UNDERGRADUATE RESEARCH IN NATURAL AND CLINICAL SCIENCE AND TECHNOLOGY (URNCST) JOURNAL
Read more URNCST Journal articles and submit your own today at: https://www.urncst.com

REVIEW OPEN ACCESS

OSTEO-AI: A Systematic Review and Meta-Analysis of Artificial Intelligence Models for Osteoarthritis and Osteoporosis Detection and Prognosis

Melina Alborzi, BSc [1]*, Parsa Abadi, MSc [2]

[1] Faculty of Science, McMaster University, Hamilton, Ontario, Canada L8S 4L8
[2] Department of Computer Science, University of Western Ontario, London, Ontario, Canada N6A 3K7

*Corresponding Author: alborzim@mcmaster.ca

Abstract

Introduction: Osteoarthritis (OA) and osteoporosis are leading degenerative bone diseases that diminish quality of life and impose significant socioeconomic costs. Traditional diagnostic approaches, including imaging and bone density assessments, often fail to detect disease in its early stages, delaying critical interventions. Emerging artificial intelligence (AI) techniques, particularly those employing machine learning (ML) and deep learning (DL), offer promising avenues for early detection and more accurate prognostication.

Methods: We conducted a systematic review of AI models developed between 2018 and 2024, assessing their performance in diagnosing and predicting the progression of OA and osteoporosis. Studies utilizing supervised or unsupervised methods applied to imaging modalities (e.g., X-ray, MRI, DXA) or clinical data were included. We evaluated model accuracy, reliability, clinical applicability, and generalizability. Quality and risk of bias were assessed using a modified CLAIM framework, ensuring alignment with transparency, validity, and clinical integration standards.

Results: Of 2,300 identified articles, 33 studies met the inclusion criteria. Top-performing models for OA reached up to 97% accuracy, with one study achieving an AUC of 0.93 for MRI-based progression prediction. For osteoporosis, the strongest models attained a C-index of 0.90 using DXA imaging, indicating robust fracture risk prediction. Nevertheless, many studies relied on geographically or demographically homogeneous datasets, limiting broader applicability. Only 15% included external validation, and a substantial proportion lacked interpretability features essential for clinical adoption.

Discussion: AI-driven models outperformed conventional diagnostic tools in accuracy and early disease detection. However, the limited dataset diversity, infrequent external validation, and insufficient model interpretability pose barriers to clinical integration. The reliance on male-dominant datasets for osteoporosis and geographically narrow cohorts for OA underscores the need for broader data representation. Standardizing evaluation metrics and improving explainability will enhance cross-study comparisons and support adoption in practice.

Conclusion: AI holds transformative potential for improving OA and osteoporosis diagnostics, facilitating earlier interventions, and informing personalized patient management. Future work should prioritize diverse, well-validated datasets; transparent, clinician-friendly interfaces; and standardized performance metrics. Addressing these challenges will enable AI to evolve from a promising innovation into a cornerstone of global musculoskeletal healthcare.

Keywords: artificial intelligence; osteoarthritis; osteoporosis; diagnostic models; imaging modalities; machine learning; clinical integration; disease progression; systematic review; dataset diversity

Introduction

Osteoporosis and Osteoarthritis (Epidemiology, Pathophysiology, Diagnosis)

Osteoporosis and osteoarthritis (OA) are two of the most prevalent degenerative bone diseases, affecting millions of individuals worldwide and placing a substantial socioeconomic burden due to healthcare costs and loss of productivity [1, 2]. Osteoporosis is a systemic skeletal disorder characterized by low bone mineral density, micro-architectural deterioration of bone tissue leading to more porous bone, and a consequent increase in fracture risk [3]. OA is the most common joint disorder clinically defined as degeneration of joints causing pain, swelling and stiffness, affecting a person's ability to move and activities of daily living (ADLs) [4]. Both conditions lead to severe functional limitations, increased fracture risk, and lower quality of life [5, 6]. Traditional diagnostic methods for these diseases, such as magnetic resonance imaging (MRI), X-rays, Fracture Risk Assessment Tool (FRAX), and Dual-energy X-ray Absorptiometry (DXA), primarily focus on assessing structural damage in OA and bone mineral density (BMD) in osteoporosis [3, 7]. However, these methods

have limitations in accurately predicting disease progression and identifying early-stage disease, often resulting in delayed interventions [8]. Delayed diagnosis allows the degenerative process to continue unchecked, resulting in severe cartilage loss and bone damage that cannot be reversed [9]. Early detection allows for the implementation of therapeutic strategies aimed at slowing disease progression, such as pharmacological treatments, lifestyle modifications, and physical therapies [9].

Emergence of Artificial Intelligence

In recent years, advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) have let us better detect and predict the progression of both OA and osteoporosis by being capable of analyzing complex datasets [10]. AI has been extensively applied to OA detection using various imaging modalities like X-rays, CT, and MRI, achieving high diagnostic accuracy [11]. Several DL models, particularly Convolutional Neural Networks (CNNs), have successfully classified OA severity using the Kellgren-Lawrence scale, a radiographic grading system that assesses factors such as osteophytes, joint space narrowing, and subchondral changes to determine OA progression. For instance, Muham et al. constructed a deep learning model that reached an accuracy of 97% for the early detection and classification of knee OA, underscoring the potential of AI as an adjunctive tool in radiological assessment [12]. Similarly, AI has been used to diagnose osteoporosis, where models predict BMD from CT and X-ray with accuracy rates ranging from 82% to 96% and is a non-invasive approach to DXA scans [13, 14]. Some AI-based Fracture Risk Assessment Models (ex., CatBoost) have also performed better than conventional tools like FRAX, with the added advantage of using more parameters and big data [15]. Despite its promise, the application of AI in detecting and predicting osteoporosis and osteoarthritis faces several challenges. Existing AI models often vary in terms of their simplicity of use, reliability, and accuracy, which limits their integration into clinical practice [13-15]. Furthermore, many models lack a standardized approach to evaluating and comparing their performance, making it challenging to identify the most effective ones for clinical settings [13-15].

The primary aim of this study is to first systematically identify supervised and unsupervised AI models developed between 2018 and 2024 that utilize imaging modalities or clinical data for osteoporosis and OA detection and progression. Next, we aim to compare these models based on their reliability, accuracy and potential clinical applications. From this comparison, we intend to identify the top three best-performing models.

Research Aims

Our research aims to explore two questions. (1) How do supervised or unsupervised AI models that utilize imaging modalities or clinical data compare to other AI models regarding reliability, accuracy, and potential clinical applicability for detecting and predicting the progression of OA and osteoporosis in adults aged 18 and older? (2) What are the top 3 performing AI/ML models developed between 2018 and 2024 for detecting and predicting the progression of OA and osteoporosis in adults, based on reliability, accuracy, and potential clinical application?

Methods

Study Design

A systematic review was conducted to identify and evaluate supervised and unsupervised AI models developed between 2018 and 2024 for detecting and predicting the progression of OA and osteoporosis in adults. Inclusion and exclusion criteria are listed in Table 1.

Table 1. Inclusion Criteria for Studies Developing AI Models Utilizing Imaging Modalities for the Diagnosis and Prognosis of Osteoarthritis and Osteoporosis

Criteria	Description
Study Type	Peer-reviewed studies published between January 2018 and October 2024. Studies not peer-reviewed, including conference abstracts, preprints, editorials, reviews, or case reports are excluded.
Population	Adult patients aged 18 years and older diagnosed with osteoarthritis OA or osteoporosis.
Intervention	Studies utilizing supervised or unsupervised AI/machine learning models (e.g., CNN, Recurrent Neural Networks [RNN]) for disease detection, prediction, or progression tracking.
Outcomes	Studies reporting performance metrics such as accuracy, precision, recall, F1-score, Area Under the Curve (AUC) or Area Under the Receiver Operating Characteristic Curve (ROC-AUC).
Data Input	Use of imaging modalities (DXA, X-rays, CT scans, MRI) as inputs for AI models. Studies not employing imaging modalities or exclusively using clinical/non-imaging datasets are excluded.
Language	Articles in English only.
Data set	Publicly available "gold standard" datasets. For instance: OAI, MOST, UK biobank, MrOS. Studies not using publicly available or validated gold standard datasets (e.g., studies using privately curated or inaccessible datasets without transparency) are excluded.

In Table 1, please note that "gold standard" datasets refer to publicly available, high-quality datasets widely recognized and validated for osteoarthritis and osteoporosis research. These include datasets such as the Osteoarthritis Initiative (OAI) and the Multicenter Osteoarthritis Study (MOST) for osteoarthritis and datasets like the MrOS (Osteoporotic Fractures in Men Study) and UK Biobank for osteoporosis. These datasets serve as benchmarks for training and evaluating AI models, as they provide comprehensive, well-annotated imaging data and clinical information critical for assessing the performance of diagnostic and prognostic algorithms. Their established reliability ensures a robust foundation for comparing AI model outcomes against clinically validated standards.

Data Extraction and Search Strategy

A comprehensive search was performed across multiple electronic databases, including PubMed, CINAHL, Web of Science, and Ovid MEDLINE. The search strategy combined keywords and Medical Subject Headings (MeSH) terms related to AI and targeted diseases. Keywords include: "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" AND "Osteoarthritis" AND "Osteoporosis" AND "Osteoporotic Fractures" OR "Bone Density".

The results of these database searches were then uploaded to Covidence for both abstract and full-text screening. Two authors independently conducted the screening, and any disagreements were resolved by discussion among the authors.

Results

Study Selection and Study Characteristics

The initial database search yielded 2,300 studies, and 930 duplicates were excluded. All studies underwent screening based on their title and abstract, resulting in the exclusion of 1304 for not meeting the inclusion and exclusion criteria. A total of 66 studies proceeded to full-text evaluation. After full-text screening, 33 studies were excluded. Following this process, 33 studies were included in the final analysis. Conflicts during the selection process were resolved through discussion. This review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent and replicable methodology [18]. The detailed selection process is illustrated in the PRISMA flow diagram (see Figure 1).

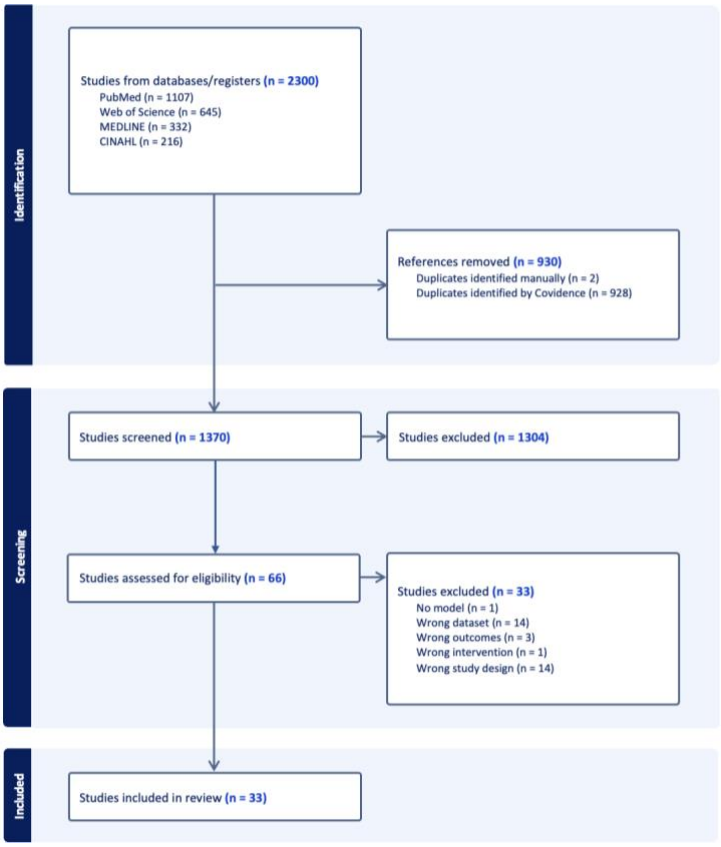

Figure 1. PRISMA Flow Diagram of the Study Selection Process. The diagram shows the identification, screening, eligibility assessment, and inclusion of studies in the systematic review, along with reasons for exclusion at each stage. This figure has been created using Covidence.

Quality Assessment

We evaluated studies for quality and risk of bias using a modified version of the Checklist for Artificial Intelligence in Medical Imaging (CLAIM), which is specifically designed to ensure transparency, reproducibility, and clinical applicability in AI research [19]. CLAIM includes key considerations across six domains: Study Participants and Dataset Transparency, Model Development and Design, Model Evaluation and Validation, Reporting and Transparency, Bias and Generalizability, and Clinical Impact and Usability. Adjustments were made to the Bias and Fairness domain (renamed Bias and Generalizability) to emphasize dataset diversity and real-world alignment, and to the Clinical Applicability domain (renamed Clinical Impact and Usability) to focus on the potential clinical utility of the models. These adjustments better align with the objectives of our systematic review.

Each study was systematically assessed using these modified domains (Table 2). Ratings for risk of bias were assigned as Low, Moderate, High, or Unclear for each domain, with considerations for both the training and testing datasets. The distribution of risk levels across the six CLAIM domains, as shown in Figure 2, highlights trends in the quality and risk of bias among the included studies indicating that while internal validation is robust in many cases, external validation and practical application are often less addressed [19].

Table 2. Checklist for Artificial Intelligence in Medical Imaging (CLAIM) for Systematic Reviews Focused on AI Models in Osteoarthritis and Osteoporosis

Domain	Description
1. Study Participants and Dataset Transparency	Evaluates whether the study population and datasets are representative of the intended clinical population and clearly described.
2. Model Development and Design	Focuses on the AI model's architecture, training process, and reproducibility of design.
3. Model Evaluation and Validation	Assesses the metrics used to evaluate model performance, methods to avoid overfitting, and external validation to ensure generalizability.
4. Reporting and Transparency	Ensures that the study is sufficiently transparent to allow reproducibility and that data and model details are accessible.
5. Bias and Generalizability	Focuses on the study's efforts to assess demographic and dataset diversity, relevance to the target clinical population, and practical generalizability of results.
6. Clinical Impact and Usability	Evaluates whether the study provides meaningful insights into the model's potential clinical utility, simplicity of integration, and the actionability of predictions for clinicians.

Notes: This table is adapted from Mongan et al. (2020) "Checklist for Artificial Intelligence in Medical Imaging (CLAIM): A Guide for Authors and Reviewers" [19].

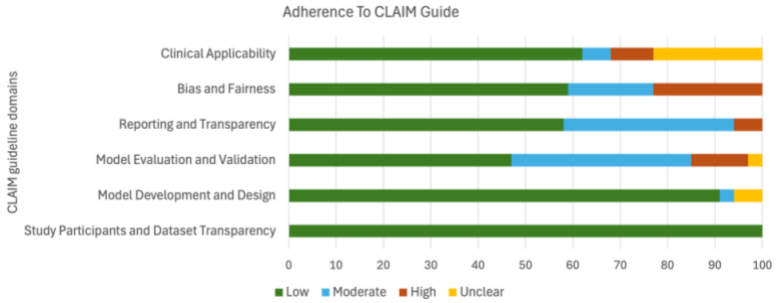

Figure 2. Bar Chart of the Percentage Distribution of Studies Evaluated for Risk of Bias Across the Six Domains of the CLAIM. Risk levels are categorized as Low (green), Moderate (blue), High (brown), and Unclear (yellow) (n=33, studies included). This figure has been created using Microsoft Excel.

Meta-Analysis

We developed a comprehensive scoring system to ensure a fair and consistent comparison of the diagnostic and prognostic models for osteoarthritis and osteoporosis included in this meta-analysis (Table 3). Since the models in the analyzed papers vary widely in terms of reported metrics, dataset sizes, validation approaches, and other methodological factors, this scoring system standardizes the evaluation process across four domains: Dataset Quality, Performance, Clinical Applicability, and Technical Rigor, each contributing 25 points to a total score of 100. The system accounts for variations in dataset size, validation methods, metric reporting, clinical integration, and reproducibility, while mandatory

criteria ensure the inclusion of essential machine learning metrics and validation details. This framework enables an objective comparison of models, highlighting those with the greatest potential for clinical application while identifying gaps in current research practices.

Detailed results for each study, including datasets used, numbers of images in training and testing, and model scores, are summarized in Table 4 (focused on OA) and Table 5 (focused on osteoporosis).

Table 3. Comprehensive Scoring Framework for Evaluating AI Models in OA and Osteoporosis Research Based on Dataset Quality, Performance, Clinical Applicability, and Technical Rigor

Category	Criteria	Scoring
Dataset Quality	Sample Size (10 points)	>30,000: 10 10,000-30,000: 9 5,000-10,000: 8 1,000-5,000: 6 <1,000: 4
	Data Quality (5 points)	Well documented: 5 Partially documented: 3 Poor documentation: 1
	Validation (10 points)	Cross-dataset external: 10 Multiple external: 9 Single external: 8 Internal only: 6
Performance	Primary Metrics (15 points)	Full metrics + CIs + significance: 15 Full metrics + CIs: 13 Full metrics only: 11 Partial metrics: 8
	Secondary Metrics (10 points)	Comprehensive validation: 9-10 Basic validation: 7-8 Limited validation: 4-6
Clinical	Integration (10 points)	Ready for clinical use: 9-10 Needs minor adaptation: 7-8 Needs major adaptation: 4-6
	Interpretability (10 points)	Full interpretability features: 9-10 Basic interpretability: 7-8 Limited interpretability: 4-6
	Efficiency (5 points)	Real-time: 5 Reasonable: 3 Slow: 1
Technical	Methodology (10 points)	Comprehensive: 9-10 Adequate: 7-8 Limited: 4-6
	Reproducibility (10 points)	Code/data available: 9-10 Partial availability: 7-8 Limited availability: 4-6
	Error Analysis (5 points)	Comprehensive: 5 Basic: 3 Limited: 1
Mandatory Criteria	Complete Performance Metrics	
	Clear Validation Approach	
	Transparent Data Usage	
	Comprehensive Model Description	
	Error Analysis and Uncertainty	
	Clinical Relevance and Clinical Integration Potential	

Table 4. Comprehensive Overview of Studies Focusing on OA diagnosis and Progression

First Author	Year	Imaging Modality	Target Condition	Dataset	Number of Images Per Set			Reference Standard	Model Output Metrics	Score out of 100
					Training	Validation	Testing			
Namiri [20]	2021	MRI	Knee OA Progression	OAI	3090 (70%)	440 (10%)	880 (20%)	Radiologist-labeled ROAMES phenotypes derived from MOAKS.	AUC, Accuracy	93
Khalid [21]	2023	X-ray	Knee OA Diagnosis	OAI	7808	Split into subsets	1958	Radiologist consensus	AUC, Accuracy	92
Tiulpin [22]	2018	X-ray	Knee OA Diagnosis	OAI, MOST	18,376 MOST	2,957 OAI	5,960 OAI	Radiologist consensus	AUC, Average Multi-class Accuracy	91
Wang [23]	2024	MRI	Knee OA Diagnosis	OAI	1,271	318	2,503	Radiologist consensus, MOAKS	Accuracy, TPR, TNR	89
von Schacky [24]	2020	X-ray	Hip OA Diagnosis	OAI	3,494	437	437	Radiologist consensus	AUC, Accuracy	88
Muhammad [25]	2021	X-ray	Knee OA Diagnosis	OAI	22,796	7,601	7,599	Radiologist consensus	Accuracy, F1 score, TPR	88
Yoon [26]	2023	X-ray	Knee OA Diagnosis	OAI	44,193	810	400	Orthopedic and radiologist consensus	Accuracy, F1 score	87
Salis [27]	2024	X-ray	Knee OA Progression	OAI, MOST	3,114 OAI	606 OAI	1,602 MOST	Expert consensus	KL grading	86
Guan [28]	2022	X-ray	Knee OA Progression	OAI	4,200	300	400	FNIH criteria	AUC, TPR, TNR	85
Xu [29]	2024	X-ray	Hip OA Progression	OAI	528	104	104	Orthopedic consensus	AUC, Accuracy, TPR, TNR	84
Bayramoglu [30]	2021	X-ray	Knee OA Diagnosis	MOST	18,436	NR	NR	Expert consensus	ROC AUC, Average Precision	83
Guan [31]	2020	X-ray	Knee OA Progression	OAI	1,400	150	400	FNIH criteria	AUC, TPR, TNR	83
Almhdie-Imjabbar [32]	2022	X-ray	Knee OA Progression	OAI, MOST	2,740 OAI, 845 MOST	NR	NR	OARSI grades	AUC, Accuracy	82
Pedoia [33]	2019	MRI	Knee OA Diagnosis	OAI	2,849	877	658	Expert consensus, KL	AUC, TPR, TNR	82
Jang [34]	2023	X-ray	Hip OA Progression	OAI	7,672	1,920	1,920	Expert consensus	AUROC, AUPRC	82
Hu [35]	2024	MRI	Knee OA Progression	OAI	960	NR	240	Radiologist consensus	AUC	81
Leung [36]	2020	X-ray	Knee OA Progression	OAI	520	104	104	KL, OARSI	AUC, TPR, TNR	81
Chang [37]	2020	MRI	Knee OA Diagnosis	OAI	1,054	225	226	Radiologist consensus	AUC	80

First Author	Year	Imaging Modality	Target Condition	Dataset	Number of Images Per Set			Reference Standard	Model Output Metrics	Score out of 100
					Training	Validation	Testing			
Kinger [38]	2024	X-ray	Knee OA Diagnosis	OAI	4,000	500	500	Radiologist consensus	Accuracy	80
Li [39]	2024	MRI	Knee OA Progression	OAI	549	NR	137	Radiologist consensus	AUC, TPR, TNR	79
Lee [40]	2024	MRI	Knee OA Progression	OAI, MOST	5,966 OAI	1,193 OAI	3,392 MOST	Radiologist consensus	AUC, Accuracy, F1 score	
Daneshmand [41]	2024	X-ray	Knee OA Diagnosis, Prognosis	OAI	4,279	4279	1070	Radiologist consensus, OARSI	AUC, AP	78
Norman [42]	2018	X-ray	Knee OA Diagnosis	OAI	25,873	7,779	5,941	Radiologist consensus	TPR, TNR	78
Brahim [43]	2019	X-ray	Knee OA Diagnosis	OAI	1,024	NR	NR	Expert consensus	Accuracy, TPR, TNR	77
Joseph [44]	2022	MRI	Knee OA Progression	OAI	887	887	157	Radiologist consensus	AUC	77
Costello [45]	2023	MRI	Knee OA Progression	MOST	663	NR	284	Radiologist consensus	AUC	76
Su [46]	2023	X-ray	Knee OA Progression	OAI	3,357	NR	1,439	KL grading	Accuracy, F1 score	76
Ntakolia [47]	2021	X-ray	Knee OA Progression	OAI	4,849	1,213	6,062	Expert consensus	AUC, Accuracy	75

Notes: Studies are ordered from highest to lowest based on our developed scoring framework (Table 3). For the full breakdown of the scores refer to Appendix, Table A.

Table 5. Comprehensive Overview of Studies Focusing on Osteoporosis Diagnosis and Progression

First Author	Year	Imaging Modality	Target Condition	Dataset	Number of Images Per Set			Reference Standard	Model Output Metrics	Score out of 100
					Training	Validation	Testing			
Lehmann [48]	2024	DXA scan	Osteoporotic fracture	Swiss Osteoporosis Registry, UK Biobank	4,755	951 Swiss Osteoporosis Registry, 5,474 UK Biobank	1,189	Genant SQ grading system	C-index, confidence intervals	90
Cross [49]	2024	X-ray	Osteoporotic fracture	MrOS	1000	1000	176	Genant SQ grading system	AUC-ROC, TPR, TNR, Accuracy	88
Chang [50]	2024	X-ray	Osteoporotic fracture	MrOS	6,695	1,310	2,346	Genant SQ Grading System	F1 score	85
Dong [51]	2022	X-ray	Osteoporotic fractures	MrOS	11,872	1,319	2,333	Genant SQ Grading System	AUC-ROC, TPR, TNR, PPV	83
Zhang [52]	2019	QCT	Osteoporotic fractures	MrOS	58	20	22	Expert consensus, FEA	MSE, R^2, SD	66

Notes: Studies are ordered from highest to lowest based on our developed scoring framework (Table 3). For the full breakdown of the scores refer to Appendix, Table B.

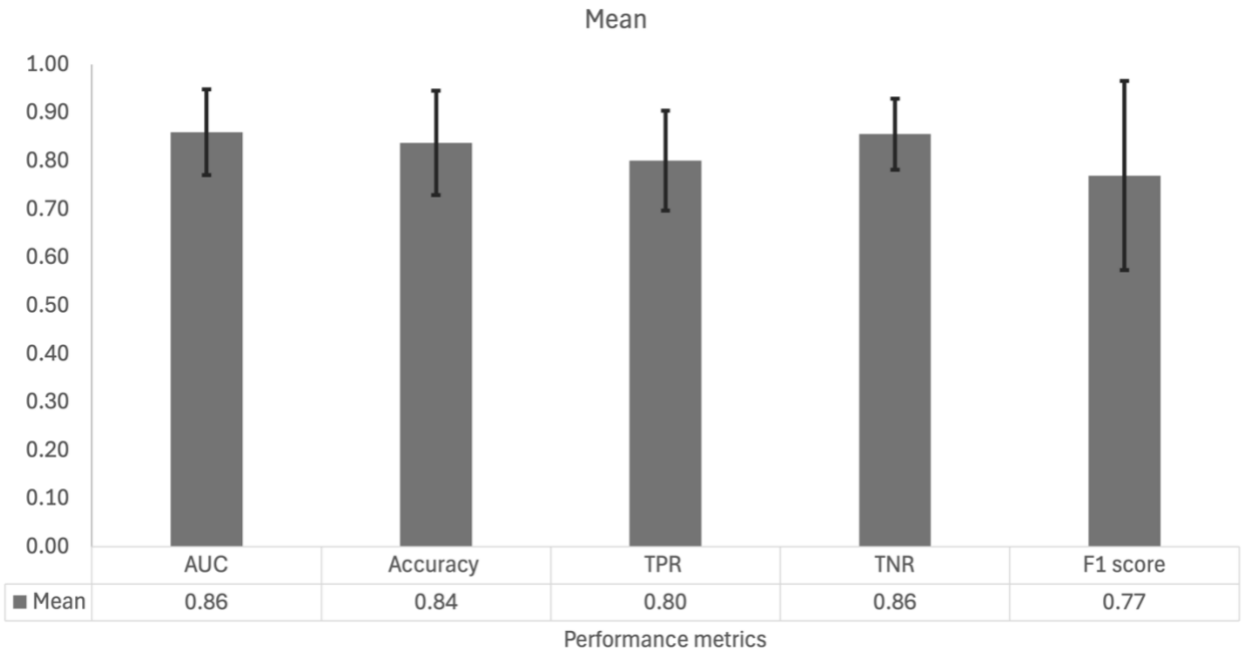

Figure 3. Mean Performance Metrics of AI Models for Osteoarthritis and Osteoporosis Diagnosis and Prognosis. The bar chart illustrates the average values for key performance indicators: AUC, accuracy, TPR (True Positive Rate, sensitivity), TNR (True Negative Rate, specificity), and F-1 score across all reviewed studies. Error bars represent the standard deviation for each metric, reflecting variability among the models. The data is based on 33 studies included in the systematic review, covering AI models utilizing imaging modalities like X-ray, MRI, and DXA. These metrics highlight the overall reliability of AI models in this domain. This figure has been created on Microsoft Excel.

Figure 3 presents the mean performance metrics (AUC, Accuracy, TPR, TNR, F1 score) reported across 33 studies of AI models for OA and osteoporosis diagnosis. As shown by the bar chart, the average AUC among the 23 studies that reported this metric was 0.86, while the corresponding mean Accuracy across 14 studies was 0.84. For sensitivity (TPR), the mean value was 0.80 (n=11), and the mean specificity (TNR) among the same studies was 0.86. A smaller subset of five studies reported F1 scores, averaging 0.77. The error bars in Figure 3 illustrate the standard deviation of these metrics, indicating variability in model performance

Discussion

This systematic review highlights significant advancements in AI models for the detection and prediction of OA and osteoporosis progression between January 2018 and October 2024. The analyzed studies demonstrate that AI, particularly deep learning techniques, has achieved promising diagnostic and prognosis accuracy (Figure 3). Conventional methods such as X-rays, MRI, CT scans, and DXA scans, while instrumental in visualizing structural changes and assessing bone mineral density, have significant limitations in early detection and disease progression prediction [53]. These limitations arise because these methods primarily focus on static assessments of structural damage or bone density without capturing the complex, multi-dimensional patterns indicative of early pathological changes [54]. AI-driven techniques, on the other hand, excel by integrating vast datasets to detect subtle patterns and anomalies that may escape human interpretation [53, 54]. For instance, high-resolution imaging modalities like CT and MRI, discussed in the literature, provide detailed insights into bone microarchitecture and quality, but their application in clinical settings remains constrained by accessibility and technical challenges, and risk factors of high dose of radiation [55]. AI can bridge this gap by enhancing image interpretation, facilitating the identification of predictors such as trabecular microstructure, cortical porosity, and volumetric density, which are critical for assessing fracture risk and treatment efficacy [54]. This ability to leverage detailed imaging data highlights the ability of AI in advancing diagnostic precision and personalized prognostication [53-55].

Interpretation of Results

The high-performance metrics reported across these studies highlight AI's potential to revolutionize musculoskeletal diagnostics (Figure 3). The ability of AI models to process and analyze complex imaging data allows for earlier detection of disease progression, which is crucial for timely intervention and improved patient outcomes [9].

Models that integrated data from multiple sources, such as Tiulpin et al. (2018) [22], who utilized both the OAI and

MOST datasets, demonstrated improved generalizability. This suggests that training AI models on diverse datasets enhances their robustness and applicability to different populations. Additionally, studies focusing on fracture risk prediction rather than solely bone mineral density, like Cross et al. (2024) [49], offer practical clinical relevance by addressing outcomes that directly impact patient care.

Osteoarthritis

1. Namiri et al. (2021) achieved an AUC of 0.93 in knee OA progression prediction using MRI data from the OAI dataset, highlighting AI's capability in early-stage detection and disease monitoring. However, its reliance on OAI, a dataset predominantly featuring North American participants, limits its global applicability [20].
2. Khalid et al. (2023) employed X-rays with a radiologist consensus for grading, achieving an AUC of 0.92. Its simplicity of use positions it for clinical adoption, though its lack of external validation raises concerns about real-world performance [21].
3. Tiulpin et al. (2018) utilized X-rays from both the OAI and MOST datasets, achieving a multi-class accuracy of 91%. The inclusion of multiple datasets improves generalizability, though interpretability features necessary for clinical application remain absent [22].

Osteoporosis

1. Lehmann et al. (2024) achieved a C-index of 0.90 using DXA scans from the Swiss Osteoporosis Registry and UK Biobank. By combining data from diverse sources, the study demonstrated robust fracture risk prediction. However, the reliance on DXA scans, a less accessible imaging modality, limits widespread implementation [48].
2. Cross et al. (2024) utilized X-rays from the MrOS dataset, achieving an AUC-ROC of 0.88. The study addressed osteoporotic fracture risk rather than BMD, offering practical clinical relevance. However, the all-male MrOS dataset undermines the model's generalizability to female osteoporosis population [49].
3. Chang et al. (2024) achieved an F1-score of 0.85 using X-rays from the MrOS dataset, emphasizing fracture risk prediction. While the large dataset size and robust annotation methods are strengths, the gender bias in the dataset remains a limitation [50].

Analysis of Limitations

Despite these promising advancements, several challenges hinder the clinical translation of AI models in healthcare. A significant limitation is the reliance on homogeneous datasets, such as the Osteoarthritis Initiative (OAI) and the MrOS study [56]. These datasets lack demographic diversity, OAI is predominantly North American, and MrOS includes only male participants, raising concerns about the models' applicability to broader, more varied populations [56, 57]. This issue is further compounded by the global disparities in dataset representation, with a significant overrepresentation of data from high-income countries like the U.S. and China. Such imbalances risk perpetuating healthcare inequities, as AI models may fail to generalize effectively to underrepresented groups, including women and ethnically diverse populations [57, 58]. Addressing these biases requires diversifying data sources and implementing robust external validation protocols to ensure the relevance and fairness of AI applications in clinical settings [57].

Another critical issue is the lack of external validation. Only 15% of the studies performed cross-dataset external validation, which is essential for assessing a model's performance in real-world settings (Figure 2). Without rigorous external validation, the applicability of these models outside controlled research environments remains uncertain [57].

Furthermore, only 60% of the AI models presented potential clinical applicability, with 40% (Figure 2) needing more interpretability features crucial for clinical adoption. Clinicians must understand the rationale behind a model's predictions to trust and effectively integrate them into decision-making processes [58, 59]. The absence of clinician-friendly interfaces and actionable insights limits the practical usability of these models in everyday clinical workflows [58].

Implications for Clinical Practice

The findings suggest that while AI models have the potential to enhance diagnostic accuracy and enable early intervention, significant efforts are needed to address the current limitations so that they can be integrated into clinical practice effectively. Emphasizing dataset diversity and conducting thorough external validations are imperative for developing generalizable and reliable models across various patient populations [59].

Improving interpretability is also essential. Models should provide transparent decision-making processes and actionable outputs that clinicians can readily understand and utilize [58, 59]. This will foster trust and facilitate the seamless integration of AI tools into existing clinical workflows.

Future Considerations

Future research must focus on several key areas to fully realize AI's potential in musculoskeletal healthcare. Enhancing dataset diversity is crucial; incorporating a wide range of populations in terms of gender, ethnicity, and geography will improve the generalizability of AI models. Conducting rigorous external validations using independent datasets is essential to assess real-world performance and ensure reliability across clinical settings [56]. Improving interpretability is also a priority; developing models with transparent algorithms and providing clear explanations for predictions will foster clinician trust and facilitate

integration into clinical workflows [55-58]. Standardizing metrics and reporting protocols will enable objective comparisons between models and studies, promoting reproducibility and transparency. Collaborations between clinicians, data scientists, and other stakeholders are vital to align AI development with clinical needs and ensure that these tools are practical and actionable in everyday medical practice [58, 59]. By addressing these areas, AI models can move closer to becoming indispensable tools in diagnosing and managing OA and osteoporosis.

Conclusions

This review highlights the potential of artificial intelligence (AI) in diagnosing and predicting osteoarthritis (OA) and osteoporosis progression. The top-performing models, such as Namiri et al. (2021) [20] with an AUC of 0.93 for OA progression and Lehmann et al. (2024) [48] with a C-index of 0.90 for fracture risk prediction, demonstrate AI's ability to complement clinical workflows, enabling earlier detection and personalized care. This capability facilitates early detection and supports the development of targeted interventions, which can reduce the disease burden and associated healthcare costs [2, 54].

The study raises important research questions that must be addressed to advance the field. One critical question is how AI models can be developed to ensure generalizability across diverse populations. This involves exploring strategies for training models on heterogeneous datasets that accurately reflect the global patient population. Another significant question is what methods can enhance the interpretability of AI models for clinical use. Investigating techniques that make AI algorithms more transparent and their predictions more explainable to clinicians is essential for fostering trust and acceptance. Determining how standardized evaluation frameworks can be established in AI research is crucial. Identifying universal metrics and reporting standards that can be adopted across studies will enable objective comparisons and improve the reproducibility of research findings.

By addressing these areas, AI has the potential to become an integral component of musculoskeletal healthcare, improving diagnosis, informing treatment decisions, and ultimately enhancing patient outcomes worldwide. The transition from experimental innovation to a cornerstone of personalized, equitable healthcare will require concerted efforts to overcome current limitations and foster widespread clinical adoption.

List of Abbreviations

AI: artificial intelligence
OA: osteoarthritis
BMD: bone mineral density
DXA: dual-energy X-ray absorptiometry
MRI: magnetic resonance imaging
CT: computed tomography
MeSH: medical subject headings
AUC: area under the curve
ROC: receiver operating characteristic
TPR: true positive rate (sensitivity)
TNR: true negative rate (specificity)
AP: average precision
BA: balanced accuracy
CLAIM: checklist for artificial intelligence in medical imaging
CNN: convolutional neural network
DL: deep learning
F1-score: F1 score (harmonic mean of precision and recall)
FEA: finite element analysis
FNIH: foundation for the national institutes of health
FRAX: fracture risk assessment tool
KL: Kellgren-Lawrence scale
MOAKS: mri osteoarthritis knee score
MOST: multicenter osteoarthritis study
MrOS: osteoporotic fractures in men study
OAI: osteoarthritis initiative
OARSI: osteoarthritis research society international
PPV: positive predictive value
QCT: quantitative computed tomography
RNN: recurrent neural network
SD: standard deviation
UK Biobank: United Kingdom biobank
WOMAC: Western Ontario and McMaster Universities osteoarthritis index

Conflicts of Interest

The authors declare that they have no conflict of interests.

Ethics Approval and/or Participant Consent

The study did not require any ethics approval and/or participant consent.

Authors' Contributions

MA and PA: Equally made substantial contributions to study design, planning, collection and analysis of data, interpretation of the data, drafting the manuscript, reviewing data and gave approval for the final version to be published.

Acknowledgements

The authors acknowledge Amel Sassi, their URNCST Journal competition mentor, who helped support our writing throughout the process.

Funding

This study was not funded.

References

[1] Salari N, Ghasemi H, Mohammadi L, Behzadi M hasan, Rabieenia E, Shohaimi S, et al. The global prevalence of osteoporosis in the world: A comprehensive systematic review and meta-analysis. Journal of Orthopaedic Surgery and Research. 2021 Oct 17;16(1). https://doi.org/10.1186/s13018-021-02772-0

[2] Chen X, Tang H, Lin J, Zeng R. Temporal trends in the disease burden of osteoarthritis from 1990 to 2019, and projections until 2030. PLOS ONE. 2023 Jul 24;18(7). https://doi.org/10.1371/journal.pone.0288561

[3] Adejuyigbe B, Kallini J, Chiou D, Kallini JR. Osteoporosis: Molecular pathology, diagnostics, and therapeutics. International Journal of Molecular Sciences. 2023 Sept 26;24(19):14583. https://doi.org/10.3390/ijms241914583

[4] Martel-Pelletier J. Pathophysiology of osteoarthritis. Osteoarthritis and Cartilage. 2004;12:31–3. https://doi.org/10.1016/j.joca.2003.10.002

[5] Kumar T, Pandey V, Kumar A, Elhence A, Choudhary V. Quality of life and self-reported disability in patients with osteoarthritis: Cross-sectional descriptive study. Journal of Education and Health Promotion. 2023 Mar;12(1). https://doi.org/10.4103/jehp.jehp_1055_22

[6] Rizzo M, Tammaro G, Guarino A, Basso M, Cozzolino A, Mariconda M. Quality of life in osteoporotic patients. Orthopedic Reviews. 2022 Oct 13;14(6). https://doi.org/10.52965/001c.38562

[7] Abramoff B, Caldera FE. Osteoarthritis. Medical Clinics of North America. 2020 Mar;104(2):293–311. https://doi.org/10.1016/j.mcna.2019.10.007

[8] Oei EH, Runhaar J. Imaging of early-stage osteoarthritis: The needs and challenges for diagnosis and classification. Skeletal Radiology. 2023 May 8;52(11):2031–6. https://doi.org/10.1007/s00256-023-04355-y

[9] Siris ES, Miller PD, Barrett-Connor E, Faulkner KG, Wehren LE, Abbott TA, et al. Identification and fracture outcomes of undiagnosed low bone mineral density in postmenopausal women. JAMA. 2001 Dec 12;286(22):2815. https://doi.org/10.1001/jama.286.22.2815

[10] Gatineau G, Shevroja E, Vendrami C, Gonzalez-Rodriguez E, Leslie WD, Lamy O, et al. Development and reporting of artificial intelligence in osteoporosis management. Journal of Bone and Mineral Research. 2024 Aug 20;39(11):1553–73. https://doi.org/10.1093/jbmr/zjae131

[11] Mohammadi S, Salehi MA, Jahanshahi A, Shahrabi Farahani M, Zakavi SS, Behrouzieh S, et al. Artificial intelligence in osteoarthritis detection: A systematic review and meta-analysis. Osteoarthritis and Cartilage. 2024 Mar;32(3):241–53. https://doi.org/10.1016/j.joca.2023.09.011

[12] Mahum R, Rehman SU, Meraj T, Rauf HT, Irtaza A, El-Sherbeeny AM, et al. A novel hybrid approach based on deep CNN features to detect knee osteoarthritis. Sensors. 2021 Sept 15;21(18):6189. https://doi.org/10.3390/s21186189

[13] Krishnaraj A, Barrett S, Bregman-Amitai O, Cohen-Sfady M, Bar A, Chettrit D, et al. Simulating dual-energy X-ray absorptiometry in CT using deep-learning segmentation cascade. Journal of the American College of Radiology. 2019 Oct;16(10):1473–9. https://doi.org/10.1016/j.jacr.2019.02.033

[14] Yasaka K, Akai H, Kunimatsu A, Kiryu S, Abe O. Prediction of bone mineral density from computed tomography: Application of deep learning with a convolutional neural network. European Radiology. 2020 Feb 14;30(6):3549–57. https://doi.org/10.1007/s00330-020-06677-0

[15] Kong SH, Ahn D, Kim B, Srinivasan K, Ram S, Kim H, et al. A novel fracture prediction model using machine learning in a community-based cohort. JBMR Plus. 2020 Feb 10;4(3). https://doi.org/10.1002/jbm4.10337

[16] Gornale SS, Patravali PU, Hiremath PS. Automatic detection and classification of knee osteoarthritis using Hu's invariant moments. Frontiers in Robotics and AI. 2020 Nov 16;7. https://doi.org/10.3389/frobt.2020.591827

[17] Khan KS, Kunz R, Kleijnen J, Antes G. Five steps to conducting a systematic review. JRSM. 2003 Mar 1;96(3):118–21. https://doi.org/10.1258/jrsm.96.3.118

[18] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021 Mar 29; https://doi.org/10.1136/bmj.n71

[19] Mongan J, Moy L, Kahn CE. Checklist for artificial intelligence in medical imaging (CLAIM): A guide for authors and reviewers. Radiology: Artificial Intelligence. 2020 Mar 1;2(2). https://doi.org/10.1148/ryai.2020200029

[20] Namiri NK, Lee J, Astuto B, Liu F, Shah R, Majumdar S, et al. Deep learning for large scale MRI-based morphological phenotyping of osteoarthritis. Scientific Reports. 2021 May 25;11(1). https://doi.org/10.1038/s41598-021-90292-6

[21] Khalid A, Senan EM, Al-Wagih K, Ali Al-Azzam MM, Alkhraisha ZM. Hybrid techniques of X-ray analysis to predict knee osteoarthritis grades based on fusion features of CNN and handcrafted. Diagnostics. 2023 May 2;13(9):1609. https://doi.org/10.3390/diagnostics13091609

[22] Tiulpin A, Thevenot J, Rahtu E, Lehenkari P, Saarakkala S. Automatic knee osteoarthritis diagnosis from plain radiographs: A deep learning-based approach. Scientific Reports. 2018 Jan 29;8(1). https://doi.org/10.1038/s41598-018-20132-7

[23] Wang M, Yu C, Li M, Zhang X, Jiang K, Zhang Z, et al. One-stop detection of anterior cruciate ligament injuries on magnetic resonance imaging using deep learning with multicenter validation. Quantitative Imaging in Medicine and Surgery. 2024 May; 14(5):3405–16. https://doi.org/10.21037/qims-23-1539

[24] von Schacky CE, Sohn JH, Liu F, Ozhinsky E, Jungmann PM, Nardo L, et al. Development and validation of a multitask deep learning model for severity grading of hip osteoarthritis features on radiographs. Radiology. 2020 Apr;295(1):136–45. https://doi.org/10.1148/radiol.2020190925

[25] Muhammad MB, Yeasin M. Interpretable and parameter optimized ensemble model for knee osteoarthritis assessment using radiographs. Scientific Reports. 2021 Jul 12;11(1). https://doi.org/10.1038/s41598-021-93851-z

[26] Yoon JS, Yon C-J, Lee D, Lee JJ, Kang CH, Kang S-B, et al. Assessment of a novel deep learning-based software developed for automatic feature extraction and grading of radiographic knee osteoarthritis. BMC Musculoskeletal Disorders. 2023 Nov 8;24(1). https://doi.org/10.1186/s12891-023-06951-4

[27] Salis Z, Driban JB, McAlindon TE. Predicting the onset of end-stage knee osteoarthritis over two- and five-years using machine learning. Seminars in Arthritis and Rheumatism. 2024 Jun;66:152433. https://doi.org/10.1016/j.semarthrit.2024.152433

[28] Guan B, Liu F, Mizaian AH, Demehri S, Samsonov A, Guermazi A, et al. Deep learning approach to predict pain progression in knee osteoarthritis. Skeletal Radiology. 2022 Feb;51(2):363–73. https://doi.org/10.1007/s00256-021-03773-0

[29] Xu Y, Xiong H, Liu W, Liu H, Guo J, Wang W, et al. Development and validation of a deep-learning model to predict total hip replacement on radiographs. Journal of Bone and Joint Surgery. 2023 Dec 12;106(5):389–96. https://doi.org/10.2106/jbjs.23.00549

[30] Bayramoglu N, Nieminen MT, Saarakkala S. Automated detection of patellofemoral osteoarthritis from knee lateral view radiographs using deep learning: Data from the multicenter osteoarthritis study (MOST). Osteoarthritis and Cartilage. 2021 Oct;29(10):1432–47. https://doi.org/10.1016/j.joca.2021.06.011

[31] Guan B, Liu F, Haj-Mirzaian A, Demehri S, Samsonov A, Neogi T, et al. Deep learning risk assessment models for predicting progression of radiographic medial joint space loss over a 48-month follow-up period. Osteoarthritis and Cartilage. 2020 Apr;28 (4):428–37. https://doi.org/10.1016/j.joca.2020.01.010

[32] Almhdie-Imjabbar A, Nguyen K-L, Toumi H, Jennane R, Lespessailles E. Prediction of knee osteoarthritis progression using radiological descriptors obtained from bone texture analysis and Siamese neural networks: Data from OAI and most cohorts. Arthritis Research and Therapy. 2022 Mar 8;24(1). https://doi.org/10.1186/s13075-022-02743-8

[33] Pedoia V, Lee J, Norman B, Link TM, Majumdar S. Diagnosing osteoarthritis from T2 maps using deep learning: An analysis of the entire osteoarthritis initiative baseline cohort. Osteoarthritis and Cartilage. 2019 Jul;27(7):1002–10. https://doi.org/10.1016/j.joca.2019.02.800

[34] Jang SJ, Fontana MA, Kunze KN, Anderson CG, Sculco TP, Mayman DJ, et al. An interpretable machine learning model for predicting 10-year total hip arthroplasty risk. The Journal of Arthroplasty. 2023 Jul;38(7). https://doi.org/10.1016/j.arth.2023.03.087

[35] Hu J, Peng J, Zhou Z, Zhao T, Zhong L, Yu K, et al. Associating knee osteoarthritis progression with temporal-regional graph convolutional network analysis on images. Journal of Magnetic Resonance Imaging. 2024 Apr 30; https://doi.org/10.1002/jmri.29412

[36] Leung K, Zhang B, Tan J, Shen Y, Geras KJ, Babb JS, et al. Prediction of total knee replacement and diagnosis of osteoarthritis by using deep learning on knee radiographs: Data from the osteoarthritis initiative. Radiology. 2020 Sept;296(3):584–93. https://doi.org/10.1148/radiol.2020192091

[37] Chang GH, Felson DT, Qiu S, Guermazi A, Capellini TD, Kolachalama VB. Assessment of knee pain from MR imaging using a convolutional Siamese network. European Radiology. 2020 Feb 13;30(6):3538–48. https://doi.org/10.1007/s00330-020-06658-3

[38] Kinger S. Deep learning for automatic knee osteoarthritis severity grading and classification. Indian Journal of Orthopaedics. 2024 Sept 11;58 (10):1458–73. https://doi.org/10.1007/s43465-024-01259-4

[39] Li S, Cao P, Li J, Chen T, Luo P, Ruan G, et al. Integrating radiomics and neural networks for knee osteoarthritis incidence prediction. Arthritis and Rheumatology. 2024 Jul 8;76(9):1377–86. https://doi.org/10.1002/art.42915

[40] Lee DW, Han H, Ro DH, Lee YS. Development of the machine learning model that is highly validated and easily applicable to predict radiographic knee osteoarthritis progression. Journal of Orthopaedic Research. 2024 Oct;43(1):128–38. https://doi.org/10.1002/jor.25982

[41] Daneshmand M, Panfilov E, Bayramoglu N, Korhonen RK, Saarakkala S. Deep learning based detection of osteophytes in radiographs and magnetic resonance imagings of the knee using 2D and 3D morphology. Journal of Orthopaedic Research. 2024 Feb 7;42(7): 1473–81. https://doi.org/10.1002/jor.25800

[42] Norman B, Pedoia V, Noworolski A, Link TM, Majumdar S. Applying densely connected convolutional neural networks for staging osteoarthritis severity from plain radiographs. Journal of Digital Imaging. 2018 Oct 10;32(3):471–7. https://doi.org/10.1007/s10278-018-0098-3

[43] Brahim A, Jennane R, Riad R, Janvier T, Khedher L, Toumi H, et al. A decision support tool for early detection of knee osteoarthritis using X-ray imaging and machine learning: Data from the osteoarthritis initiative. Computerized Medical Imaging and Graphics. 2019 Apr;73:11–8. https://doi.org/10.1016/j.compmedimag.2019.01.007

[44] Joseph GB, McCulloch CE, Nevitt MC, Link TM, Sohn JH. Machine learning to predict incident radiographic knee osteoarthritis over 8 years using combined MR imaging features, demographics, and clinical factors: Data from the osteoarthritis initiative. Osteoarthritis and Cartilage. 2022 Feb;30(2):270–9. https://doi.org/10.1016/j.joca.2021.11.007

[45] Costello KE, Felson DT, Jafarzadeh SR, Guermazi A, Roemer FW, Segal NA, et al. Gait, physical activity and tibiofemoral cartilage damage: A longitudinal machine learning analysis in the multicenter osteoarthritis study. British Journal of Sports Medicine. 2023 Mar 3;57(16):1018–24. https://doi.org/10.1136/bjsports-2022-106142

[46] Su K, Yuan X, Huang Y, Yuan Q, Yang M, Sun J, et al. Improved prediction of knee osteoarthritis by the machine learning model XGBoost. Indian Journal of Orthopaedics. 2023 Jul 29;57(10):1667–77. https://doi.org/10.1007/s43465-023-00936-0

[47] Ntakolia C, Kokkotis C, Moustakidis S, Tsaopoulos D. A machine learning pipeline for predicting joint space narrowing in knee osteoarthritis patients. 2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE). 2020 Oct;934–41. https://doi.org/10.1109/bibe50027.2020.00158

[48] Lehmann O, Mineeva O, Veshchezerova D, Häuselmann H, Guyer L, Reichenbach S, et al. Fracture risk prediction in postmenopausal women with traditional and machine learning models in a nationwide, prospective cohort study in Switzerland with validation in the UK biobank. Journal of Bone and Mineral Research. 2024 Jun 5;39(8):1103–12. https://doi.org/10.1093/jbmr/zjae089

[49] Cross NM, Perry J, Dong Q, Luo G, Renslo J, Chang BC, et al. Subject-level spinal osteoporotic fracture prediction combining deep learning vertebral outputs and limited demographic data. Archives of Osteoporosis. 2024 Sept 10;19(1). https://doi.org/10.1007/s11657-024-01433-z

[50] Chang BC, Renslo J, Dong Q, Johnston SK, Perry J, Haynor DR, et al. Using an ensemble of segmentation methods to detect vertebral bodies on radiographs. American Journal of Neuroradiology. 2024 Aug;45 (10):1512–20. https://doi.org/10.3174/ajnr.A8343

[51] Dong Q, Luo G, Lane NE, Lui L-Y, Marshall LM, Kado DM, et al. Deep learning classification of spinal osteoporotic compression fractures on radiographs using an adaptation of the Genant semiquantitative criteria. Academic Radiology. 2022 Dec;29(12):1819–32. https://doi.org/10.1016/j.acra.2022.02.020

[52] Zhang M, Gong H, Zhang K, Zhang M. Prediction of lumbar vertebral strength of elderly men based on quantitative computed tomography images using machine learning. Osteoporosis International. 2019 Aug 10;30(11):2271–82. https://doi.org/10.1007/s00198-019-05117-0

[53] Seidenberg PH, Howe AH. Musculoskeletal imaging. Medical Clinics of North America. 2014 Jul;98(4):895–914. https://doi.org/10.1016/j.mcna.2014.04.003

[54] Fuggle NR, Lu S, Breasail M, Westbury LD, Ward KA, Dennison E, et al. OA22 machine learning and computer vision of Bone microarchitecture can improve the fracture risk prediction provided by DXA and clinical risk factors. Rheumatology. 2022 Apr 23;61(Supplement_1). https://doi.org/10.1093/rheumatology/keac132.022

[55] Krug R, Burghardt AJ, Majumdar S, Link TM. High-resolution imaging techniques for the assessment of osteoporosis. Radiologic Clinics of North America. 2010 May;48(3):601–21. https://doi.org/10.1016/j.rcl.2010.02.015

[56] Soh S-E, Barker AL, Morello RT, Ackerman IN. Applying the international classification of functioning, disability and health framework to determine the predictors of falls and fractures in people with osteoarthritis or at high risk of developing osteoarthritis: Data from the osteoarthritis initiative. BMC Musculoskeletal Disorders. 2020 Feb 29;21(1). https://doi.org/10.1186/s12891-020-3160-5

[57] Celi LA, Cellini J, Charpignon M-L, Dee EC, Dernoncourt F, Eber R, et al. Sources of bias in artificial intelligence that perpetuate healthcare disparities—A global review. PLOS Digital Health. 2022 Mar 31;1(3). https://doi.org/10.1371/journal.pdig.0000022

[58] Maleki Varnosfaderani S, Forouzanfar M. The role of AI in hospitals and clinics: Transforming healthcare in the 21st century. Bioengineering. 2024 Mar 29;11(4): 337. https://doi.org/10.3390/bioengineering11040337

[59] Deniz-Garcia A, Fabelo H, Rodriguez-Almeida AJ, Zamora-Zamorano G, Castro-Fernandez M, del Pino Alberiche Ruano M, et al. Quality, usability, and effectiveness of mHealth apps and the role of artificial intelligence: Current scenario and challenges. Journal of Medical Internet Research. 2023 May 4;25. https://doi.org/10.2196/44030

Article Information
Managing Editor: Jeremy Y. Ng
Peer Reviewers: Amel Sassi, Mia Wilkinson
Article Dates: Received Dec 08 24; Accepted Feb 06 25; Published Feb 14 25

Citation
Please cite this article as follows:
Alborzi M, Abadi P. OSTEO-AI: A systematic review and meta-analysis of artificial intelligence models for osteoarthritis and osteoporosis detection and prognosis. URNCST Journal. 2025 Feb 14: 9(2).
https://urncst.com/index.php/urncst/article/view/783
DOI Link: https://doi.org/10.26685/urncst.783

URNCST Journal
"Research in Earnest"

Funded by the Government of Canada | Canada