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Bridging Radiology and AI: A Systematic Review of Deep Learning Models for Meniscus Tear Diagnosis Using Magnetic Resonance Imaging

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ABSTRACT

Meniscus informatics is a growing subject of study in the healthcare industry. One of the major hindrances to the healthcare system's transformation is obtaining knowledge and meaningful information from complicated, high-dimensional, and diverse sources. Modern biomedical research, for instance, has seen an increase in the use of complex, dissimilar, poorly documented, and generally unstructured electronic health records, imaging, sensor data, and text. Even after many current techniques were used to extract more robust and useful elements from the data for analysis. New efficient standards for building end-to-end learning models from complex data. Therefore, the current study aims to examine the most recent research on the use of deep learning techniques for diagnosing meniscus problems and recommend creating comprehensive and meaningful interpretable structures that might benefit the healthcare industry. We also draw attention to shortcomings and the need for better technique development, and we provide new perspectives about this exciting new development in the field.

1. Introduction

Meniscal injury is a common cause of knee joint pain and a significant factor for the development of knee osteoarthritis (KOA) [1]. The medial and lateral menisci act as vital shock absorbers and stabilisers, distributing load evenly across the joint surface [2]. The incidence of meniscal injury is estimated at 6-7 per 10,000 in the general population, arising from acute trauma or degenerative wear [3,4]. This results in a substantial clinical burden, with approximately 850,000 meniscus-related

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surgical procedures performed annually [5]. Countless cases of meniscal injuries are reported each year globally; however, it is noteworthy that not all instances necessitate surgical treatment [5,61]. Figure 1 shows the intraoperative arthroscopic images of meniscus injury [3,62].

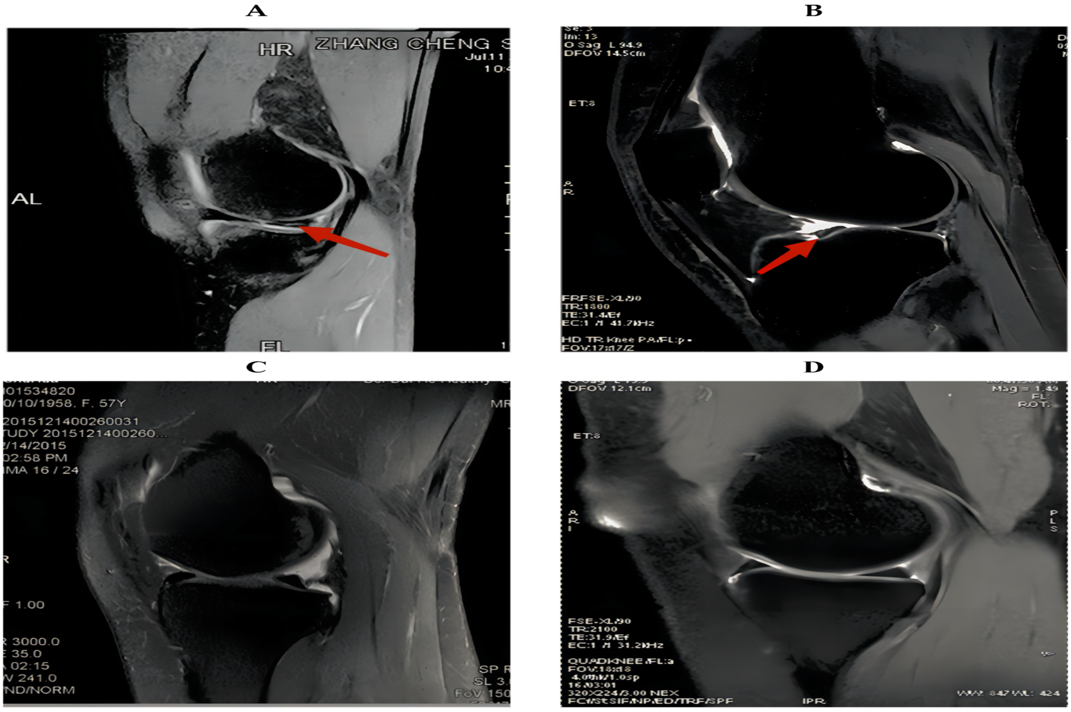

Fig.1 Meniscus injury. The arrows point to the meniscus injury, Source [3]

Magnetic Resonance Imaging (MRI) is the primary non-invasive modality for diagnosing meniscal tears [6,7]. However, precise grading can be hindered by the complex signal characteristics observed in a full knee MRI [8,58]. Although MRI exhibits high sensitivity and specificity, reportedly 96% and 88% for medial meniscal tears at 3.0T, diagnostic accuracy still depends on radiologist expertise and is subject to interpretive variability [9]. Arthroscopy, while often considered the definitive diagnostic standard for intra-articular pathology, is an invasive procedure with associated risks [10,11]. To enable intelligent, quantifiable grading of meniscal injuries, a visual, interpretable, fine-grading (VIFG) diagnostic model has been established in this work [12,59]. Figure 2 shows the proposed workflow for MRI-based meniscus injury analysis, integrating meniscus segmentation, signal-intensity feature extraction using a Swin Transformer, and clinical validation through arthroscopic correlation and heatmap visualisation of the injury gradient [13,60].

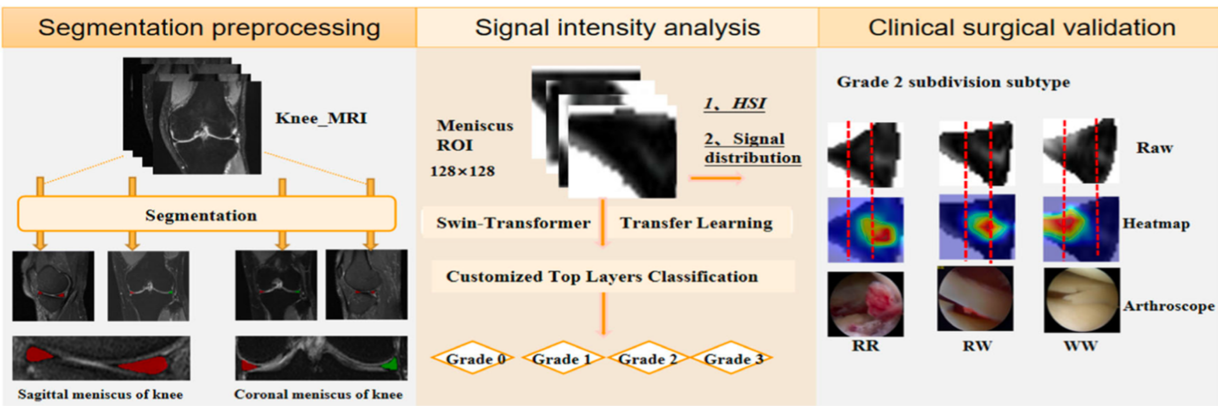

Fig.2 Schematic representation of the workflow for the meniscal injury intelligent grading system [13]

2. Methodology

2.1 Study Design and Reporting Framework

This study was conducted as a systematic scoping review to comprehensively map recent deep learning (DL) approaches for diagnosing meniscal injuries using magnetic resonance imaging (MRI). The review followed the Preferred Reporting Items for systematic reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR) guidelines to ensure transparency, reproducibility, and methodological rigour.

A scoping review methodology was selected because the field of deep learning-based meniscus diagnosis is rapidly evolving, methodologically heterogeneous, and includes diverse model architectures, outcome measures, and clinical objectives. This approach is appropriate for identifying research trends, methodological gaps, and future research directions, but not for quantitative synthesis.

2.2 Information Sources and Database Search

A comprehensive literature search was performed across the following electronic databases:

- PubMed/MEDLINE
- Scopus
- Web of Science
- Embase
- Cochrane Library

In addition, Google Scholar was used as a supplementary source to identify potentially missed studies and recently published articles not yet indexed in traditional databases. The final search was conducted in September 2025

2.3 Search Strategy

The search strategy combined controlled vocabulary terms and free-text keywords related to meniscal injury, MRI, and deep learning. Boolean operators (“AND”, “OR”) were used to construct the search strings. The core search terms included:

- Meniscus OR meniscal tear OR meniscal injury
- Magnetic resonance imaging (MRI)
- Deep learning, OR convolutional neural network, OR artificial intelligence, OR computer-aided diagnosis

A comprehensive search strategy was developed using controlled vocabulary (MeSH/Emtree terms) and free-text keywords related to meniscus injury, MRI, and deep learning/AI. **The complete search** strategy for PubMed/MEDLINE is provided in Supplementary File 1. Search strings were adapted as needed for the syntax of other databases (Scopus, Web of Science, Embase, Cochrane Library).and syntax.

To enhance coverage, manual reference list screening (snowballing) was performed on all included studies to identify additional relevant publications.

2.4 Eligibility Criteria

Studies were selected according to predefined inclusion and exclusion criteria

Inclusion Criteria

- Articles published between January 2024 and September 2025
- Original research studies
- Use of MRI as the image modality
- Application of deep learning-based methods for meniscus tear detection, classification, localisation, or segmentation
- Studies reporting quantitative performance metrics (e.g., accuracy, AUC, sensitivity, specificity)
- Articles published in English

Exclusion Criteria

- Review articles, meta-analyses, editorials, commentaries, conference abstracts, or study protocols
- Studies published before 2024
- Studies not focused on meniscal pathology
- Studies not employing deep learning models
- Non-MRI-based imaging studies
- Non-English publications

2.5 Rationale for Timeframe Selection

The review period was restricted to publications from 2024 onwards to capture recent methodological advances, including the increasing use of 3D deep learning models, object detection architectures, attention mechanisms, and explainable AI techniques. Earlier foundational studies have been extensively covered in prior reviews, whereas this review focuses on contemporary developments relevant to current and near-future clinical implementation.

2.6 Study Selection Process

All retrieved records were exported into a reference management system, and duplicates were removed. This selection process consisted of three sequential stages:

1. **Title screening** to remove clearly irrelevant articles
2. **Abstract screening** to assess relevance based on eligibility criteria
3. **Full-text review** to determine final inclusion

2.7 Data Extraction

A standardised data extraction form was developed to ensure consistency. The following information was extracted from each included study:

- Author(s) and year of publication
- Deep learning model architecture
- Dataset characteristics (sample size, source, MRI sequence)
- Clinical task (classification, localisation, segmentation, grading)
- Validation strategy (train-test split, cross-validation, external validation)
- Performance metrics (accuracy, sensitivity, specificity, F1-score)
- Use of explainable AI techniques

- Clinical relevance or intended application
  Extracted data were cross-checked for accuracy before synthesis.

2.8 Data Synthesis and Analysis

Given the heterogeneity of datasets, model architectures, and evaluation metrics, a quantitative meta-analysis was not performed. Instead, results were synthesised, and studies were grouped according to:

- Type of deep learning task (classification, localisation, segmentation)
- Model family (2D CNN,3D CNN, hybrid models, object detection frameworks)
- Clinical objectives (screening, diagnostic support, surgical planning)

This structured synthesis enabled the identification of methodological trends, performance patterns, and current limitations in the field[14,15,16].

2.9 Protocol Registration

The review protocol was prospectively registered in the **International Prospective Register of Systematic Reviews (PROSPERO)** under registration number **CRD420251272347**. The full protocol is available at: https://www.crd.york.ac.uk/PROSPERO/view/CRD420251272347.
The review was conducted in accordance with the registered protocol and in line with the **PRISMA-ScR** reporting guidelines to ensure methodological transparency and reproducibility.

2.10 Ethical Consideration

Ethical approval was not required for this study, as it involved the analysis of previously published data that did not include human participants or identifiable patient information.

2.11 Reporting the Review

Among the retrieved studies, Scopus-indexed journals accounted for the largest proportion (29%), followed by Embase (25%), PubMed/MEDLINE (21%), and Web of Science (20%), while a smaller proportion of studies were published in journals indexed in the Cochrane Library (6%).

3. Results

3.1 Study Selection

The database search identified a total of **1,677 records**, including 1,496 records retrieved from electronic databases and 181 records identified through supplementary sources. After removing 412 duplicates, 1,265 records were screened based on titles and abstracts. Of these, 1,158 records were excluded because they did not meet the inclusion criteria. A total of 107 full-text articles were assessed for eligibility. Following a full-text review, 68 modalities were excluded due to insufficient methodological detail or a non-English language. Ultimately,39 studies were included in the final scoping review. The study selection process is summarised in the PRISMA-ScR flow diagram (Figure 3).

IDENTIFICATION

Records identified from databases
(n = 1,496)

- PubMed/MEDLINE (n=32)
- Scopus (n=428)
- Web of Science (n=295)
- Embase (n=367)
- Cochrane Library (n=94)

↓

Records from other sources

- (n = 181)
- Google Scholar (n=143
- Citation snowballing (n=38)

↓

Total records identified
(n = 1,677)

↓

Duplicates removed

(n = 412)

SCREENING

Records screened (title & abstract)

(n = 1,265)

Records excluded (title/abstract)
(n = 1,158)

- No deep learning model applied (n=19)
- Non-MRI imaging modality (n=14)
- Meniscus not primary outcome (n=12)
- Insufficient methodological detail or missing performance metrics (n=15)
- Non-English full text (n=8)
- Other reasons (n=1,110)

Full-text articles assessed for eligibility

(n = 107)

Full-text articles excluded
(n = 68)

- No deep learning model applied (n=19)
- Non-MRI imaging modality (n=14)
- Meniscus not primary outcome (n=12)
- Insufficient methodological detail or missing performance metrics (n=15)
- Non-English full text (n=8)

19+14+12+15+8 = 68 ✓

INCLUDED

Studies included in the scoping review
(n = 39)

Fig.3 PRISMA-ScR flow diagram illustrating the study selection process for deep learning–based MRI diagnosis of meniscal injuries

3.2 Characteristics of Included Studies

The 39 included studies were published between 2024 and 2025, reflecting the surge in deep learning applications in musculoskeletal imaging. Most studies used retrospective designs and datasets from a single institution, with sample sizes ranging from fewer than 100 MRI examinations to more than 10.000 scans.

MRI protocols varied across studies, but most included sagittal and coronal sequences, with proton-density and T2-weighted images most frequently analysed. Ground truth labels were primarily derived from radiologist reports, arthroscopic findings, or expert manual annotations [16,17,18].

Performance evaluation strategies varied substantially across studies. Although internal validation using train-test splits or cross-validation was common, external validation was conducted in only a limited number of studies, highlighting a key gap in clinical generalisability [19,20,21].
Table 1 presents representative studies illustrating the major deep learning tasks, model architectures, and clinical objectives identified across the 39 included studies. All included studies contributed to the thematic synthesis and classification framework, even when not individually tabulated. The publication venues of the extracted studies from the defined databases are shown in Figure 3. The studies found were published between **January 2024 and September 2025.** Reflecting recent research activity in deep learning–based MRI analysis for musculoskeletal and meniscal injuries.

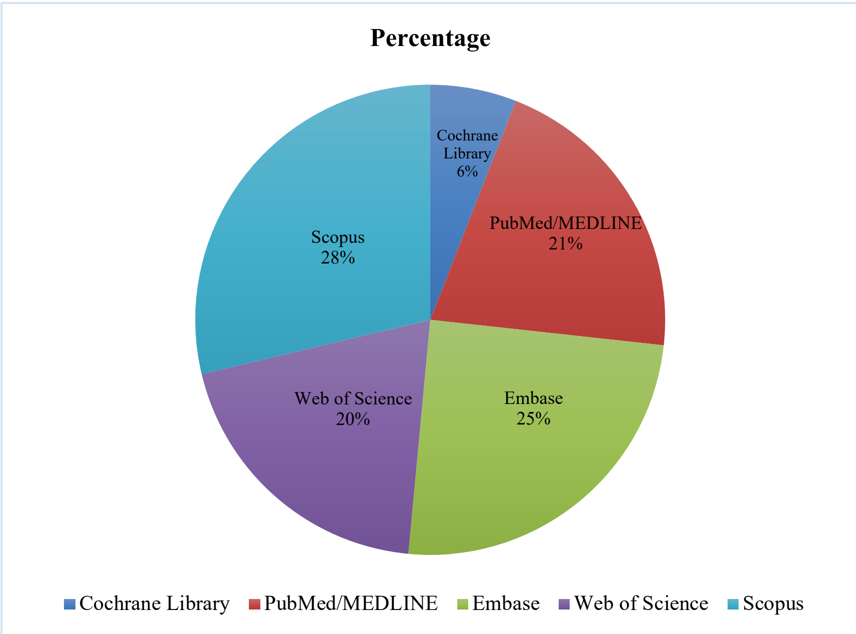

Fig.4 Publication venues of finalised studies

Despite their success, the application of CNNs in meniscus tear diagnosis faces several challenges. The "black box" nature of CNNs often limits their interpretability, making it difficult for clinicians to trust and adopt these models in clinical practice[22,23]. To address this, researchers have incorporated explainability techniques, such as Grad-CAM (Gradient-weighted Class Activation Mapping) and attention mechanisms, to visualise the regions of interest that influence the model's predictions [24,25,26]. These techniques provide clinicians with transparent insights into the decision-making process, thereby enhancing the clinical relevance of CNN-based diagnostics [27,28].

As evidenced by the survey in **Table 1**, CNN-based and object detection models (e.g., YOLO series) are the most prevalent for meniscus tear detection and localisation. However, hybrid models show promise for improved accuracy on complex tasks [56,57].

Table.1
Model Architecture Comparison

Model Family	Studies (Count)	Key Architectures Used	Typical Application
CNN-based (2D/3D)	18	ResNet,VGG, DenseNet, AlexNet, EfficientNet	Binary classification, feature extraction
Object Detection	9	YOLO series (v4, v5, v8), Mask R-CNN, Faster R-CNN	Tear localization, bounding box prediction
Hybrid/Ensemble	6	CNN+SVM, 2D+3D CNN, CRF+CNN, LGSA-UNet	Multi-task learning, improved accuracy
Transformer-based	3	Swin Transformer, AnkleNet, VIFG model	Multi-label classification, attention-based analysis
Traditional ML	2	Random Forest, SVR, SVM	Risk prediction, feature-based analysis
Segmentation-focused	1	U-Net, V-net	Meniscus segmentation, anatomical analysis

3.3 Model Performance and Validation Strategies

Reported performance metrics varied widely across studies. Binary classification models consistently achieved the highest accuracy and AUC values, whereas segmentation and localisation tasks exhibited greater variability [29,30,31].

Validation strategies were predominantly limited to internal validation, with only a minority of studies performing external or multi-institutional validation[55]. This limitation raises concerns about model robustness and generalizability across MRI protocols and clinical settings [32,33].

3.4 Use of Explainable Artificial Intelligence

Explainable AI (XAI) techniques were incorporated into a subset of studies, most commonly through gradient-based visualisation methods. These techniques were primarily used for qualitative assessment rather than for systematic clinical validation [34,35,36]. Although XAI approaches have improved transparency, their integration has remained inconsistent, and few studies have assessed how explanations affect clinical trust or decision-making [37, 38, 39].

3.5 Key Trends and Research Gaps

Several recurring trends and gaps were identified across the reviewed literature:

- High diagnostic performance is observed for binary classification, whereas limited reliability is noted in localisation and grading tasks [40].
- Heavy reliance on retrospective, single-centre datasets limits external validity [41,42].
- Inconsistent use of explainability methods reduces clinical interpretability [43].
- Minimal evaluation of real-world clinical workflow integration [44,45].

These findings highlight the need for standardised evaluation protocols, multi-centre datasets, and clinically oriented validation studies.

The generalisation capability of these models remains a major concern. **Table 2** highlights that only a minority of studies employed external validation, with results such as those of Hung et al. (2024) demonstrating a notable performance drop (95.4% to 78.8%), underscoring the risk of overfitting to single-centre data.

Table.2
Performance & Validation Summary

Category	Studies (Count)	Key Findings	Limitations
High Performers (Acc >90%)	12	Shetty, Hung, Güngör, Srinivasan, Wang (2024), etc.	Mostly binary tasks, single-center data
Moderate Performers (Acc 75–90%)	15	Jiang, Samantha, Ma, Zhen, etc.	Multi-class tasks, localization challenges
Limited Performance Data	8	Berrimi, Kong, Yu, etc.	Incomplete metrics, focus on methodology
Review/non-empirical	4	Adams, Chambers, Herman, etc.	Theoretical analysis only
External Validation	3	Hung et al. (2023), Yin et al. (2025)	Shows generalization gap (e.g., 95.4% → 78.8%)
XAI/Explainability	5	Lin et al. (2024), Parekh et al. (2024), Wang et al. (2024)	Grad-CAM, heatmaps, but limited clinical validation

4. Conclusions

Recent advances in deep learning algorithms have shown high efficacy in diagnosing meniscal pathologies from MRI data for binary classification [46]. However, the gap between research performance and real-world application limits their current clinical utility. Most models perform poorly at localising tears and assessing their severity, limiting their usefulness for treatment planning and patient management [47,48,49].

The overrepresentation of retrospective, single-centre studies suggests that current models prioritise optimisation over clinical applicability. This misalignment reduces clinical trust and limits advances in patient care, as inconsistent or unproven tools cannot reliably support clinical decisions. The inability to provide adequate explanations is another important issue, making deep learning algorithms less applicable in real-world clinical settings [50,51,52]. Without clinically interpretable findings, physicians may be reluctant to use these tools for diagnostic and treatment decisions, potentially diminishing patient benefit [53,54].

To bridge the gap between research and clinical practice, it is essential to prioritise multicentre, prospective studies and the integration of clinically focused, explainable models. Accelerating these efforts will maximise the impact and adoption of deep learning in diagnosing meniscal pathologies.

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