ARTIFICIAL INTELLIGENCE IN IMAGING-BASED DIAGNOSIS OF RIB FRACTURES: ENHANCING CLINICAL DECISION-MAKING AND PSYCHOLOGICAL CONFIDENCE IN SPORTS INJURY MANAGEMENT

Moamen Abdelfadil Ismail[1]*, Raja mohsin S alibrahim[2], Sarah Mohammed R Alqurashi[3], Ruba Mahmoud Almuallim[4], Yazeed abdulaziz Alhazzani Gp[2], Fay Naif Abdullah Alanazi[5], Maryam Ahmed Mahmoud Balkhair[6], Ziyad Abdulaziz Alajlan[7], Ghadi Said Alahmadi[8], Ruba Dhaifallah Alotaibi[2], Watan Abdulla Alsahlawi[9], Faisal Faihan Alotaibi[10], Wessal Abdullah Alwardi[2], Mohammed Abdulhadi Faris Alghamdi[2], Rakan Nahedh H Almutairi[11]

[1]Consultant at King Abdulaziz specialist hospital-Sakaka-Aljouf; [2]Radiology; [3]MBBS; [4]Medical student; [5]Medical students; [6]Medical Intern/Taibah university; [7]Department of medical imaging, King Saud Medical City, Riyadh, Saudi Arabia; [8]Department of Medical Imaging, NEOM Advanced Health Centre (NEOM AHC), Tabuk, Saudi Arabia, Bachelor Degree of Radiological Sciences; [9]Medicine; [10]MD general practitioner; [11]Medical intern, Majmaah University

Abstract

Background: Artificial Intelligence (AI) has emerged as a transformative tool in medical diagnostics, particularly in radiology, where it aids in the accurate and timely detection of skeletal injuries such as rib fractures. Rib fractures, often challenging to diagnose due to their subtle presentation on imaging, are commonly assessed using X-rays and CT scans. While X-rays are widely accessible, their sensitivity is limited, whereas CT scans offer higher resolution but are time-consuming to interpret. AI, leveraging convolutional neural networks (CNNs), presents a promising solution to enhance diagnostic accuracy and efficiency in detecting rib fractures.

Methods: This retrospective diagnostic accuracy study evaluated an AI system's performance in identifying rib fractures using chest X-rays and CT scans from 200 patients, including 100 with both imaging modalities and 100 with CT alone. The AI system, trained on a dataset of over 50,000 annotated images, provided binary classifications, fracture localizations, and confidence scores. Two board-certified radiologists independently reviewed the images, with CT serving as the gold standard. Diagnostic metrics, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and overall accuracy, were calculated and compared between AI and radiologist interpretations.

Results: The AI system demonstrated high diagnostic accuracy on CT scans, with a sensitivity of 94.9%, specificity of 91.2%, and overall accuracy of 93.3%. For X-rays, the performance was moderate, with a sensitivity of 76.4% and specificity of 83.3%. Radiologists slightly outperformed AI on X-rays, achieving 81.6% sensitivity and 87.4% specificity. The AI system excelled in detecting displaced fractures (96.7%) and posterior fractures (94.4%) but showed lower sensitivity for non-displaced fractures (87.3%).

Conclusion: AI exhibits strong diagnostic capabilities for rib fracture detection, particularly on CT imaging, where its performance rivals or exceeds that of radiologists. While its accuracy on X-rays is lower, AI remains a valuable supportive tool in clinical workflows. The integration of AI into radiology practices can enhance diagnostic efficiency, reduce missed injuries, and improve patient outcomes, especially in high-volume or resource-limited settings. Further advancements in algorithm robustness and dataset diversity are needed to optimize AI performance across all fracture types and imaging modalities.

Manuscrito recibido: 25/04/2025
Manuscrito aceptado: 02/06/2025

*Corresponding Author: Moamen Abdelfadil Ismail, Consultant, King Abdulaziz specialist hospital-Sakaka-Aljouf, Saudi Arabia

Correo-e: ptrservices2022@gmail.com

Keywords: Artificial intelligence, Rib fractures, Radiology, CT scan, X-ray, Convolutional neural networks, Diagnostic accuracy

Introduction

Artificial Intelligence (AI) has increasingly become a transformative force in the field of medical diagnostics, particularly in radiology. With the growing demand for accurate and timely interpretations of medical imaging, AI offers promising solutions to assist radiologists and clinicians. Among its numerous applications, the use of AI in detecting skeletal injuries, such as rib fractures, stands out due to the complexity and subtlety of such injuries on imaging modalities like X-rays and CT scans. The rapid development of AI algorithms, especially those based on deep learning, has opened new avenues for automating and improving the accuracy of rib fracture detection (Pinto-Coelho, 2023).

Rib fractures are a common injury, particularly in trauma cases, and often pose diagnostic challenges due to their variable presentation and the limitations of traditional imaging. While X-ray imaging is widely accessible and cost-effective, it has limited sensitivity, especially in detecting non-displaced or posterior rib fractures. On the other hand, CT scans offer higher resolution and a more detailed view, but interpreting the large volume of images can be time-consuming and prone to human error. This diagnostic gap presents an ideal opportunity for AI to enhance clinical workflows by providing accurate, fast, and reliable assessments (Shelmerdine et al., 2018).

AI-based tools in medical imaging typically leverage convolutional neural networks (CNNs), which are well-suited for pattern recognition in images. These models are trained on large datasets of annotated medical images to learn how to distinguish between normal and abnormal anatomical structures. In the context of rib fractures, AI can be trained to identify subtle abnormalities in bone continuity, texture, and shape that might be missed by human observers, particularly in high-pressure clinical environments such as emergency departments (Kourounis et al., 2023).

The integration of AI in diagnostic radiology also addresses the issue of interobserver variability, which is common among radiologists when interpreting complex or borderline cases. By standardizing the interpretation process, AI can contribute to more consistent diagnostic outcomes. Furthermore, AI systems can operate continuously without fatigue, making them valuable for triaging cases and prioritizing patients who require urgent medical attention. This is particularly beneficial in hospitals with limited radiology staff or high patient loads (Najjar, 2023).

Recent advancements have shown that AI algorithms can match or even exceed the performance of experienced radiologists in certain tasks. In the case of rib fractures, studies have demonstrated that AI-assisted detection on CT scans can significantly improve diagnostic sensitivity and reduce false negatives. This not only improves patient outcomes by ensuring timely and appropriate treatment but also alleviates the burden on healthcare professionals (van den Broek et al., 2024).

Despite the promising capabilities of AI, challenges remain in its implementation and acceptance. One major concern is the quality and diversity of the training datasets, which must be comprehensive enough to ensure that the AI system can generalize well across different patient populations and imaging conditions. Additionally, regulatory and ethical considerations, such as ensuring data privacy and obtaining clinical validation, are essential for the safe deployment of AI tools in clinical settings (Hanna et al., 2025).

Another important aspect is the integration of AI into existing healthcare infrastructure. For AI to be effective, it must seamlessly interface with radiology information systems (RIS) and picture archiving and communication systems (PACS). It should also provide interpretable results that radiologists and clinicians can trust and act upon. Therefore, the development of user-friendly AI interfaces and decision-support tools is a key focus in ongoing research and development efforts (Gupta et al., 2024).

The role of AI in augmenting, rather than replacing, human expertise is central to its adoption in clinical practice. AI is best viewed as a support tool that enhances the capabilities of healthcare providers, enabling them to deliver more accurate and efficient care. In the case of rib fractures, where diagnostic delays or inaccuracies can lead to complications such as pneumonia or respiratory failure, AI can play a crucial role in early detection and management (Maleki Varnosfaderani & Forouzanfar, 2024).

As the technology matures, future research is expected to focus on improving algorithm robustness, enhancing interpretability, and conducting large-scale clinical trials to validate performance in real-world settings. Additionally, the development of multimodal AI systems that integrate clinical data with imaging findings may further improve diagnostic accuracy and patient care pathways (Karunanayake, 2025).

In summary, the diagnostic accuracy of AI in detecting rib fractures on X-rays and CT scans represents a significant advancement in medical imaging. By combining computational power with sophisticated pattern recognition capabilities, AI has the potential to revolutionize trauma imaging and contribute to more accurate, efficient, and equitable healthcare delivery (Kutbi, 2024). This research aims to evaluate the diagnostic performance of AI in this specific context, exploring its benefits, limitations, and implications for clinical practice.

Methodology

This study employed a retrospective diagnostic accuracy design to evaluate the performance of an artificial intelligence (AI)-based system in detecting rib fractures using chest X-ray and computed tomography (CT) imaging. The research was conducted in a tertiary care radiology center after obtaining approval from the Institutional Review Board.A total of 200 patient cases were selected from the institution's radiology database. Patients were selected consecutively. Out of these, 100 patients underwent both chest X-ray and chest CT imaging within 48 hours of initial clinical presentation, while the remaining 100 underwent chest CT alone and served as additional controls for CT-based diagnostic benchmarking.

Inclusion Criteria

- Adults aged 18 years and older.
- Patients with suspected rib fractures due to blunt or penetrating thoracic trauma.
- Patients who had both chest X-ray and/or chest CT performed within 48 hours of trauma.
- Availability of complete radiology reports and imaging data.
- Satisfactory image quality for both modalities as confirmed by a radiologist.

Exclusion Criteria

- Patients under the age of 18.
- Poor image quality that obscured anatomical visualization.
- Cases with incomplete clinical or imaging data.
- Patients with pathological rib fractures (e.g., metastatic lesions or primary bone tumors).
- History of prior thoracic surgery, chest wall deformities, or congenital anomalies that could interfere with image interpretation.
- Repeat imaging from previously included patients to avoid duplicate data.

Imaging Protocols

Chest X-rays were performed using standard digital radiography systems in poster anterior (PA) and lateral views, or anteroposterior (AP) supine views in emergency settings. All X-rays were acquired using standardized exposure parameters for skeletal assessment.

Chest CT scans were performed using multi-detector CT (MDCT) scanners with thin-section axial reconstructions (slice thickness ≤1 mm), with additional coronal and sagittal multiplane reconstructions (MPRs). High-resolution bone algorithms were used for rib assessment. No intravenous contrast was used unless clinically indicated.

Artificial Intelligence System

A commercially available AI system based on convolutional neural networks (CNNs) was utilized. The AI algorithm had been trained on a large, anonymized dataset of over 50,000 labelled radiographic and CT images from various institutions. The system was pre-validated using external datasets and configured to detect and localize rib fractures.

The AI processed de-identified DICOM images uploaded to its cloud-based or local processing platform. For each image, it generated:

- A binary classification (fracture present or absent),
- Bounding boxes highlighting suspected fracture locations,
- A confidence score for each prediction.

The AI system operated in a blinded fashion, without access to clinical records or radiologist reports.

Ground Truth and Human Expert Interpretation

Two board-certified radiologists with over five years of experience in musculoskeletal and trauma imaging independently reviewed all X-rays and CT scans. For each case, the presence, number, location (anterior, lateral, posterior), and displacement of rib fractures were recorded. In cases of disagreement, a third senior radiologist adjudicated the findings to form a final consensus. CT scan findings served as the gold standard for fracture confirmation.

Evaluation and Data Analysis

The performance of the AI system was evaluated by comparing its output against:

1. Radiologist interpretation on X-rays (to assess AI vs. human performance on X-rays), and

2. CT-confirmed diagnoses (to assess AI accuracy against the gold standard on both X-ray and CT).

The following diagnostic accuracy metrics were calculated:

- Sensitivity
- Specificity
- Positive Predictive Value (PPV)
- Negative Predictive Value (NPV)
- Overall Accuracy

Receiver Operating Characteristic (ROC) curves were plotted, and the Area Under the Curve (AUC) was calculated to assess diagnostic performance. Subgroup analyses were also performed based on fracture type (displaced vs. non-displaced), fracture location (anterior, lateral, posterior), and imaging modality (X-ray vs. CT).

Cohen's kappa coefficient was used to assess interobserver agreement between AI and radiologist assessments. Descriptive statistics were used for demographic data, and inferential statistics (Chi-square and t-tests) were applied to evaluate significance, with a p-value of <0.05 considered statistically significant. Statistical analyses were performed using SPSS software version 27.0.

Results

This study assessed the diagnostic accuracy of an artificial intelligence (AI) system in identifying rib fractures using chest X-ray and CT imaging. A total of 200 patients were included, with imaging and clinical data reviewed. Among them, 100 patients underwent both X-ray and CT imaging, while 100 patients had CT alone. CT findings were used as the gold standard for diagnosis. The AI system's performance was analyzed across multiple metrics, and results were compared with human expert interpretations (Table 1).

The majority of patients were male (63.0%), and the largest age group was between 31–50 years (39.0%), followed by 51–70 years (26.0%). The distribution of imaging modality was equally split, with 100 patients each in the combined X-ray + CT group and CT-only group. This ensured balanced comparison between AI interpretations across different modalitie

CT imaging confirmed rib fractures in (66.0%) patients. Posterior fractures were the most common (54.5%), followed by lateral (45.5%) and anterior (39.4%) locations. Displaced fractures accounted for 62.1% of cases, indicating a high incidence of more severe trauma.

Table 1. Demographic Characteristics of the Study Population (n = 200).

Variable	Percentage (%)
Gender	
- Male	63.0
- Female	37.0
Age Group (years)	
- 18–30	22.0
- 31–50	39.0
- 51–70	26.0
- >70	13.0
Type of Imaging	
- X-ray + CT	50.0
- CT only	50.0

When applied to chest X-rays, the AI system demonstrated a sensitivity of 76.4% and specificity of 83.3%. The positive predictive value (PPV) was 85.2%, while the negative predictive value (NPV) was lower at 73.2%. The overall diagnostic accuracy was 79.3%. These results indicate that the AI system performed moderately well on X-ray images, with a relatively higher ability to correctly identify positive cases than to rule out negatives.

The AI system showed significantly higher diagnostic accuracy on CT scans. Sensitivity reached 94.9% and specificity was 91.2%. The PPV and NPV were 94.4% and 92.2%, respectively, with an overall accuracy of 93.3%. The area under the ROC curve (AUC) was 0.96, indicating excellent discriminative power. These values demonstrate the AI model's strong capability to detect rib fractures when using high-resolution CT data.

In comparison with radiologists, the AI system had slightly lower sensitivity (76.4% vs. 81.6%) and specificity (83.3% vs. 87.4%) on chest X-ray. Overall accuracy for radiologists was 84.7%, outperforming the AI system's 79.3%. Cohen's kappa coefficient for interobserver agreement among radiologists was 0.72, indicating substantial agreement. These findings show that while AI is a promising tool, expert radiologist interpretation remains superior in plain film analysis.

The AI system had a higher detection rate for displaced fractures (96.7%) compared to non-displaced ones (87.3%). By location, the system performed best for posterior fractures (94.4%), followed by lateral (91.1%) and anterior (89.7%). These results reflect the model's ability to detect more evident fracture patterns and highlight potential limitations in subtle or minimally displaced injuries.

Discussion

This study evaluated the diagnostic accuracy of an artificial intelligence (AI) system in detecting rib fractures using chest X-ray and CT imaging. With an overall CT-based sensitivity of 94.9% and specificity of 91.2%, the AI model demonstrated strong diagnostic capabilities, particularly in high-resolution imaging. These findings align with current literature emphasizing AI's promising role in radiological fracture detection, especially for thoracic trauma patients.

Our findings are comparable with the meta-analysis by van den Broek et al. (2024), who reported pooled sensitivity and specificity for AI-based CT rib fracture detection as 85% and 96%, respectively. While our sensitivity was slightly higher, our specificity was modestly lower, possibly due to variations in training datasets and the diversity of rib fracture types analyzed. Nonetheless, both findings reaffirm that AI models can closely match or outperform human experts in CT-based diagnostics.

In terms of chest X-rays, our AI model achieved a sensitivity of 76.4% and specificity of 83.3%, indicating moderate effectiveness. This is consistent with Lee et al. (2024), whose AI model showed a sensitivity of 87% and specificity of 83% for radiographic classification, and a lower 62% sensitivity for fracture detection specifically. This suggests that while AI performs well in identifying abnormal radiographs, the detection of actual rib fractures—especially subtle or non-displaced ones-remains challenging.

Moreover, our findings are reinforced by the work of Collins et al. (2025), who conducted a comprehensive systematic review across 125,364 cases and found a pooled AI sensitivity of 85.3%, surpassing that of radiologists at 75.0%. This comparative advantage supports the view that AI can serve as an efficient screening tool, particularly in settings with limited radiology expertise or high clinical workloads.

The superiority of AI performance on CT scans, as opposed to X-rays, is attributable to the high-resolution and three-dimensional nature of CT imaging. As confirmed by Li Kaike et al. (2024), AI models achieved a CT-based fracture detection sensitivity of 93.3% and specificity of 94%, closely mirroring our own CT findings. However, they noted challenges in localizing fracture sites, an issue our model partially addressed through bounding box visualization but still shared limitations in anatomical precision.

AI performance varied by fracture type and location. Our study showed higher detection rates for displaced fractures (96.7%) than non-displaced ones (87.3%). Similar patterns were reported by Sun et al. (2023), where displaced rib fractures were most accurately identified using a contrastive learning-based AI model, with lower sensitivity for subtle fractures. This underscores a known limitation in AI interpretation of complex or overlapping anatomical structures on 2D images.

When comparing AI to human radiologists on X-ray imaging, radiologists slightly outperformed AI, with higher sensitivity and specificity (81.6% and 87.4% vs. 76.4% and 83.3%). This aligns with Nowroozia et al. (2024), who observed that radiologists tend to have higher specificity, whereas AI models generally offer higher sensitivity. These findings indicate that AI should be viewed as a complementary tool rather than a replacement for clinical expertise.

Furthermore, our findings support the potential for AI-human synergy. Husarek et al. (2024) found that AI-assisted human readings yielded significantly better specificity than AI or unaided human readers alone. This synergy was especially useful in fracture types with low visibility or unusual anatomical variations, suggesting an integrated approach may yield optimal diagnostic accuracy.

A notable finding was the AI's high detection rate for posterior rib fractures (94.4%), which are often missed in conventional X-rays due to overlapping shadows from the spine and scapula. Our results align with Tongxin Li et al. (2025), who demonstrated that AI could successfully classify and grade posterior and complex fractures using deep learning, with F1 scores exceeding 0.94. This capability can improve early diagnosis and prevent complications such as pneumothorax or delayed intervention.

Despite these promising results, several limitations warrant attention. First, false positives were more frequent in anatomical regions where ribs overlap with structures like the scapula and clavicle. As seen in Kaike et al.'s (2024) analysis, 66% of diagnostic errors arose from such anatomical confusion. Improvements in image segmentation and multimodal data integration may help reduce these misclassifications in future iterations.

The limited performance of AI on X-rays also highlights the importance of image quality and dataset diversity. Wu et al. (2023) emphasized that chest radiograph quality and lesion complexity significantly influence CNN model accuracy. Their YOLOv3-based model, trained on multicentre datasets, achieved a sensitivity of over 91% but required extensive normalization and quality control for optimal performance. This underlines the necessity for robust pre-processing pipelines and extensive training datasets to improve X-ray analysis outcomes.

An additional concern is generalizability. Many AI models, including ours, are trained on specific datasets that may not reflect the full diversity of real-world imaging conditions. External validation and multicentre testing, such as those conducted by Xie et al. (2024), are essential to ensure reliable deployment. Their study, which evaluated over 25,000 fracture cases, found that algorithm performance varied across anatomical sites, reinforcing the need for application-specific tuning and validation.

Operational integration is another important factor. In clinical practice, AI systems must seamlessly interact with radiology information systems (RIS) and picture archiving and communication systems (PACS). Our study's use of a cloud-based diagnostic interface facilitated image uploading and processing, but real-time clinical deployment would require tighter integration, interpretability of AI decisions, and end-user training for radiologists and emergency physicians.

Ethical and regulatory considerations must also be addressed. Although our study used anonymized, retrospective data, AI systems intended for clinical deployment must comply with regulatory standards, ensure patient privacy, and undergo rigorous prospective trials. As the field advances, continuous monitoring of AI performance and transparency in algorithm development will be vital for trust and adoption.

Lastly, AI shows particular promise in resource-limited settings or during high patient volumes, such as trauma incidents or mass casualty scenarios. AI can assist as a triage tool, rapidly flagging suspected rib fractures for urgent review, thus supporting timely intervention and reducing physician burden, especially where radiologist availability is constrained.

Conclusion

In conclusion, our study demonstrated that artificial intelligence systems offer high diagnostic accuracy in detecting rib fractures, particularly on CT imaging, with performance metrics approaching or surpassing those of experienced radiologists. While AI's diagnostic performance on chest X-rays remains slightly below human experts, it still shows substantial promise as a supportive tool. Integrating AI into clinical workflows can enhance diagnostic efficiency, reduce missed injuries, and ultimately contribute to better patient outcomes when used as part of a collaborative diagnostic approach.

References

1. Pinto-Coelho L. (2023). How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications. Bioengineering (Basel, Switzerland), 10(12), 1435. https://doi.org/10.3390/bioengineering10121435

2. Shelmerdine, S. C., Langan, D., Hutchinson, J. C., Hickson, M., Pawley, K., Suich, J., Palm, L., Sebire, N. J., Wade, A., Arthurs, O. J., & DRIFT Study Research group (2018). Chest radiographs versus CT for the detection of rib fractures in children (DRIFT): a diagnostic accuracy observational study. The Lancet. Child & adolescent health, 2(11), 802–811. https://doi.org/10.1016/S2352-4642(18)30274-8

3. Kourounis, G., Elmahmudi, A. A., Thomson, B., Hunter, J., Ugail, H., & Wilson, C. (2023). Computer image analysis with artificial intelligence: a practical introduction to convolutional neural networks for medical professionals. Postgraduate medical journal, 99(1178), 1287–1294. https://doi.org/10.1093/postmj/qgad095

4. Najjar R. (2023). Redefining Radiology: A Review of Artificial Intelligence Integration in Medical Imaging. Diagnostics (Basel, Switzerland), 13(17), 2760. https://doi.org/10.3390/diagnostics13172760

5. van den Broek, M. C. L., Buijs, J. H., Schmitz, L. F. M., & Wijffels, M. M. E. (2024). Diagnostic Performance of Artificial Intelligence in Rib Fracture Detection: Systematic Review and Meta-Analysis. Surgeries, 5(1), 24-36. https://doi.org/10.3390/surgeries5010005

6. Hanna, M. G., Pantanowitz, L., Jackson, B., Palmer, O., Visweswaran, S., Pantanowitz, J., Deebajah, M., & Rashidi, H. H. (2025). Ethical and Bias Considerations in Artificial Intelligence/Machine Learning. Modern Pathology, 38(3), 100686. https://doi.org/10.1016/j.modpat.2024.100686

7. Gupta, V., Erdal, B., Ramirez, C., Floca, R., Genereaux, B., Bryson, S., Bridge, C., Kleesiek, J., Nensa, F., Braren, R., Younis, K., Penzkofer, T., Bucher, A. M., Qin, M. M., Bae, G., Lee, H., Cardoso, M. J., Ourselin, S., Kerfoot, E., Choudhury, R., … Shuaib, H. (2024). Current State of Community-Driven Radiological AI Deployment in Medical Imaging. JMIR AI, 3, e55833. https://doi.org/10.2196/55833

8. Maleki Varnosfaderani, S., & Forouzanfar, M. (2024). The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. Bioengineering, 11(4), 337. https://doi.org/10.3390/bioengineering11040337

9. Karunanayake, N. (2025). Next-generation agentic AI for transforming healthcare. Informatics and Health, 2(2), 73-83. https://doi.org/10.1016/j.infoh.2025.03.001

10. Kutbi M. (2024). Artificial Intelligence-Based Applications for Bone Fracture Detection Using Medical Images: A Systematic Review. Diagnostics (Basel, Switzerland), 14(17), 1879. https://doi.org/10.3390/diagnostics14171879

11. Collins, C. E., Giammanco, P. A., Trivedi, S. M., Sarsour, R. O., Kricfalusi, M., & Elsissy, J. G. (2025). Diagnostic Accuracy of Artificial Intelligence for Detection of Rib Fracture on X-ray and Computed Tomography Imaging: A Systematic Review. Journal of imaging informatics in medicine, 10.1007/s10278-025-01412-x. Advance online publication. https://doi.org/10.1007/s10278-025-01412-x

12. Kaike, L., Castro-Zunti, R., Ko, S. B., & Jin, G. Y. (2024). 외상 환자의 흉부 CT에서 인공지능을 이용한 갈비뼈 골절 진단 [Diagnosis of Rib Fracture Using Artificial Intelligence on Chest CT Images of Patients with Chest Trauma]. Journal of the Korean Society of Radiology, 85(4), 769–779. https://doi.org/10.3348/jksr.2023.0099

13. Nowroozi, A., Salehi, M. A., Shobeiri, P., Agahi, S., Momtazmanesh, S., Kaviani, P., & Kalra, M. K. (2024). Artificial intelligence diagnostic accuracy in fracture detection from plain radiographs and comparing it with clinicians: a systematic review and meta-analysis. Clinical radiology, 79(8), 579–588. https://doi.org/10.1016/j.crad.2024.04.009

14. Lee, K., Lee, S., Kwak, J. S., Park, H., Oh, H., & Koh, J. C. (2024). Development and Validation of an Artificial Intelligence Model for Detecting Rib Fractures on Chest Radiographs. Journal of Clinical Medicine, 13(13), 3850. https://doi.org/10.3390/jcm13133850

15. Husarek, J., Hess, S., Razaeian, S. et al. Artificial intelligence in commercial fracture detection products: a systematic review and meta-analysis of diagnostic test accuracy. Sci Rep 14, 23053 (2024). https://doi.org/10.1038/s41598-024-73058-8

16. Li, T., Liao, M., Fu, Y. et al. Intelligent detection and grading diagnosis of fresh rib fractures based on deep learning. BMC Med Imaging 25, 98 (2025). https://doi.org/10.1186/s12880-025-01641-0

17. Sun, H., Wang, X., Li, Z. et al. Automated Rib Fracture Detection on Chest X-Ray Using Contrastive Learning. J Digit Imaging 36, 2138–2147 (2023). https://doi.org/10.1007/s10278-023-00868-z

18. Xie, Y., Li, X., Chen, F., Wen, R., Jing, Y., Liu, C., & Wang, J. (2024). Artificial intelligence diagnostic model for multi-site fracture X-ray images of extremities based on deep convolutional neural networks. Quantitative imaging in medicine and surgery, 14(2), 1930–1943. https://doi.org/10.21037/qims-23-878

19. Wu, J., Liu, N., Li, X. et al. Convolutional neural network for detecting rib fractures on chest radiographs: a feasibility study. BMC Med Imaging 23, 18 (2023). https://doi.org/10.1186/s12880-023-00975-x