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APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN IMAGING-BASED DIAGNOSIS OF ORTHOPEDIC INJURIES

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ABSTRACT

Background and Objective: Medical imaging is fundamental in evaluating musculoskeletal injuries. The recent expansion of artificial intelligence (AI), especially in deep learning techniques, has led to new possibilities in image-based diagnostics. This review explores current AI-driven methods used in orthopedic trauma imaging and discusses their relevance in clinical settings.

Scope of Review: The review encompasses studies from 2015 to 2025 that apply AI tools to the interpretation of X-rays, computed tomography (CT), and magnetic resonance imaging (MRI) in the context of fractures, ligament tears, and joint-related damage. It also includes predictive systems and decision-support technologies.

Findings: AI solutions demonstrate notable performance in trauma detection, sometimes reaching diagnostic levels comparable to radiology experts. Deep neural networks are particularly effective in identifying soft tissue injuries in MRI, such as anterior cruciate ligament damage. Implementation is still hindered by insufficient clinical trials, data limitations, and the absence of universal methodological frameworks.

Conclusions: AI applications in orthopedic imaging show strong promise. However, broader clinical adoption depends on further validation, methodological standardization, and effective integration into healthcare workflows.

KEYWORDS

Artificial Intelligence, Orthopedic Trauma, Medical Imaging, Neural Networks, Clinical Decision Support, Radiology

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1. Introduction

Artificial intelligence (AI), particularly machine learning and deep learning, is reshaping medical diagnostics. In orthopedics—where fast and accurate identification of injuries is critical—AI offers tools for image analysis that can match or surpass human performance [1–4]. AI models can detect fractures, assess ligament damage, segment anatomical structures, and assist with predictive analytics [5,6].

Despite rapid progress, real-world implementation remains limited by challenges related to standardization, data quality, clinical integration, and legal accountability [7,8].

2. Materials and Methods

This review covers studies from 2015 to 2025 retrieved from PubMed, Scopus, and Web of Science. Search terms included “artificial intelligence,” “orthopedic imaging,” “fracture detection,” “MRI,” and “machine learning.” Inclusion criteria: peer-reviewed studies applying AI in musculoskeletal radiology. Exclusion: non-English and theoretical works without clinical relevance.

3. Clinical Applications of AI in Orthopedic Diagnostics

The use of artificial intelligence (AI) in imaging-based diagnosis of orthopedic injuries encompasses multiple clinical domains—from initial fracture detection to classification of soft tissue injuries and advanced clinical decision support. The key applications of AI in this area are described below.

3.1 Fracture Detection in X-ray and CT Imaging

Convolutional neural network (CNN) algorithms have achieved high accuracy (>90%) in identifying common fracture types, including femoral neck, rib, spinal, and distal radius fractures [1–3,5,10,14,16]. DenseNet and ResNet-based models, trained on large datasets, demonstrate diagnostic performance comparable to experienced radiologists [3,10]. For instance, Zhou et al. [14] showed that CNNs effectively detect rib fractures in chest CT scans. Increasingly, these models incorporate attention mechanisms, improving the detection of subtle or easily overlooked fractures.

3.2 Diagnosis of Ligament and Joint Injuries in MRI

When it comes to soft tissue imaging—such as ligaments and menisci—AI proves to be highly effective. Deep learning models can detect anterior cruciate ligament (ACL) tears, meniscal damage, and labral lesions with sensitivity reaching up to 92.7% and AUC values around 0.89 [6–8,12,13]. Studies by Bien et al. [6] and Liang et al. [7] highlighted that attention-based CNNs improve diagnostic accuracy and facilitate the identification of complex cases. Furthermore, multi-plane analysis enhances anatomical interpretation, which is particularly valuable in knee and shoulder imaging [13].

3.3 Segmentation of Anatomical Structures

Accurate segmentation of bones and joints is essential for surgical planning and biomechanical simulations. Deep learning models—particularly 3D U-Net architectures—show excellent performance in CT and MRI-based segmentation tasks. Anttila et al. [17] demonstrated a 3D U-Net model for distal radius segmentation with a Dice similarity coefficient of 0.93. Similarly, Collins et al. [18] reported that AI-based rib segmentation matched radiologist performance while significantly reducing analysis time. Radiomics-based segmentation, as discussed by van Timmeren et al. [24], enables the extraction of quantitative image features that enhance outcome prediction. Transformer-based architectures are also emerging, providing contextual interpretation of more complex anatomical structures [27].

3.4 Clinical Decision Support Systems (CDSS)

The integration of AI with radiology information systems (RIS), picture archiving systems (PACS), and electronic medical records (EMR) has enabled the development of advanced clinical decision support systems. These systems can automatically flag potential injuries, alert clinicians to abnormalities, and expedite diagnosis [2,8,10]. CDSS reduce diagnostic delays and minimize the risk of missed findings, especially in high-volume clinical settings.

For example, Aidoc is a commercially available tool that analyzes CT scans for fractures and hemorrhages in real time [16].

3.5 Prediction of Complications and Personalized Treatment

AI models combining imaging data with clinical and demographic information can predict post-operative complications and support treatment personalization. Rodriguez et al. [22] proposed an AI-based model for forecasting outcomes in rotator cuff injury treatment, which outperformed traditional statistical methods (AUC 0.84 vs. 0.79). These approaches represent an important step toward precision medicine in orthopedics.

3.6 Support for Emergency and Low-Resource Settings

AI is particularly valuable in settings where radiologist availability is limited—such as small clinics or night shifts. These systems can assist in triage by prioritizing urgent cases and flagging critical findings. Studies by Minici et al. [11] and Farda et al. [15] showed that AI-assisted evaluation of shoulder and foot injuries improved early detection of conditions often missed during initial reads. Additionally, Krogue et al. [9] developed a model for pelvic fracture classification that performed well even on low-quality images, highlighting AI's potential in resource-limited environments.

3.7 Practical Implementations – Example AI Systems

Several commercial AI solutions have been introduced into clinical practice in recent years:

Aidoc – assists in the detection of intracranial hemorrhages and pelvic fractures from CT images, widely used in emergency settings [16].

Zebra Medical Vision – analyzes X-rays for osteoporosis and spinal compression fractures [24].

DeepMind – developed AI tools for detecting ligament injuries in knee MRI based on advanced CNN models [6,25].

OrthoAI – supports classification of pelvic and long bone fractures using X-ray and CT imaging [3,14].

4. Challenges and Limitation

Despite rapid advancements in artificial intelligence (AI) applied to musculoskeletal imaging, numerous obstacles continue to hinder its widespread clinical adoption. These challenges span technical, ethical, legal, and systemic domains, and must be addressed to ensure safe, effective, and equitable integration into healthcare workflows.

4.1 Limited Generalizability Across Populations

One of the primary limitations of current AI systems is their restricted ability to generalize across different patient populations and imaging settings. Most deep learning models are trained on datasets collected from a single institution or region, often lacking demographic diversity. This can result in performance degradation when the models are applied to unseen populations or imaging protocols, particularly in cases involving pediatric, geriatric, or underrepresented ethnic groups [1,16,24]. Addressing this issue requires the creation of multi-institutional, heterogeneous datasets and the implementation of data augmentation or domain adaptation techniques.

4.2 Lack of Transparency and Explainability

Deep learning algorithms, especially convolutional and transformer-based neural networks, are often perceived as “black boxes” due to their complex and opaque internal workings. While visualization tools such as saliency maps or Grad-CAM can highlight areas of interest in an image, they do not offer a full explanation of the model’s reasoning process [7,24,25]. This lack of interpretability remains a significant barrier to clinician trust and legal accountability. Research in Explainable AI (XAI) is actively exploring ways to bridge this gap by incorporating interpretable layers, attention mechanisms, or post-hoc model analysis tools.

4.3 Regulatory and Legal Uncertainty

Most AI applications in orthopedics lack full regulatory clearance, such as CE marking in Europe or FDA approval in the United States. In clinical environments, this creates ambiguity regarding legal responsibility when errors occur. For example, if an AI tool fails to detect a critical fracture, it remains unclear whether the liability rests with the manufacturer, the institution, or the physician relying on the tool’s recommendation [2,22,23]. As AI becomes more autonomous, regulatory frameworks must evolve to clearly define the boundaries of usage, validation requirements, and accountability standards.

4.4 Integration into Clinical Workflows

Even highly accurate AI systems may fail to deliver clinical value if they are not seamlessly integrated into existing diagnostic workflows. Standalone tools that operate outside radiology information systems (RIS) or picture archiving systems (PACS) often require manual input, creating inefficiencies rather than improving throughput [2,8]. Resistance among clinicians may increase when technology is perceived as burdensome or redundant. To address this, AI must be embedded into user-friendly interfaces and operate in real time, ideally as part of a unified diagnostic ecosystem.

4.5 Data Privacy, Security, and Ethical Concerns

The development and deployment of AI models depend heavily on access to large volumes of medical imaging data. However, storing, processing, and sharing such data raise critical concerns regarding patient privacy, data anonymization, and compliance with regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) [28–30]. There is also a growing risk of patient re-identification using advanced reconstruction techniques. Privacy-preserving approaches, such as federated learning or differential privacy, are being explored to mitigate these risks while still enabling model training across institutions.

4.6 Bias, Trust, and Resistance Among Clinicians

Bias in AI systems may stem from imbalanced training data, leading to decreased diagnostic accuracy for specific subgroups—such as women, ethnic minorities, or pediatric patients [7,21,24]. In addition, many healthcare providers remain cautious about relying on AI, either due to a lack of trust in machine-generated decisions or concern over being replaced by automation. Overcoming this resistance requires transparent validation processes, continuous clinician education, and emphasizing the role of AI as an assistive—not replacement—technology. Collaborative development between engineers and healthcare professionals is essential to building systems that are both technically robust and clinically relevant.

4.7 Ethical and Legal Considerations in Clinical AI Deployment

The integration of artificial intelligence (AI) into orthopedic imaging brings not only technical challenges but also a complex array of ethical and legal concerns. As AI systems become more involved in diagnostic decision-making, new questions arise concerning patient autonomy, informed consent, liability, data ownership, and algorithmic fairness.

One of the primary ethical dilemmas relates to informed consent. Patients are often unaware that their imaging data may be processed by AI systems for diagnostic or research purposes. Although anonymization protocols are commonly implemented, they may not fully protect against re-identification, especially with advanced data reconstruction techniques [28]. Ethical guidelines should mandate that patients are informed, in clear language, about the use of AI in their care, and given the opportunity to opt out when appropriate.

Another critical concern is accountability in clinical errors. In cases where an AI tool misses a critical fracture or generates a false positive diagnosis, the legal responsibility remains ambiguous. Current laws in most jurisdictions do not clearly establish whether the blame lies with the physician using the tool, the institution, or the AI developer [22,23]. This legal vacuum is problematic, especially as AI tools gain increasing autonomy and influence in diagnostic pathways. Establishing regulatory frameworks and institutional policies to define liability and ensure transparency is crucial.

Equity and fairness are also pressing issues. AI systems trained on non-representative datasets may amplify existing healthcare disparities, providing less accurate results for underrepresented populations such as women, minorities, or patients with rare disorders [7,21,24]. Ethical deployment must include bias auditing, demographic performance testing, and ongoing model refinement to ensure equitable performance across all patient groups.

Lastly, the need for ethical oversight is growing. Hospitals and healthcare networks considering AI implementation should establish interdisciplinary ethics committees—including clinicians, data scientists, legal experts, and patient representatives—to evaluate risks and guide responsible deployment [24,25]. Transparent documentation of model behavior, validation methods, and known limitations should be shared with both clinicians and patients.

5. Future Perspectives

The growing integration of artificial intelligence (AI) into orthopedic imaging is expected to fundamentally transform diagnostic pathways and clinical workflows in the coming years. However, the full realization of AI's potential will depend on further advancements in data integration, model interpretability, privacy-preserving techniques, and interdisciplinary collaboration. The future of AI in musculoskeletal diagnostics lies in making systems more personalized, explainable, and scalable across diverse healthcare environments.

5.1 Personalized and Multi-Modal AI Models

One key direction involves the development of personalized AI systems that go beyond image interpretation to integrate diverse data sources—including clinical history, laboratory values, genetic information, and patient-reported outcomes [22]. By combining radiological features with patient-specific variables, such models can generate more accurate predictions related to injury severity, treatment response, and long-term functional outcomes.

Multi-modal learning approaches allow for holistic risk assessment and precision treatment planning, aligning with the broader goals of personalized medicine.

5.2 Federated and Decentralized Learning Frameworks

Traditional centralized training of AI models often involves transferring large volumes of sensitive medical data to a central server, raising concerns about privacy and compliance. Federated learning has emerged as a promising alternative, enabling AI models to be trained across multiple institutions without data ever leaving its source [7,24]. This technique not only enhances data security but also improves model generalizability by exposing it to more heterogeneous populations. Future research will likely focus on optimizing federated architectures for speed, accuracy, and resistance to bias.

5.3 Explainable Artificial Intelligence (XAI)

For AI tools to gain widespread clinical acceptance, they must offer a clear and understandable rationale for their predictions. Explainable AI (XAI) seeks to address this challenge by developing methods that highlight how and why a model reaches a specific conclusion [1,24]. Techniques such as heatmaps, attention maps, feature attribution, and layer-wise relevance propagation allow clinicians to visualize and verify decision logic. This transparency is vital for trust-building, legal defensibility, and educational use in radiology training.

5.4 Integration with Augmented Reality and Intraoperative Guidance

The future may also see AI-powered solutions extending beyond diagnostic imaging into intraoperative settings. Combining AI with augmented reality (AR) could provide real-time anatomical overlays and trajectory guidance during orthopedic procedures [6,7]. Such systems could assist surgeons in locating fracture lines, placing implants, or navigating complex anatomical regions with increased accuracy. Although still in experimental stages, AR-AI integration represents an exciting frontier in orthopedic innovation.

Beyond diagnostics, the combination of AI with augmented reality (AR) holds significant promise for intraoperative and preoperative support in orthopedic surgery. AI-enhanced AR platforms can project real-time, patient-specific anatomical overlays onto the surgical field, assisting surgeons in visualizing fracture lines, implant trajectories, and critical structures without shifting attention from the operative site [6,7].

Such systems are currently under experimental development but show early success in spine surgery, total joint arthroplasty, and fracture fixation procedures. For instance, by leveraging AI for preoperative planning and AR for intraoperative guidance, surgeons can potentially reduce operative time, improve accuracy, and lower the risk of complications [23].

In addition, AR-AI integration may serve an important role in medical education and surgical simulation. Trainees can use AR models based on real patient imaging data to practice procedures in a controlled environment, while AI-based feedback systems assess their performance in real time [25].

5.5 Natural Language Processing (NLP) for Clinical Insight

Another frontier in AI development is the application of natural language processing (NLP) to extract relevant clinical insights from unstructured textual data, such as radiology reports, surgical notes, and patient histories [2]. NLP models trained on orthopedic terminology can assist in structuring diagnostic summaries, flagging contradictions, or identifying clinical trends. Incorporating NLP into clinical decision support systems may further enhance efficiency by reducing cognitive load and enabling more comprehensive patient assessment.

Natural language processing (NLP) is increasingly recognized as a key AI tool for extracting structured information from unstructured clinical texts. In orthopedic settings, NLP models can analyze radiology reports, operative notes, and patient histories to identify diagnostic entities, flag inconsistencies, and track treatment progress over time [2].

For example, NLP systems have been used to automatically classify fracture types based on descriptive reports, detect mentions of complications in follow-up notes, or identify candidates for reimaging based on worsening symptoms. These tools can also assist in the retrospective review of imaging cases for audit or quality improvement initiatives [30].

Moreover, by linking NLP-derived data with imaging features, researchers can build rich, longitudinal patient profiles that inform personalized treatment recommendations [24]. Integration of NLP with clinical decision support systems (CDSS) may significantly reduce clinician workload and allow for earlier detection of subtle clinical signals that would otherwise remain hidden in free-text documentation [2,8].

5.6 Case Example: Emergency Department Deployment

A recent deployment of AI-assisted diagnostic tools in a European trauma center highlighted the real-world value of such systems. During overnight emergency shifts, integration of the Aidoc platform for CT triage reduced the average time to diagnosis by 23%. In particular, pelvic fracture detection sensitivity improved by 17% when radiologists used AI-generated alerts [3,16]. This case illustrates the practical utility of AI in time-sensitive and high-volume environments, reinforcing its role as a supportive technology rather than a standalone decision-maker.

6. Research Gaps and Recommendations

While the current body of research showcases the promising potential of AI in orthopedic imaging, several key gaps remain unaddressed, limiting real-world implementation and clinical trust.

First, there is a paucity of large-scale, prospective clinical trials evaluating AI performance in live diagnostic environments. Most studies cited in the literature are retrospective, relying on curated datasets with ideal image quality [1, 10, 16]. These studies, while valuable, often fail to capture the variability and complexity of real-world clinical scenarios.

Second, AI models often lack validation across diverse populations and imaging systems. Differences in scanner calibration, imaging protocols, and patient demographics may significantly affect model accuracy. There is a clear need for multicenter collaborations that share diverse datasets to improve generalizability [24, 27].

Another notable gap is the limited understanding of clinician–AI interaction. Few studies examine how physicians actually interpret and act upon AI-generated outputs, how trust is calibrated over time, or how user interfaces affect decision-making [7, 25]. Future research should include qualitative and usability studies involving frontline radiologists and orthopedic surgeons.

Furthermore, regulatory guidance remains fragmented and inconsistent. Harmonized standards for AI validation, explainability, documentation, and real-time monitoring are urgently needed [22, 23]. National and international medical societies should develop consensus guidelines to support consistent evaluation and deployment practices.

To accelerate clinical adoption, researchers are encouraged to:

- Conduct prospective randomized controlled trials (RCTs) involving AI-supported diagnostics [22],
- Collect and report demographic performance metrics [21],
- Include clinicians in all phases of model development [24],
- Focus on real-time workflow integration and cost-effectiveness analyses [2, 8].

7. Discussion

The use of artificial intelligence (AI) in orthopedic imaging presents a paradigm shift in diagnostic radiology. This review has demonstrated that deep learning models—particularly convolutional neural networks (CNNs)—can achieve diagnostic performance comparable to or exceeding that of experienced radiologists, particularly in the detection of fractures and soft tissue injuries. However, these promising findings must be interpreted in light of several limitations and contextual factors.

First, many studies demonstrating high diagnostic accuracy were conducted in controlled environments using retrospective datasets with optimal image quality. In real-world clinical practice, image variability, noise, and limited annotation accuracy may reduce model performance. Furthermore, despite high reported metrics (e.g., sensitivity or AUC), few studies provided information on model robustness in edge cases or rare pathologies.

Another critical issue is the lack of clinical trials assessing the impact of AI on real-time decision-making and patient outcomes. While commercial systems like Aidoc and Zebra Medical Vision are in use, comprehensive evaluation in multi-center, prospective trials remains limited. Additionally, few studies examine clinician–AI interaction, trust calibration, or workflow disruptions during implementation.

Integration challenges also persist. AI systems that do not seamlessly plug into PACS/RIS environments or require manual input may paradoxically reduce efficiency. Moreover, concerns over legal liability, data privacy, and regulatory uncertainty continue to slow the pace of deployment. These barriers suggest that AI should be viewed not as a replacement for clinical judgment but as an assistive tool requiring careful implementation and oversight.

The reviewed literature also highlights disparities in model generalizability, especially across age groups, ethnic backgrounds, and imaging modalities. Ensuring fairness and minimizing bias will require investment in inclusive, diverse datasets and transparent reporting standards.

Despite these challenges, the long-term potential of AI in orthopedic imaging is substantial. Future systems that integrate radiological data with clinical and genetic information may offer highly personalized diagnostics. Moreover, as explainable AI (XAI) and federated learning mature, issues of trust, accountability, and privacy may become more manageable.

8. Conclusions

AI significantly improves diagnostic accuracy, efficiency, and triage in orthopedic imaging. Yet, barriers remain—most notably in trust, explainability, and infrastructure. Future models must be transparent, personalized, and clinically validated. AI should augment, not replace, clinical judgment, and success will require ongoing cooperation between technologists and clinicians.

List of Abbreviations

AI - Artificial Intelligence
AR - Augmented Reality
AUC - Area Under the Curve
ACL - Anterior Cruciate Ligament
CDSS - Clinical Decision Support System(s)
CNN - Convolutional Neural Network(s)
CT - Computed Tomography
DL - Deep Learning
EMR - Electronic Medical Record(s)
GDPR - General Data Protection Regulation
HIPAA - Health Insurance Portability and Accountability Act
MRI - Magnetic Resonance Imaging
NLP - Natural Language Processing
PACS - Picture Archiving and Communication System
RIS - Radiology Information System
SOR - Szpitalny Oddział Ratunkowy (Emergency Department – Polish term)
XAI - Explainable Artificial Intelligence

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