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IP International Journal of Orthopaedic Rheumatology

Journal homepage: https://www.ijor.org/

Review Article

Artificial intelligence in the prediction of radiographic progression in ankylosing spondylitis: Current evidence and future directions

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Abstract

Ankylosing spondylitis (AS), a chronic inflammatory disease affecting the spine, is marked by gradual structural damage that often remains undetected in early stages. Predicting radiographic progression is crucial for timely intervention and personalized treatment. Traditional scoring systems, though validated, are limited by subjectivity, delayed detection, and poor sensitivity to change. Recent advances in artificial intelligence (AI), particularly machine learning and deep learning, offer novel tools for early and accurate prediction of progression. These AI models leverage imaging, clinical, laboratory, and genetic data to identify high-risk patients and stratify disease phenotypes. Studies have shown that AI-based systems can outperform traditional approaches in sensitivity and efficiency. Despite promising results, challenges remain in model generalizability, interpretability, and clinical integration. Future research must focus on explainable, multi-modal AI systems validated across diverse populations to fully harness their potential in improving AS management. Clinicians and researchers should now focus on integrating these validated AI tools into real-world care pathways to enable early intervention and data-driven treatment planning.

Key Messages: 1. AI models predict radiographic progression in AS more accurately than traditional scoring systems; 2. Integration of imaging, clinical, and genetic data enhances predictive power and personalization; 3. Explainable and validated AI tools are essential for real-world clinical adoption in AS care.

Keywords: Ankylosing spondylitis, Radiographic progression, Artificial intelligence, Machine learning, Deep learning, Predictive modelling, mSASSS.

Received: 18-06-2025; **Accepted:** 21-10-2025; **Available Online**: 10-12-2025

1. Introduction

Axial spondyloarthritis (axSpA) is a chronic, progressive, immune-mediated inflammatory condition that primarily affects the axial skeleton, including the spine and sacroiliac joints.[1-3] Its pathogenesis involves a complex interplay of genetic susceptibility and environmental influences.[4] Ankylosing spondylitis (AS), the radiographic subset of axial spondyloarthritis (axSpA), is marked by chronic inflammatory back pain, reduced spinal mobility, and gradual structural deterioration. Over time, the condition leads to the fusion of vertebral joints, producing the characteristic "bamboo spine" appearance on radiographs due to ossification of ligaments and joints.[5] Radiographic spinal progression is observed in roughly 20% to 50% of individuals with ankylosing spondylitis within two years.[6-8] Although the axial skeleton is the primary site of involvement, peripheral joints may also be affected, with patients commonly experiencing morning stiffness and pain. Moreover, extra-articular manifestations such as anterior uveitis, psoriasis, and inflammatory bowel disease (IBD) are frequently observed, particularly in Western populations.[5]

A major clinical challenge in AS lies in its delayed diagnosis. Radiographic changes often lag behind clinical symptoms and inflammatory activity by several years, contributing to diagnostic delays ranging from 8 to 10 years in many patients.[5,9] This delay can result in missed opportunities for early therapeutic intervention, during which disease-modifying therapies such as tumor necrosis factor (TNF) inhibitors or interleukin-17 (IL-17) blockers may be most effective.[5,9,10] While MRI has improved early detection by visualizing active inflammation in the sacroiliac joints, the ability to predict long-term radiographic progression remains limited.[9,10] The sensitivity of MRI in the diagnosis of AS ranges from 54% to 95%, whereas the specificity ranges from

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https://doi.org/10.18231/j.ijor.11861.1763373152

83% to 100%.[11-13] Accurate prediction of structural damage is essential not only to optimize clinical decision-making but also to guide treatment strategies and personalize care pathways.

Recent advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), offer promising solutions for these unmet needs. By leveraging complex, high-dimensional datasets—including imaging, clinical, and laboratory data—AI systems can detect hidden patterns, stratify risk, and make predictive inferences with increasing accuracy. In rheumatology, AI applications are gaining traction for diagnostic support, disease activity monitoring, and prognostication. In AS, AI-driven models can potentially transform care by enabling early identification of high-risk patients, anticipating radiographic progression, and supporting timely, targeted interventions.

This comprehensive review explores the current landscape of AI-based methods for predicting radiographic progression in patients with ankylosing spondylitis. We evaluate the types of data used, the range of machine learning and deep learning models applied, their performance metrics, and the clinical applicability of these tools. By synthesizing the existing evidence, this article aims to provide clinicians, researchers, and digital health stakeholders with insights into the readiness and future potential of AI for structural progression prediction in AS.

2. Methodology

To identify relevant studies, a comprehensive search of the English-language medical literature was conducted on 1st May 2025, utilizing databases including PubMed, Ovid Medline, and Google Scholar. The search was then updated on 2nd, May 2025.

We employed a combination of keywords related to our topic: "Deep learning," “Machine learning”, "artificial intelligence," and "radiographic progression in ankylosing spondylitis". These terms, along with their MeSH terms, were strategically combined using the Boolean operators "AND" and "OR" to ensure comprehensive and relevant results. Articles retrieved from the initial search were screened for eligibility and thematic relevance based on their titles and abstracts. Additionally, the reference lists of the included articles were examined to identify any further pertinent publications. By utilizing a broad range of search terms across multiple databases, we aimed to minimize publication bias. However, it is important to acknowledge that some bias may still be present due to the exclusion of non-English language literature, conference proceedings, and unpublished studies.

3. Discussion

3.1. Radiographic progression in ankylosing spondylitis

Radiographic changes in ankylosing spondylitis (AS) develop gradually, often becoming apparent only after 1–2 years of disease onset. The earliest identifiable change is cortical bone definition loss, particularly on the iliac side of the sacroiliac joints, followed by subchondral erosions, joint space narrowing or widening, and syndesmophyte formation. The modified Stoke Ankylosing Spondylitis Spinal Score (mSASSS) remains the standard tool for quantifying spinal damage by assessing anterior vertebral corners from the lower cervical to upper lumbar spine. Syndesmophytes at baseline strongly predict future progression, with even a single new lesion over two years deemed clinically significant.[10,14] Radiographic progression is generally slow, with 40–44% of patients showing detectable changes over two years, especially those with existing syndesmophytes,[9,10] and tends to occur more rapidly in men.[15]

Several factors influence this progression, including high baseline mSASSS, elevated inflammatory markers (ESR, CRP, cytokines, MMPs, adipokines, and bone metabolism indicators), longer disease duration, hip involvement, and smoking.[16-20] Serum alkaline phosphatase (ALP), indicating bone turnover, has emerged as an early biochemical marker of structural progression.[16,20] Obesity is a newly recognized predictor across sexes, while bisphosphonate use has been linked to increased progression in women.[15] Although anemia does not directly reflect disease severity, it is associated with heightened disease activity and functional decline.[22]

Ciurea et al. reported comparable clinical outcomes between non-radiographic axSpA (nr-axSpA) and those with bilateral grade 2 sacroiliitis, while more severe sacroiliac damage correlated with greater progression and a better response to TNFi therapy.[23] Radiographic progression is strongly associated with baseline inflammation, particularly elevated CRP levels, but this is modulated by the fibrin clot phenotype—patients with loose, fibrinolysis-prone clots show stronger CRP-progression correlations.[24] Circulating biomarkers such as anti-PPM1A antibodies are also predictive; elevated levels are linked with increased syndesmophyte formation and mSASSS progression, particularly in anti-TNF-treated patients.[25] Additionally, low leptin and high-molecular-weight adiponectin levels, especially in men, have shown inverse associations with radiographic progression, suggesting a protective adipokine effect.[26]

3.2. Current radiographic scoring systems in AS

Radiographic evaluation remains a cornerstone in the diagnosis and monitoring of ankylosing spondylitis (AS), particularly in detecting and quantifying structural damage. The mSASSS assesses anterior vertebral corners in the cervical and lumbar spine, scoring structural damage on a 0–

3 scale with a maximum score of 72. A change of ≥2 points over two years is considered clinically meaningful.[9,16,27] Despite its validation, it excludes the thoracic spine and exhibits low sensitivity to short-term change.

The Bath Ankylosing Spondylitis Radiology Index (BASRI) is another scoring method that evaluates both the cervical and lumbar spine along with the sacroiliac joints. But it is limited by ceiling effects and poor sensitivity to subtle changes, making it less favorable in detecting disease progression on radiography.[9,28]

The original and modified New York criteria for the diagnosis of ankylosing spondylitis (AS) emphasized radiographic evidence of sacroiliitis as a central factor, combined with clinical symptoms such as low back pain, reduced lumbar spinal mobility, and chest expansion limitation. A patient is considered positive for radiographic sacroiliitis if the score is greater than or equal to grade II bilaterally or greater than or equal to grade III unilaterally. However, it is limited by low sensitivity and significant inter-reader variability.[9,29]

The Assessment of SpondyloArthritis International Society (ASAS) for ankylosing spondylitis introduces two diagnostic pathways: an imaging-based arm requiring evidence of sacroiliitis on radiographs or MRI alongside one spondyloarthritis (SpA) feature, and a clinical arm based on HLA-B27 positivity with at least two SpA features. This framework has shown diagnostic performance with a sensitivity of 82.9% and a specificity of 84.4%. Compared to older criteria, the ASAS system showed improved specificity. These refinements allow for earlier and more accurate classification, especially in non-radiographic cases.[30]

MRI-based tools such as the Spondyloarthritis Research Consortium of Canada (SPARCC) score detect early inflammation but are limited in assessing chronic structural changes and are primarily used in research settings.[31] CT offers high-resolution visualization of bone damage but is constrained by radiation exposure.[9]

Table 1 presents the current ankylosis spondylitis radiographic scoring systems with their strengths and limitations.

3.3. Artificial Intelligence-based approaches in predicting Radiographic progression in AS

Artificial intelligence (AI) technologies, like machine learning (ML) and deep learning (DL), are increasingly being integrated into clinical settings to predict radiographic progression in ankylosing spondylitis (AS), with promising results. The current scoring systems in use are accurate, but they hold many limitations.

3.3.1 Image-based AI model

Manual scoring systems, like mSASSS or the Modified New York Criteria, suffer from subjectivity, time constraints, inter-reader variability, and limited scalability. This reduces the generalizability of these methods and overall accuracy. Convolutional neural networks (CNNs) have been deployed to automate radiographic scoring. Automated AI tools can rapidly analyze and score the radiographs, saving time and enabling real-time assessment in clinical practice. Koo et al. developed a CNN model to apply mSASSS to spinal radiographs. The CNN model was trained to analyze the plain radiographs and automatically give scores to the cervical and lumbar vertebral body corners using the mSASSS. The model was found to achieve an accuracy of 91.6%, a sensitivity of 80.3%, and a specificity of 94.2%. This tool reduced the manual workload and inter-observer variability, enhancing the overall generalizability and facilitating large-scale clinical and research applications.[32]

Table 1: Presents the current ankylosis spondylitis radiographic scoring systems with their strengths and limitations

Scoring System	Assessed Regions	Scoring Range	Strengths	Limitations
mSASSS (Modified Stoke AS Spine Score)	Cervical & lumbar spine (anterior corners)	0–72	Most sensitive for progression; widely validated; used in clinical trials	Thoracic spine not included; slow progression (over 2 years) may limit short-term detection
BASRI (Bath AS Radiology Index)	SI joints, lumbar, and cervical spine	0–12	Simple to use; includes SI joints	Ceiling effects, limited sensitivity to change over time
SASSS (Original Stoke Score)	Lumbar spine (anterior + posterior corners)	0–72	Useful for lumbar spine damage	Poor sensitivity to change; posterior scoring is less reliable
Modified New York Criteria	Sacroiliac joints	Qualitative (Grade 0–4)	Basis for AS diagnosis/classification, more weightage on clinical symptoms	Low sensitivity in early disease; inter-observer variability
SPARCC (MRI-based)	SI joints and spine (MRI inflammation)	Variable	Sensitive to early inflammation; good for treatment monitoring	Limited in assessing chronic/structural changes; costly; MRI availability varies
CT-based scoring	Sacroiliac joints, spine	Variable (depends on study)	High-resolution visualization of bone damage	High radiation dose; not suitable for frequent monitoring

Traditional scoring systems that use plain radiographs often miss early and subtle inflammatory and structural changes that may precede the visible syndesmophytes or ankylosis. Detecting significant progression using mSASSS methods requires monitoring for ≥2 years, which limits their use in short-term prediction. Deep learning models can use enhanced resolution to extract subclinical changes from the radiographs or integrate MRI for early detection of damage invisible to the human eye. It can also detect micro-level clinically significant progression, enabling early intervention.

3.3.2 Clinical data-based model

Koo et al. investigated the application of machine learning techniques to forecast radiographic progression in ankylosing spondylitis, utilizing longitudinal data extracted from electronic medical records (EMRs).[33] Machine learning models like logistic regression with least absolute shrinkage and selection operation (LASSO), random forests (RF), and XGBoost (extreme gradient boosting) were applied to a set of data comprising features like demographics, laboratory tests, medication history, and disease activity indices. Among the above algorithms tested, random forest (RF) showed the best performance with an area under the curve (AUC) of 0.79, accurately identifying key predictors of radiographic progression like baseline mSASSS, age, and alkaline phosphatase levels.[33] This approach may contribute to early intervention decisions by identifying patients at high risk of progression.

Radiographic progression is the structural damage influenced by the combined interactions of clinical, laboratory, and environmental factors. Baek IW et al. employed two ML models—artificial neural networks (ANN) and generalized linear models (GLM)—to predict radiographic progression using clinical, laboratory, and radiographic documents from the medical records. They concluded that machine learning models were feasible in real-world settings and displayed good performance. ANN performed better than GLM overall and was a better-suited model for analysis.[2]

3.3.3 Multi-modal AI model

Current scoring systems consider imaging data and often ignore other disease parameters, like genetic factors. Advanced AI models can integrate imaging with clinical, laboratory, and genetic data to provide a comprehensive risk prediction model for progression. Y.B. Joo et al used AI tools such as generalized linear model (GLM), naïve Bayes (NB), decision trees (DT), K nearest neighbors (KNN), and support vector machines (SVM) to stratify 412 AS patients into three distinct progression phenotype clusters based on baseline mSASSS data, incorporating 23 clinical factors like sex, age at diagnosis, smoking, HLA-B27, uveitis, and peripheral arthritis. The results emphasize the role of smoking in the high baseline syndesmophyte development in ankylosing spondylitis. This approach highlights the heterogeneity in AS and demonstrates how AI can reveal hidden patterns for personalized treatment planning.[34]

3.3.4 Group-based trajectory and decision trees-based model

Kang et al. (2022) utilized group-based trajectory modeling to identify three distinct patterns of radiographic progression in AS patients. Multivariate logistic regression identified clinical factors associated with each trajectory. A decision tree was then developed using clinical factors such as sex, age at diagnosis, ocular involvement, and peripheral joint involvement to classify patients into these trajectory groups, aiding in personalized prognosis and treatment planning. The team assessed structural damage in the spinal radiographs using mSASSS. Group-based trajectory modeling (GBTM) was employed to classify patients into distinct progression patterns based on longitudinal mSASSS data.[35]

3.3.5 Anatomy-centred model

Incorporating anatomy-centred deep learning in AI algorithms enhances their utility and reliability in the prediction of radiographic sacroiliitis. A novel deep learning model focusing exclusively on the sacroiliac joints (SIJs) was tested against models trained on full pelvic radiographs. The anatomy-centered model achieved higher AUC scores of 0.899-0.957 compared to the standard models. The significance of the study is highlighted by the fact that anatomy-centered models were consistent with their results despite changes in disease prevalence and severity, emphasizing their applicability in real-world variation. Secondly, it effectively reduced the irrelevant anatomical structures, enhancing the overall accuracy of disease detection and predicting progression to sacroiliitis.[1]

These AI-driven methodologies represent a paradigm shift in predicting radiographic progression of ankylosing spondylitis, moving toward personalized prognostics and early intervention strategies through automated, interpretable, and data-rich predictive modeling.

3.4. Challenges in real-world deployment

The application of artificial intelligence (AI) in real-world clinical settings for the diagnosis and monitoring of ankylosing spondylitis (AS) has demonstrated considerable potential, yet several challenges persist that hinder its widespread adoption. A major limitation in existing studies is the reliance on datasets obtained from single-center registries, which are often affected by inherent biases such as incomplete data, inconsistent imaging quality, and restricted geographic and demographic representation. These issues compromise the generalizability and robustness of AI models across diverse ethnic groups and healthcare systems. To

enhance external validity, future research must prioritize the inclusion of multi-center and multi-ethnic cohorts.

Moreover, the complexity of AI systems poses practical challenges for clinical integration. These systems must be designed with interpretability in mind to facilitate adoption by physicians and other healthcare professionals. The development of hybrid AI models that incorporate explainability techniques, such as Shapley Additive Explanations (SHAP) and Gradient-weighted Class Activation Mapping (Grad-CAM), is essential for improving clinician trust and usability.

Despite the automation advantages conferred by AI, many models continue to rely heavily on large volumes of expert-labeled data, which introduces risks of annotation bias and inter-observer variability. To address this, the adoption of semi-supervised or self-supervised learning approaches is recommended, as they can reduce dependence on manual labeling while maintaining model performance.

4. Future Directions

Artificial intelligence (AI) has made notable strides in recent years, offering transformative potential in the diagnostic and prognostic evaluation of various diseases, including ankylosing spondylitis (AS). In the realm of radiographic progression prediction in AS, AI is expected to evolve through the integration of heterogeneous data sources—encompassing imaging, clinical records, genetic profiles, and laboratory parameters—to enable individualized risk stratification and disease forecasting. However, despite this promise, only six AI-based research models have been developed to predict radiographic progression in AS, revealing a critical gap in current efforts.

To advance this field, future research should focus on the development of robust, interpretable AI models that are both clinically relevant and technically sound. Emphasis must be placed on explainable AI methodologies to enhance clinician trust, support regulatory compliance, and facilitate seamless integration into clinical workflows. Real-time implementation via electronic health records and radiology information systems can significantly improve early detection and disease management. Additionally, the incorporation of emerging technologies, such as wearable devices and digital biomarkers, may further refine the continuous monitoring of disease activity and treatment outcomes.

Collaboration across institutions and regions is essential to generate large, demographically diverse datasets that ensure the generalizability and external validity of AI models. A multidisciplinary approach involving clinicians, data scientists, and regulatory stakeholders will be key to translating AI innovations into practical tools for everyday rheumatologic care. Ultimately, the expansion and refinement of AI in predicting radiographic progression in AS holds the potential to optimize therapeutic decision-making, anticipate treatment response, and personalize disease management strategies.

5. Conclusion

Ankylosing spondylitis (AS) is a complex, progressive inflammatory condition with significant variability in its clinical and radiographic manifestations. Traditional diagnostic criteria, including the modified New York and ASAS classification systems, have played a pivotal role in early recognition and classification of AS, yet limitations such as inter-reader variability and sensitivity issues persist. Recent advancements in artificial intelligence (AI) have opened new avenues for the diagnosis and monitoring of AS, particularly through radiographic imaging analysis and clinical data integration. Despite promising developments, challenges remain in the form of dataset biases, lack of generalizability, and the need for model interpretability. Future research should prioritize the inclusion of diverse, multi-institutional datasets, the development of explainable AI models, and integration into clinical workflows. With continued innovation and validation, AI holds the potential to revolutionize AS management by enabling early diagnosis, monitoring disease progression, and informing personalized treatment strategies.

6. Source of Funding

None.

7. Conflict of Interest

The authors declare that there is no conflict of interest. The authors have no relevant financial or non-financial interests to disclose.

8. Acknowledgements

None.

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Cite this article: Chaturvedi VP, Rawat S, Shanmugam H, Airen L. Artificial intelligence in the prediction of radiographic progression in ankylosing spondylitis: Current evidence and future directions. *IP Int J Orthop Rheumatol*. 2025;11(2):55-61.