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Ai-Driven Multimodal Knee Osteoarthritis Detection, Progression Prediction and Personalized Rehabilitation Recommendation System

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ABSTRACT:
Knee osteoarthritis (KOA) is a chronic, progressive musculoskeletal disorder characterized by structural deterioration of the knee joint, pain, stiffness, reduced range of motion, muscle weakness, impaired physical function, and limitations in activities of daily living. The condition represents a major cause of disability and loss of mobility, particularly among older adults and individuals with obesity, previous joint injury, or prolonged mechanical loading. The knee is the most frequently affected joint in osteoarthritis, and a substantial proportion of individuals with osteoarthritis may benefit from rehabilitation interventions.Conventional KOA assessment generally relies on a combination of clinical examination, patient-reported symptoms, functional assessment, and medical imaging, particularly plain radiography. Radiographic severity is commonly characterized using the Kellgren–Lawrence (KL) grading system. Although radiographic assessment provides valuable information regarding structural joint changes, imaging findings alone may not fully represent an individual's pain, functional impairment, or future disease trajectory. Furthermore, patients with similar radiographic severity may experience substantially different symptoms and functional limitations.The heterogeneous nature of KOA creates a significant challenge for disease progression prediction and individualized treatment planning. Conventional statistical models may have limited ability to capture complex nonlinear relationships between imaging characteristics, demographic variables, clinical symptoms, functional status, behavioral factors, and longitudinal disease changes. Therefore, there is a need for intelligent computational approaches capable of integrating heterogeneous patient information within a unified predictive framework.

KEYWORD: Knee Osteoarthritis; Artificial Intelligence; Deep Learning; Multimodal Machine Learning; Knee X-ray; Clinical Data; Kellgren–Lawrence Grading; Osteoarthritis Progression; Progression Prediction; Risk Stratification; Explainable AI; Personalized Rehabilitation; Clinical Decision Support System; Precision Medicine; Patient-Centered Care

1. INTRODUCTION

Knee osteoarthritis (KOA) is a chronic, progressive, and multifactorial musculoskeletal disorder that affects the entire knee joint, including cartilage, subchondral bone, synovium, ligaments, and surrounding musculature. It is characterized by structural joint deterioration, pain, stiffness, reduced range of motion, muscle weakness, impaired physical function, and progressive limitations in mobility and activities of daily living. Osteoarthritis represents a substantial global health burden, with approximately 528 million people estimated to be living with the condition worldwide in 2019. The knee is the most frequently affected joint, with approximately 365 million people affected globally. In addition, approximately 344 million people living with osteoarthritis have moderate or severe disease that could potentially benefit from rehabilitation. The growing prevalence of obesity, population ageing, and joint injury is expected to further increase the burden of KOA.KOA is not exclusively a disease of ageing. Although increasing age is one of the strongest risk factors, the development and progression of KOA are influenced by multiple interacting factors, including obesity, previous knee injury, joint overuse, occupational loading, physical inactivity, muscle weakness, genetic susceptibility, metabolic factors, and biomechanical abnormalities. These factors contribute to substantial heterogeneity between patients. Two individuals with similar radiographic abnormalities may experience very different levels of pain and functional impairment, while patients with comparable symptoms may exhibit different degrees of structural joint damage. Consequently, effective KOA management requires consideration of both structural and patient-centered clinical information rather than relying on a single diagnostic measurement.

2. LITERATURE SURVEY

Knee osteoarthritis (KOA) is a complex, chronic, and progressive musculoskeletal disorder involving multiple components of the knee joint, including articular cartilage, subchondral bone, synovium, menisci, ligaments, and surrounding musculature. Unlike diseases that can be characterized by a single measurable biomarker, KOA is a heterogeneous condition in which structural abnormalities, pain, functional limitations, biomechanical factors, demographic characteristics, lifestyle, previous injuries, and patient-specific risk factors interact over time. Consequently, accurate assessment of KOA requires consideration of multiple dimensions of the disease rather than relying exclusively on a single clinical or imaging measurement.Traditional KOA assessment generally combines clinical examination, patient history, patient-reported outcomes, functional assessment, and medical imaging. Plain knee radiography remains one of the most widely used imaging techniques for evaluating structural features of KOA because it is relatively inexpensive, accessible, rapid, and suitable for longitudinal assessment. Radiographs can reveal important characteristics such as joint-space narrowing, osteophyte formation, subchondral sclerosis, and other structural changes. The Kellgren–Lawrence (KL) grading system is commonly used to categorize radiographic disease severity.However, conventional assessment has several limitations. Radiographic severity does not always correspond directly to pain or functional impairment. Patients with similar KL grades may report substantially different symptoms and may have different physical capabilities. Similarly, a patient with relatively modest radiographic abnormalities may experience considerable pain or disability. This clinical-radiographic discordance demonstrates that KOA cannot be completely characterized by imaging alone.Another important limitation is that conventional assessment is primarily focused on the patient's **current state**. Although the clinician can determine the current severity of disease, predicting how rapidly an individual patient will progress remains challenging. KOA progression varies substantially between individuals. Some patients remain relatively stable for long periods, whereas others experience rapid structural and functional deterioration. Therefore, identifying individuals at high risk of progression is an important objective for personalized monitoring and intervention.The increasing availability of large medical datasets has created opportunities to address these limitations using artificial intelligence (AI). Machine learning (ML) and deep learning (DL) algorithms can identify complex nonlinear relationships among clinical variables and can automatically extract high-dimensional representations from medical images. As a result, AI-based KOA research has progressed from traditional feature-based classification toward automated image interpretation, severity grading, progression prediction, multimodal learning, explainable AI (XAI), and clinical decision support.

3. METHODOLOGY

AI-driven multimodal framework for knee osteoarthritis (KOA) detection, severity estimation, disease progression prediction, explainable risk assessment, and personalized rehabilitation recommendation. The methodology is designed to overcome the limitations of conventional KOA assessment methods, which generally depend on a combination of clinical examination, patient-reported symptoms, and radiographic evaluation. Although these approaches remain important in clinical practice, they may not fully exploit the large amount of information available from medical images, demographic characteristics, clinical measurements, functional status, and longitudinal patient records.Knee osteoarthritis is a complex and progressive musculoskeletal disorder involving multiple interacting factors. Structural changes in the knee joint may include cartilage degeneration, joint-space narrowing, osteophyte formation, subchondral bone alterations, and changes in joint alignment. At the same time, patients may experience pain, stiffness, reduced range of motion, muscle weakness, walking difficulty, reduced physical activity, and limitations in daily activities. Importantly, the relationship between structural abnormalities and symptoms is not always linear. Two patients with similar radiographic severity may experience substantially different levels of pain and functional impairment. Therefore, a system based exclusively on radiographic appearance may not provide sufficiently individualized information for prognosis or rehabilitation planning.The proposed methodology addresses this limitation by treating KOA assessment as a **multimodal, multi-task, longitudinal prediction problem**. Instead of relying on a single source of information, the proposed system combines information from multiple complementary modalities. These modalities may include knee X-ray images, MRI images when available, demographic information, clinical measurements, patient-reported outcomes, functional assessments, physical-activity information, previous injury history, and longitudinal follow-up observations.

KOA Detection

The first task determines whether a knee is affected by KOA.

where:

- = no KOA
- = KOA present

The model estimates:

where represents the available multimodal patient information.

Task 2: KOA Severity Estimation

The second task estimates radiographic severity, typically using the KL grading system.

The model estimates:

Because KL grades are ordered, the methodology should treat severity as an **ordinal prediction problem**, rather than assuming that the five classes are completely unrelated.

Task 3: Disease Progression Prediction

The third task estimates the probability of future progression.

where:

- = no predefined progression during follow-up
- = progression during follow-up

The model estimates:

where represents information available at baseline.

Workflow

Patient Data
↓
Data Preprocessing
↓
Image + Clinical + Functional Feature Extraction
↓
Multimodal Feature Fusion
↓
Multi-Task AI Model
↓
KOA Detection | Severity | Progression |
| Estimation | Prediction |
↓
Explainable AI
↓
Patient Risk Profile
↓
Safety Rule Engine
↓
Personalized Rehabilitation
↓
Clinician Review
↓
Patient Follow-up
↓
Updated AI Assessment

4. EXPERIMENTAL RESULTS

The proposed artificial intelligence (AI)-driven multimodal framework was evaluated to assess its ability to detect knee osteoarthritis (KOA), classify radiographic disease severity, predict future disease progression, and generate personalized rehabilitation recommendations. The experimental evaluation was structured according to four primary objectives: (i) KOA detection, (ii) severity classification using the Kellgren–Lawrence (KL) grading system, (iii) progression prediction, and (iv) personalized rehabilitation recommendation.

The proposed framework integrates imaging information obtained from knee radiographs and magnetic resonance imaging (MRI), together with relevant clinical information, to provide a comprehensive assessment of the patient's disease status. In addition to predictive performance, the framework incorporates explainable artificial intelligence (XAI) to improve the interpretability of model outputs and support clinical decision-making.

4.1 Dataset Characteristics

The characteristics of the dataset used for experimental evaluation are summarized in Table 1. The dataset consisted of a total of **[N] patients**, corresponding to **[N] knee observations**. A total of **[N] X-ray examinations** and **[N] MRI examinations** were available for multimodal analysis. Among the evaluated cases, **[N] ([ ]%)** were classified as KOA-negative, whereas **[N] ([ ]%)** were classified as KOA-positive. Furthermore, **[N] ([ ]%)** cases demonstrated disease progression during the defined follow-up period.

Table 1. Dataset Characteristics

Characteristic	Value
Total patients	[N]
Total knee observations	[N]
X-ray examinations	[N]
MRI examinations	[N]
KOA-negative cases	[N] ([ ]%)
KOA-positive cases	[N] ([ ]%)
Progression cases	[N] ([ ]%)

The distribution of radiographic disease severity according to the KL grading system is presented in Table 2. KL Grade 0 represents the absence of radiographic osteoarthritis, while Grades 1–4 correspond to increasing levels of structural disease severity. The dataset contained **[N] Grade 0**, **[N] Grade 1**, **[N] Grade 2**, **[N] Grade 3**, and **[N] Grade 4** cases.

Table 2. Distribution of KOA Severity According to Kellgren–Lawrence Grade

KL Grade	Severity Level	Number of Cases	Percentage
0	No OA	[N]	[ ]%
1	Doubtful	[N]	[ ]%
2	Mild	[N]	[ ]%
3	Moderate	[N]	[ ]%
4	Severe	[N]	[ ]%
Total	—	**[N]**	**100%**

The distribution demonstrates that the dataset includes the complete range of radiographic severity, enabling evaluation of the proposed model across both early and advanced stages of KOA. The inclusion of KL Grades 0–4 also permits evaluation of the model as an ordinal classification problem rather than as a simple binary classification task.

4.2 KOA Detection Results

The first experiment evaluated the ability of the proposed framework to distinguish KOA-positive cases from KOA-negative cases. Model performance was assessed using accuracy, sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUROC). These metrics were selected

to provide complementary measures of overall classification performance and the model's ability to identify affected and unaffected patients.
Four configurations were compared: an X-ray-only model, a clinical-information-only model, an X-ray plus clinical-information model, and the proposed multimodal model.

Table 3. Performance Comparison for KOA Detection

Model	Accuracy	Sensitivity	Specificity	F1-Score	AUROC
X-ray only	[ ]	[ ]	[ ]	[ ]	[ ]
Clinical only	[ ]	[ ]	[ ]	[ ]	[ ]
X-ray + Clinical	[ ]	[ ]	[ ]	[ ]	[ ]
Proposed Multimodal Model	**[ ]**	**[ ]**	**[ ]**	**[ ]**	**[ ]**

As shown in Table 3, the proposed multimodal model achieved an accuracy of **[ ]**, sensitivity of **[ ]**, specificity of **[ ]**, F1-score of **[ ]**, and AUROC of **[ ]**. Compared with the individual-modality models, the proposed framework demonstrated **[higher/comparable]** diagnostic performance.
The results indicate that combining imaging and clinical information can provide complementary information for KOA detection. While radiographic imaging provides direct information regarding structural abnormalities, clinical variables provide additional information related to patient characteristics, symptoms, and functional status. The multimodal architecture therefore enables the model to make predictions using both structural and clinical evidence.
In particular, the sensitivity of **[ ]** indicates the ability of the proposed framework to identify KOA-positive cases, which is clinically important because missed cases may delay appropriate management and rehabilitation. Similarly, the specificity of **[ ]** indicates the model's ability to correctly identify patients without radiographic evidence of KOA.
Overall, the detection experiment demonstrates the feasibility of the proposed multimodal approach for automated KOA screening and classification.

5. DISCUSSION

The present study proposed an **AI-driven multimodal framework for knee osteoarthritis (KOA) detection, severity assessment, disease progression prediction, explainable risk assessment, and personalized rehabilitation recommendation**. Unlike conventional computer-aided KOA systems that primarily focus on radiographic classification, the proposed framework integrates heterogeneous information sources, including medical imaging, demographic characteristics, clinical variables, functional measurements, and longitudinal observations. The primary objective was to develop a unified decision-support framework capable of moving beyond static disease classification toward individualized assessment of current disease status, future progression risk, and rehabilitation needs.The experimental framework was designed to evaluate four major capabilities: **(i) KOA detection, (ii) KOA severity classification, (iii) disease progression prediction, and (iv) personalized rehabilitation recommendation**. Additional experiments involving multimodal fusion, ablation analysis, explainable AI, error analysis, and subgroup evaluation were used to investigate the robustness and interpretability of the proposed approach.The overall findings should be interpreted in the context of the characteristics and limitations of the available dataset. In particular, the reported performance reflects the data distribution, labeling strategy, imaging quality, follow-up duration, and clinical variables available for model development. Therefore, strong test-set performance should be considered evidence of model capability rather than definitive evidence of clinical effectiveness.

Discussion of KOA Detection Performance

The first objective of the proposed framework was to identify the presence of KOA from multimodal patient information. The detection task represents the initial stage of the clinical decision-support pipeline because accurate identification of affected patients is necessary before severity estimation, progression assessment, and rehabilitation planning can be considered.The proposed model combines imaging and non-imaging information rather than relying exclusively on radiographic appearance. Radiographic images provide important structural information, including joint-space narrowing, osteophyte formation, and other structural characteristics associated with KOA. However, radiographic appearance does not fully represent the patient's symptoms or functional status. The inclusion of clinical and functional information therefore provides an opportunity to capture complementary aspects of the disease.The detection results should be interpreted using multiple metrics rather than accuracy alone. Sensitivity is particularly important because false-negative predictions may result in patients with KOA being incorrectly classified as disease-free. Specificity is also important because excessive false-positive predictions may increase unnecessary clinical evaluation. AUROC provides a threshold-independent measure of discrimination, whereas F1-score provides a useful summary when the class distribution is imbalanced.If the proposed multimodal model demonstrates higher AUROC, sensitivity, specificity, or F1-score than the unimodal baselines, this would support the hypothesis that combining heterogeneous information improves KOA detection. Such improvement would indicate that the model is able to exploit complementary information that is unavailable to imaging-only or clinical-only approaches.

Discussion of KOA Severity Classification

The second objective was to estimate disease severity according to the Kellgren–Lawrence grading system. Severity classification is more challenging than binary detection because the model must distinguish between multiple ordinal disease stages.A particularly important characteristic of KL grading is that the classes are ordered. A prediction of KL Grade 3 for a true Grade 2 case represents a smaller error than predicting Grade 0 for a true Grade 4 case. Therefore, accuracy alone does not fully characterize model performance. The use of macro-F1, MAE, and weighted kappa provides a more informative assessment of severity prediction.Errors between adjacent KL grades may occur because radiographic differences between neighboring severity categories can be subtle. Inter-observer variability in radiographic grading may also contribute to apparent model errors. Consequently, a model that frequently predicts an adjacent grade may still provide clinically useful severity estimation, whereas large-grade errors are more concerning.If the proposed multimodal model achieves a lower MAE and higher weighted kappa than the comparison methods, the results would suggest that multimodal information contributes to more consistent ordinal severity estimation. However, KL grading itself represents a radiographic assessment and does not necessarily capture the complete clinical experience of an individual patient. Pain and functional impairment may differ substantially among patients with the same radiographic grade.This observation provides an important motivation for the multimodal design of the proposed system. Rather than treating the KL grade as a complete representation of disease burden, the proposed framework considers it as one component of a broader patient profile.

Discussion of Disease Progression Prediction

A major contribution of the proposed framework is the inclusion of longitudinal disease progression prediction. Conventional image-classification systems primarily describe the patient's current condition. However, KOA is a chronic progressive disorder, and identifying patients at higher risk of future deterioration may support earlier monitoring and individualized intervention.The progression model estimates the probability of future disease progression using information available at baseline. This creates a fundamentally different prediction problem from cross-sectional KOA detection. The model must identify patterns associated with future outcomes rather than simply recognizing existing structural abnormalities.AUROC measures the ability of the model to distinguish patients who subsequently progress from those who do not. AUPRC provides complementary information, particularly when progression cases are relatively uncommon. The Brier score and calibration analysis are important because a clinically useful risk model should not only rank patients correctly but should also produce meaningful probability estimates.If patients categorized as high risk demonstrate a greater observed progression rate than patients classified as moderate- or low-risk, this would provide evidence that the model can meaningfully stratify patients according to future risk.Nevertheless, progression prediction is highly dependent on how progression is defined. Radiographic progression, symptomatic deterioration, functional decline, and treatment escalation represent different clinical outcomes. Therefore, the final manuscript should clearly specify the progression endpoint, observation period, and criteria used to define progression.

Importance of Multimodal Data Fusion

The multimodal analysis represents a central component of this study. KOA is influenced by multiple factors, including structural abnormalities, age, body composition, symptoms, previous injury, physical activity, functional capacity, and other patient-specific characteristics. A single modality is therefore unlikely to provide a complete representation of disease status.The imaging modality primarily captures structural characteristics, while clinical variables provide information regarding symptoms and patient characteristics. Functional information provides additional insight into mobility and physical capability, and longitudinal information describes how the condition changes over time.The multimodal fusion experiment was designed to determine whether combining these information sources improves performance compared with individual modalities.If the full multimodal configuration consistently outperforms the imaging-only and clinical-only models, the results would support the hypothesis that heterogeneous information sources provide complementary predictive information.However, multimodal learning also introduces additional challenges. Different modalities may have different missing-data patterns, scales, noise characteristics, and sampling frequencies. Furthermore, unnecessary or highly correlated features may increase model complexity without improving generalization. Therefore, multimodal fusion should be justified by measurable performance improvements rather than by the assumption that adding more data automatically produces a better model.

Discussion of the Ablation Study

The ablation analysis was performed to determine the contribution of individual components of the proposed framework. This analysis is important because the performance of a complex multimodal architecture cannot be attributed to a particular component without systematic evaluation.Removing clinical variables can determine whether patient-level information contributes to prediction beyond imaging. Similarly, removing functional information can reveal whether mobility-related characteristics provide additional predictive value. Removing longitudinal information can demonstrate the importance of temporal observations for progression prediction.The ablation of attention-based or learned fusion mechanisms can further determine whether the proposed multimodal integration strategy provides an advantage over simpler feature concatenation. Likewise, comparison with a model without multi-task learning can reveal whether simultaneous learning of detection, severity, and progression objectives improves shared feature representation.A consistent reduction in performance following removal of a particular component would indicate that the component provides useful information. Conversely, a negligible performance difference would suggest that the corresponding component may provide limited incremental value under the evaluated dataset conditions.

Explainability and Clinical Interpretability

Explainability is an important consideration in medical AI because predictive performance alone does not establish clinical trustworthiness. Healthcare professionals need to understand, at least at a practical level, why a model produced a particular prediction.For imaging data, heatmap-based approaches such as Grad-CAM can identify image regions associated with model activation. These visualizations can be used to determine whether the model focuses on anatomically relevant regions rather than irrelevant image artifacts.For structured clinical variables, feature-attribution techniques can identify variables that contribute most strongly to individual predictions. Variables such as baseline severity, age, BMI, pain, and functional limitations may contribute to risk estimation depending on the learned model.However, explainability outputs must be interpreted cautiously. A highlighted image region does not establish a causal relationship, and a high feature-importance score does not mean that the corresponding variable independently causes disease progression. Therefore, XAI should be considered a mechanism for model inspection and transparency rather than a substitute for clinical or causal analysis.

Personalized Rehabilitation Recommendation

The final component of the proposed framework extends the system from prediction toward individualized decision support. Conventional KOA management recommendations may be broadly applicable to patient populations but may not adequately reflect differences in disease severity, symptoms, progression risk, and functional capacity.The proposed system attempts to integrate these characteristics into an individualized rehabilitation profile. For example, patients with different combinations of severity and functional limitation may receive different rehabilitation categories. Similarly, progression-risk estimates can be used to identify patients who may require closer clinical monitoring.The rehabilitation module should not be interpreted as an autonomous treatment-prescription system. Exercise selection, intensity, frequency, progression, contraindications, and safety considerations require appropriate clinical assessment. The AI system should therefore function as a **decision-support tool** that organizes patient information and assists qualified healthcare professionals in developing individualized rehabilitation plans.Future validation should compare AI-generated recommendations with recommendations from qualified physiotherapists, orthopedic specialists, or rehabilitation professionals using predefined evaluation criteria.

6. FUTURE WORK

The proposed AI-based multimodal knee osteoarthritis system can be improved in several ways in future research. The major future directions are:

1. **Larger datasets:** Future studies should use larger and more diverse patient datasets to improve model accuracy and reliability.
2. **Multi-hospital validation:** The model should be tested using data from different hospitals and medical centers to verify its generalization capability.
3. **More imaging data:** Future work can combine X-ray with MRI and other medical imaging modalities for better detection of early KOA.
4. **Long-term prediction:** More longitudinal patient data can be used to predict KOA progression over longer periods.
5. **Advanced AI models:** Transformer-based models and advanced multimodal deep-learning techniques can be investigated to improve prediction performance.
6. **Wearable devices:** Gait analysis and wearable sensors can be integrated to monitor walking patterns, physical activity, and functional limitations.

7. CONCLUSION

Knee osteoarthritis (KOA) is a progressive musculoskeletal disorder that can significantly affect mobility, physical function, quality of life, and independence. Accurate assessment of KOA requires consideration of multiple factors, including structural abnormalities, symptoms, demographic characteristics, functional limitations, and disease progression. Conventional assessment approaches generally consider these factors separately, while many existing artificial intelligence systems focus primarily on automated analysis of medical images. This study therefore proposed an **AI-driven multimodal framework for KOA detection, severity assessment, disease progression prediction, explainable risk assessment, and personalized rehabilitation recommendation**.The proposed framework integrates heterogeneous patient information, including knee imaging, demographic characteristics, clinical variables, functional measurements, and longitudinal observations. Modality-specific preprocessing and feature extraction are used to obtain meaningful representations from the available data, followed by multimodal feature fusion. The integrated representation is subsequently processed through a multi-task learning framework to perform KOA detection, KL-based severity classification, and progression-risk prediction.The experimental evaluation was designed to assess the framework from multiple perspectives. KOA detection was evaluated using accuracy, sensitivity, specificity, precision, F1-score, AUROC, and AUPRC. Severity estimation was evaluated using KL-grade classification performance, macro-F1, MAE, and weighted kappa. Progression prediction was assessed using AUROC, AUPRC, sensitivity, specificity, F1-score, Brier score, and calibration analysis. Additional multimodal and ablation experiments were designed to determine the contribution of different information sources and model components.A key aspect of the proposed framework is the integration of **explainable artificial intelligence (XAI)**. Image-based explanations can identify regions contributing to model predictions, while feature-attribution methods can identify important clinical and functional variables. This improves transparency and provides additional information for understanding model behavior. However, these explanations are intended to support model interpretation and should not be considered evidence of causal relationships.The proposed framework also extends beyond diagnosis by incorporating a **personalized rehabilitation recommendation module**. By considering predicted disease severity, progression risk, pain-related information, and functional status, the system can categorize patients according to appropriate rehabilitation-support needs. The purpose of this module is to assist clinicians in developing individualized management strategies rather than to autonomously prescribe treatment.The multimodal design represents an important advantage of the proposed approach because KOA is a multifactorial condition. Imaging provides information about structural joint changes, whereas clinical and functional variables provide complementary information about symptoms and patient capability. Longitudinal information further contributes to understanding disease trajectory. Integrating these sources may therefore provide a more comprehensive patient representation than relying on a single modality.

Despite its potential, the proposed framework has several limitations. Model performance is dependent on dataset size, data quality, class distribution, labeling consistency, and availability of longitudinal observations. KL grading may also exhibit inter-observer variability and does not fully represent pain or functional impairment. Furthermore, retrospective evaluation may not accurately reflect real-world clinical workflows. Consequently, the reported experimental performance should not be interpreted as sufficient evidence for immediate clinical deployment.Future research should focus on **larger multi-center datasets, external validation, prospective clinical evaluation, improved longitudinal modeling, additional imaging modalities, wearable and gait information, uncertainty-aware AI, privacy-preserving learning, and clinically validated adaptive rehabilitation support**. The integration of patient-reported outcomes and continuous monitoring may further improve individualized risk assessment and rehabilitation planning.Overall, this study presents a comprehensive framework that moves KOA artificial intelligence from isolated image classification toward an integrated **diagnosis–severity–prognosis–rehabilitation** pipeline. The proposed approach has the potential to support earlier identification of disease, improved characterization of severity, individualized progression-risk assessment, and personalized rehabilitation decision support

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