated detection and classification, with MRNet demonstrating performance comparable to experienced radiologists [21]. AI can also segment menisci and classify tear patterns, reducing observer variability [11-14]. Radiomics provides quantitative assessment of meniscal texture and heterogeneity, with potential for identifying early degenerative changes.

6.6 Ligament Injuries

ACL, PCL, and collateral ligament injuries are common causes of joint instability. MRI remains the preferred modality for assessing ligament integrity and associated injuries. AI enables automated ligament segmentation

and injury detection and can simultaneously assess multiple joint structures [1,2,11-15]. Emerging radiomic biomarkers may characterize tissue quality and predict healing or postoperative outcomes, although further validation is needed [34].

6.7 Rheumatoid Arthritis

Rheumatoid arthritis is characterized by synovitis, cartilage destruction, and bone erosion. MRI and ultrasound are more sensitive than radiography for early inflammatory changes, including synovial hypertrophy, marrow edema, and erosions [3,4]. AI can automate lesion detection and quantify synovial volume and inflammatory burden, while radiomics may identify biomarkers associated with disease progression and treatment response [1,2,8,11-15].

6.8 Ankylosing Spondylitis

MRI is essential for detecting active sacroiliac inflammation before radiographic structural changes develop. Deep learning radiomics models have demonstrated promising performance in detecting sacroiliitis [33]. Machine learning approaches can also distinguish inflammatory sacroiliac lesions with improved consistency, supporting earlier diagnosis and treatment monitoring [56].

6.9 Sports Injuries

Sports injuries involve cartilage, ligament, tendon, muscle, and bone abnormalities requiring timely diagnosis. AI can automate detection of fractures, ligament and meniscal tears, tendon disorders, and cartilage lesions on radiography and MRI, while supporting examination prioritization [1,2,8,11-19]. Radiomics provides quantitative biomarkers of tissue integrity and healing that may assist rehabilitation monitoring [34].

6.10 Pain Prognostication

Because pain severity may correlate only modestly with structural abnormalities, quantitative biomarkers are increasingly important. AI and radiomics integrate information from cartilage, marrow, synovium, menisci, ligaments, muscles, and subchondral bone to identify imaging phenotypes associated with pain and progression [3,4,31,48]. Machine learning models incorporating imaging and clinical variables show potential for predicting osteoarthritis progression, functional decline, and treatment response [31,40,47,48]. MRI radiomic signatures may also support early OA detection and symptomatic risk stratification [31,32,39]. Clinical translation will require standardized protocols, external validation, explainable AI, and prospective multicenter studies [34,36-38].

Table 3. Clinical Applications of AI and Radiomics in Joint and Spine Disorders

Disease/Condition	Imaging Modality	AI/Radiomics Application	Clinical Benefit
Knee osteoarthritis	Radiography, MRI	Automated grading, progression prediction, cartilage radiomics	Early diagnosis and prognosis
Hip osteoarthritis	MRI, CT	Cartilage and bone radiomics	Disease characterization
Degenerative disc disease	MRI	Texture analysis, deep radiomics, automated grading	Early degeneration detection
Lumbar disc herniation	MRI	Automated detection and segmentation	Improved diagnostic accuracy
Lumbar spinal stenosis	MRI, CT myelography	Deep learning classification, radiomics	Surgical planning and severity assessment
Modic changes	MRI	MRI radiomics	Pain prediction and lesion characterization
Facet joint arthropathy	MRI	Deep learning classification	Automated diagnosis
Osteoporotic compression fractures	CT, MRI	Vertebral radiomics, opportunistic screening	Fracture risk assessment
Sacroiliitis	MRI	Deep learning radiomics	Early diagnosis of axial spondyloarthritis
Meniscal and ligament injuries	MRI	Automated detection and classification	Faster and standardized diagnosis
Rotator cuff disease	MRI, Ultrasound	AI-assisted tendon assessment	Tear detection and treatment planning
Rheumatoid arthritis	MRI, Ultrasound	Quantitative assessment of synovitis	Disease activity monitoring

7. AI-Based Clinical Decision Support Systems

Artificial intelligence (AI)-based clinical decision support systems (CDSS) are transforming musculoskeletal imaging by assisting radiologists and clinicians throughout diagnosis and treatment. By integrating imaging data with machine learning and deep learning, these systems improve diagnostic accuracy, workflow efficiency, reproducibility, and decision-making across joint and spine disorders [1,2,11-15,19,38].

7.1 Automated Detection

Automated detection is a mature AI application in musculoskeletal imaging. Convolutional neural networks (CNNs) can identify fractures, osteoarthritis, meniscal tears, ligament injuries, lumbar disc degeneration, spinal stenosis, and sacroiliitis on radiographs, CT, and MRI, with performance approaching that of expert radiologists

[20,21,23-26,33,43]. Models such as **MURA** and **MRNet** demonstrated accurate abnormality detection while reducing reporting time. These systems can also prioritize urgent examinations and improve diagnostic consistency [1,2,8,11-15].

7.2 Disease Classification

AI enables objective classification of lumbar disc degeneration, osteoarthritis, sacroiliitis, spinal stenosis, and facet arthropathy by recognizing complex imaging patterns [5,22-24,33]. Radiomic biomarkers further improve classification by capturing tissue heterogeneity and microstructural changes beyond qualitative assessment [9,10,27,28,31,34]. Automated classification provides standardized diagnostic support and reduces observer variability.

7.3 Severity Grading

AI algorithms support automated grading of knee osteoarthritis, lumbar spinal stenosis, and intervertebral disc degeneration using radiography and MRI [22,26,44-46]. Deep learning provides reproducible severity assessment, while radiomics identifies subtle biochemical and microstructural changes that may precede advanced structural damage [10,30,31].

7.4 Outcome Prediction

AI-based systems can integrate imaging biomarkers with demographic and clinical variables to predict disease progression, functional decline, postoperative recovery, and complications. Promising applications include predicting lumbar decompression requirements, osteoarthritis progression, chronic low back pain severity, and postoperative outcomes [5,35,40,47,48]. These models support individualized risk stratification and clinical decision-making.

7.5 Treatment Response Prediction

AI and radiomics may identify patients likely to benefit from specific treatments using biomarkers derived from cartilage, discs, paraspinal muscles, bone marrow, and synovium [29,31,34,35]. Longitudinal imaging and delta radiomics can monitor treatment-related tissue changes, assess therapeutic response, and identify non-responders [10,27].

7.6 Workflow Optimization

AI can automate image quality assessment, segmentation, quantitative measurements, lesion detection, structured reporting, and examination prioritization, reducing workload and reporting time [11,14,15,19]. Integration with PACS and radiology information systems can streamline interpretation while maintaining clinician oversight. Successful implementation requires standardized validation, explainability, interoperability, and adherence to ethical and regulatory standards [36-38].

8. Current Evidence from Clinical Studies

Evidence supporting AI and radiomics in musculoskeletal imaging has expanded considerably, with applications in diagnosis, classification, prognosis, and management of joint and spine disorders. Retrospective studies have reported high diagnostic performance across radiography, CT, and MRI, while radiomics provides complementary quantitative biomarkers for disease characterization and outcome prediction. However, routine clinical translation remains limited by methodological heterogeneity and insufficient prospective validation [1,2,8,9,11-15,27,28,34].

8.1 Summary of Major Studies

Landmark studies established the clinical potential of AI. **MURA** demonstrated large-scale automated abnormality detection on musculoskeletal radiographs, while **MRNet** achieved radiologist-level performance in detecting knee abnormalities on MRI [20,21]. In spine imaging, deep learning has been applied to lumbar spinal stenosis, while machine learning using CT myelography radiomic features has predicted surgical decompression levels [5,23]. Recent studies have also explored MRI radiomics for disc degeneration, Modic changes, sacroiliitis, osteoarthritis progression, and postoperative outcomes [22,29,30,31,33,35].

8.2 Diagnostic Performance

AI models have demonstrated high diagnostic accuracy for fractures, knee osteoarthritis, meniscal injuries, spinal stenosis, and disc degeneration, with performance comparable to experienced radiologists in selected applications [20-26,43-46]. Radiomics can identify subtle features associated with early osteoarthritis, chronic low back pain, vertebral marrow changes, and inflammatory sacroiliitis [10,29-33]. High sensitivity, specificity, and AUC values have been reported in selected clinical settings [1,2,8,11-15].

8.3 External Validation

External validation remains a major challenge because many AI and radiomics models are developed using retrospective, single-center datasets, increasing overfitting risk and limiting generalizability [8,11-14]. Differences in imaging protocols, scanners, acquisition parameters, and patient demographics can further affect performance. European Society of Radiology recommendations emphasize multicenter external validation, standardized reporting, transparent development, and prospective evaluation before routine implementation [37].

8.4 Meta-analysis Findings

Systematic reviews and meta-analyses support the potential of AI and radiomics in musculoskeletal imaging. Calivà et al. reported advances in AI-based MRI assessment of osteoarthritis, including cartilage evaluation and progression prediction [48]. Davey et al. found promising performance of MRI radiomics for early knee osteoarthritis but noted methodological heterogeneity [32]. Moon et al. reported high accuracy of machine learning for MRI-based sacroiliitis detection while emphasizing the need for larger prospective studies [56].

8.5 Current Evidence Gaps

Important limitations include small retrospective datasets, limited demographic diversity, inconsistent imaging protocols, and reduced reproducibility and external validity [1,2,8,11-15]. Radiomics is further affected by differences in acquisition, segmentation, feature extraction, and statistical methods [9,27,28]. Limited interpretability, insufficient prospective multicenter trials, and inadequate real-world impact assessment remain barriers. Future research should prioritize standardized pipelines, harmonized protocols, explainable AI, multicenter validation, and integration of imaging with clinical, molecular, and genomic data [34,36-38].

9. Challenges and Limitations

Despite substantial progress, AI and radiomics face technical, methodological, and regulatory challenges that limit clinical implementation. Key concerns include data quality, standardization, reproducibility, model robustness, generalizability, and regulatory oversight [1,2,8,9,11-19,27,28,34,36,37].

9.1 Small Datasets

Many studies rely on small, retrospective, single-center datasets. Limited sample sizes may fail to represent disease heterogeneity across demographics, severity, and imaging protocols, increasing bias and reducing robustness [1,2,8,11-15]. Multicenter databases and federated learning may help overcome these limitations while preserving confidentiality [12,14,15].

9.2 Lack of Standardization

Variability in image acquisition, preprocessing, segmentation, feature extraction, and statistical modelling can produce inconsistent radiomic features and hinder comparison between studies [9,27,28]. Standardization initiatives, including Image Biomarker Standardisation Initiative (IBSI) recommendations and uniform reporting guidelines, are important for reproducibility and multicenter research [9,27].

9.3 Scanner Variability

Differences in scanner manufacturers, magnetic field strength, reconstruction methods, voxel dimensions, slice thickness, sequences, and acquisition parameters can alter radiomic features [9,27,28]. Harmonization, normalization, and standardized acquisition protocols are therefore important for improving feature stability and model transferability [9,28].

9.4 Segmentation Challenges

Segmentation is a critical and labor-intensive radiomics step. Manual segmentation is time-consuming and subject to observer variability, while automated methods may struggle with unclear boundaries, artifacts, and complex anatomy [9,11-14]. Segmentation errors can directly affect feature extraction and model performance. Deep learning has improved automation, but further validation is needed for routine use [13,14,34].

9.5 Reproducibility

Reproducibility is limited by differences in study design, patient selection, preprocessing, feature extraction, and algorithms [9,27,28]. Incomplete methodological reporting, unavailable datasets, and restricted source-code access further hinder independent validation. Standardized reporting, open-source tools, benchmark datasets, and reproducible pipelines are therefore essential [9,27,28,37].

9.6 Model Generalizability

AI performance often decreases on external datasets because of differences in demographics, disease prevalence, scanners, workflows, and imaging protocols [1,2,8,11-15]. Large multicenter cohorts, prospective trials, and continuous model updating are important for improving generalizability [14,15,37].

9.7 Regulatory Issues

Clinical AI raises concerns regarding privacy, consent, data security, bias, accountability, and clinical responsibility. The black-box nature of many models may also limit interpretability and clinician trust [36,38,49-51]. Recommendations from the European Society of Radiology and the European AI Act emphasize explainability, monitoring, transparent validation, risk management, and human oversight [36,37]. Future regulation should balance innovation with patient safety and standardized evaluation.

10. Future Perspectives

AI and radiomics are increasingly shifting musculoskeletal imaging toward data-driven precision medicine. Future research should focus on robustness, reproducibility, interpretability, clinical integration, multicenter collaboration, federated learning, explainable AI, and digital biomarkers [1,2,8,9,11-19,27,28,34,36-38,49-51].

10.1 Multi-center Radiomics

Multicenter radiomics studies can improve reliability and generalizability by incorporating diverse populations, disease spectra, and imaging platforms [9,27,28]. Harmonized protocols, standardized feature extraction, and international reporting guidelines will further support reproducibility and external validation [9,27,28,37].

10.2 Automated Feature Extraction

Radiomics is moving from handcrafted features toward automated deep learning-based extraction. CNNs and foundation models can learn high-dimensional features directly from raw images, reducing manual processing and potentially capturing complex patterns beyond traditional radiomics [1,2,8,11-15,19]. Combining deep radiomics with automated segmentation may enable integrated quantitative image analysis.

10.3 Integration with Clinical Data

Future AI systems may combine radiomic biomarkers with clinical, laboratory, demographic, genetic, and molecular information. For joint and spine disorders, integrating imaging with symptoms, functional scores, inflammatory markers, and patient-specific factors may improve diagnosis, prognosis, treatment selection, and outcome prediction [10,31,34,47,48].

10.4 Federated Learning

Federated learning allows institutions to train AI models collaboratively without transferring patient data outside local servers, addressing privacy and data-sharing limitations [12,14,15]. This approach can increase dataset diversity, reduce institutional bias, and improve model robustness and external validity.

10.5 Explainable AI

Clinical adoption requires both predictive performance and transparency. Explainable AI (XAI) uses methods such as saliency maps, Grad-CAM, and attention mechanisms to show factors influencing model predictions and support error detection and accountability [36,38,49-51]. Integration of XAI into clinical decision support may improve clinician confidence and responsible deployment [36-38,49-51].

10.6 Digital Biomarkers

AI- and radiomics-derived digital biomarkers provide objective and reproducible measures of tissue composition, disease activity, progression, and treatment response [9,10,27,28]. Biomarkers from cartilage, discs, subchondral bone, marrow, synovium, muscles, and ligaments may support early detection, risk stratification, and outcome prediction in osteoarthritis, degenerative spine disorders, inflammatory arthropathies, and sports injuries [10,26,29-34,39-42,48,56]. With multicenter validation and integration into electronic health records and CDSS, these biomarkers may support personalized diagnosis, prognosis, treatment planning, and longitudinal monitoring, shifting imaging toward a predictive and precision-oriented clinical science [34,36-38].

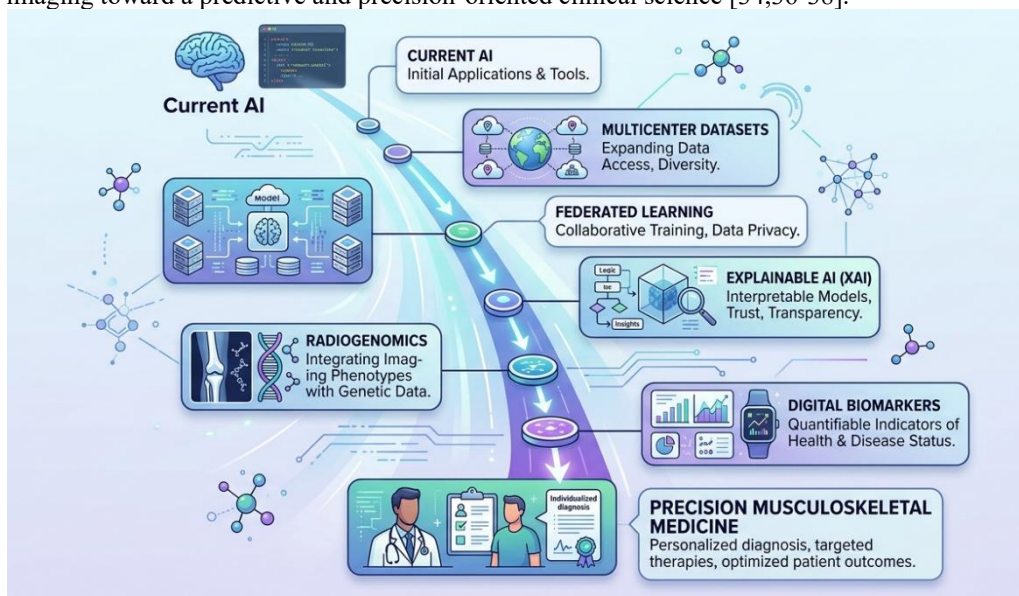


Figure 4. Future of AI in Musculoskeletal Imaging

11. CONCLUSION

Artificial intelligence (AI) and radiomics are transforming joint and spine pain imaging by shifting radiological practice from subjective visual interpretation toward objective, quantitative, and data-driven assessment. The integration of machine learning, deep learning, and radiomics with radiography, CT, MRI, and ultrasound has improved detection, classification, severity grading, and prognostic evaluation of musculoskeletal disorders, including osteoarthritis, degenerative disc disease, spinal stenosis, sacroiliitis, ligament and meniscal injuries, rotator cuff pathology, and inflammatory arthropathies. These technologies also support personalized treatment planning and clinical decision-making [1,2,5-35,39-48,52-56].

Radiomics enables extraction of high-dimensional imaging biomarkers that capture tissue heterogeneity and microstructural changes beyond human visual perception. Combined with AI and clinical information, these biomarkers support earlier disease detection, risk stratification, prediction of disease progression, postoperative outcomes, and treatment response, advancing precision musculoskeletal medicine [9,10,26-35,39-42,47,48,56]. Emerging approaches such as explainable AI, automated image analysis, federated learning, and digital biomarkers may further enhance clinical utility.

Despite these advances, clinical implementation remains limited by small datasets, imaging variability, lack of standardized radiomics workflows, segmentation inconsistencies, insufficient external validation, and concerns regarding reproducibility, interpretability, and regulatory compliance [9,27,28,36-38,49-51]. Addressing these challenges through multicenter research, standardized imaging protocols, transparent AI frameworks, and prospective clinical validation will be essential for developing reliable and generalizable decision-support systems.

Overall, AI and radiomics represent a significant shift toward quantitative and precision-oriented musculoskeletal imaging. With improved standardization and stronger clinical evidence, these technologies may become integral to routine radiological practice, supporting accurate diagnosis, individualized management, and improved outcomes in patients with joint and spine pain [34,36-38].

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