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Bone Fracture Detection Using Artificial Intelligence: A Review Of Deep Learning Architectures, Datasets And Clinical Integration

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Abstract—Bone fractures are common injuries that require accurate and timely diagnosis for appropriate treatment. Conventional detection relies on interpretation of X-ray images by radiologists or emergency physicians, and subtle fractures can be missed, particularly during busy shifts or when specialist reading is unavailable. Artificial Intelligence (AI), especially deep learning and computer vision, offers a promising way to assist fracture detection. This paper reviews AI-based fracture detection on radiographs. It examines datasets such as MURA and GRAZPEDWRI-DX, convolutional neural networks with transfer learning for classifying images as fractured or normal, object-detection models such as Faster R-CNN and YOLO for localizing fracture regions, segmentation networks, and visual explanation methods that highlight suspicious areas. Studies showing that AI assistance improves clinician sensitivity and reading efficiency are discussed. A layered architecture covering image acquisition, preprocessing, a detection engine, explanation and a clinical review interface is proposed, along with the working methodology, evaluation metrics, a comparison of model families and a discussion of challenges including image quality, dataset diversity, fracture type and clinical validation. The review concludes that AI should support rather than replace professional judgement and can help prioritize urgent cases and reduce missed fractures.

Index Terms—Bone fracture detection, deep learning, convolutional neural networks, X-ray, object detection, YOLO, Faster R-CNN, computer-aided diagnosis

I. Introduction

Fractures are among the most frequent reasons for emergency department visits. Prompt and correct diagnosis determines whether a patient receives a cast, surgery or simply reassurance. A missed fracture can lead to improper healing, chronic pain or disability, and it is one of the most common diagnostic errors in emergency medicine. Subtle fractures of the wrist, hip and small bones of the hand and foot are particularly easy to overlook.

Radiographs are typically read first by emergency physicians or junior doctors, often under time pressure and without immediate radiologist support, especially in smaller hospitals. AI systems that analyse X-ray images and highlight possible fractures can act as a second reader, improving sensitivity and consistency.

This paper reviews deep learning approaches to fracture detection, proposes a clinical architecture and discusses the challenges that must be addressed before routine use.

II. Related Work

Olczak *et al.* [1] trained several deep networks on a large set of wrist, hand and ankle radiographs from a Swedish hospital and found that the best network identified fractures with accuracy comparable to senior orthopaedic surgeons reviewing the same images at reduced resolution. Kim and MacKinnon [2] applied transfer learning with a pre-trained Inception network to wrist radiographs and achieved high discrimination, showing that good results are possible with relatively small medical datasets.

Lindsey *et al.* [3] developed a deep network trained on wrist radiographs annotated by orthopaedic surgeons and, crucially, tested it as an aid to emergency clinicians; with the model's assistance, clinicians' sensitivity and specificity improved and the misinterpretation rate fell substantially. This demonstrated the value of AI as a support tool rather than an independent reader.

Rajpurkar *et al.* [4] released MURA, a large dataset of upper-extremity musculoskeletal radiographs labelled as normal or abnormal, and found that model performance matched radiologists on some body parts but lagged on others. Yahalomi *et al.* [5] used Faster R-CNN to detect distal radius fractures with a small training set, demonstrating localization with limited data. Nagy *et al.* [6] published GRAZPEDWRI-DX, an annotated paediatric wrist trauma dataset with bounding boxes suitable for training object detectors.

Guermazi *et al.* [7] conducted a multi-reader study in which radiologists and other physicians read radiographs with and without AI assistance, and found improved sensitivity and shorter reading times with AI. Litjens *et al.* [8] place these results within the broader trend of deep learning in medical imaging. Table I summarizes the surveyed works.

Sr. No.	Ref.	Year	Methodology	Findings	Research Gap
1	[1]	2017	Deep networks on wrist, hand, ankle X-rays	Accuracy comparable to senior surgeons	Reduced-resolution comparison
2	[4]	2017	MURA dataset + DenseNet	Large upper-extremity benchmark	Below radiologists on some parts
3	[8]	2017	Survey of deep learning in imaging	Context for musculoskeletal AI	General survey
4	[2]	2018	Transfer learning (Inception) on wrist X-rays	High discrimination with small dataset	Single view and region
5	[3]	2018	Deep network as clinician aid	Improved clinicians' sensitivity and specificity	Wrist fractures only
6	[5]	2019	Faster R-CNN on distal radius	Localization with small training set	Small evaluation set
7	[6]	2022	GRAZPEDWRI-DX paediatric dataset	Box-annotated paediatric wrist images	Single centre
8	[7]	2022	Multi-reader study with AI assistance	Higher sensitivity and faster reading	Retrospective reading study

TABLE I Summary of Literature Survey

III. Preliminaries

3.1 Fracture Detection Tasks

AI can address three tasks: classification, deciding whether an image contains a fracture; localization, drawing a box around the fracture; and segmentation, outlining the fracture line or bone at the pixel level. Some systems also classify fracture type or severity. Fig. 1 summarizes the approaches.

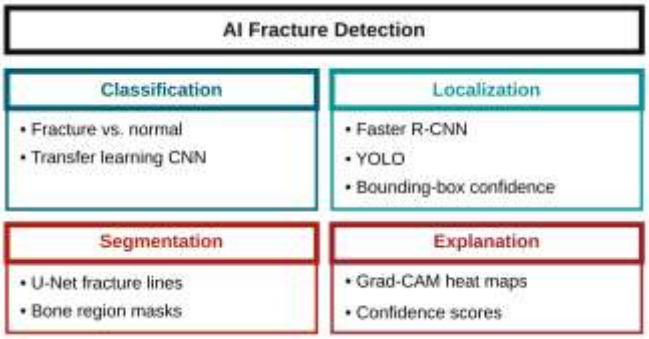


Fig. 1. AI approaches for bone fracture detection.

3.2 Deep Learning Building Blocks

Convolutional Neural Networks learn edges, textures and shapes that characterize bone discontinuities. Transfer learning starts from networks such as ResNet [9] pre-trained on natural images and fine-tunes them on radiographs. Object detectors such as Faster R-CNN [10] and YOLO [11] predict bounding boxes, and focal loss [12] helps when fractures occupy a small part of the image.

IV. Problem Statement and Objectives

4.1 Identified Research Gaps

The following gaps are identified:

1. 1) Most models focus on specific body regions; general models covering the whole skeleton remain limited.
2. 2) Datasets often come from a few hospitals, and performance on different X-ray machines and populations is uncertain.
3. 3) Subtle, non-displaced and paediatric fractures remain difficult for both humans and models.
4. 4) Few studies measure the effect of AI on patient outcomes rather than reading accuracy.
5. 5) Integration into hospital imaging systems and workflows is rarely described.

4.2 Objectives of the Review

The objectives of this review are:

O1: To review AI algorithms for fracture classification, localization and segmentation.

O2: To examine public datasets and evaluation methods for fracture detection.

O3: To propose a clinical architecture for AI-assisted fracture detection.

O4: To compare model families in accuracy, explainability and computational cost.

O5: To discuss advantages, challenges and future scope.

4.3 Proposed Framework

The proposed architecture, shown in Fig. 2, integrates AI into the radiology workflow as a second reader and triage tool.

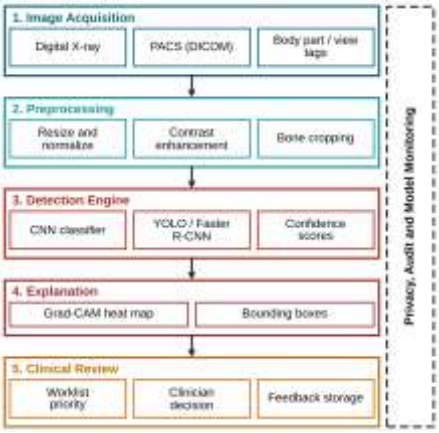


Fig. 2. Proposed architecture for AI-assisted bone fracture detection.

4.4 Image Acquisition Layer

Radiographs are captured by digital X-ray systems and stored in the hospital picture archiving system in DICOM format, along with body part and view information.

4.5 Preprocessing Layer

Images are converted to a standard size and intensity range, contrast is enhanced using methods such as adaptive histogram equalization, and the bone region is cropped. Augmentation with rotation, flipping and brightness changes is used during training.

4.6 Detection Engine

A classification network estimates the probability of a fracture, and an object detector such as YOLO or Faster R-CNN localizes suspected regions with bounding boxes and confidence scores.

4.7 Explanation Layer

Grad-CAM [13] heat maps and bounding boxes show clinicians exactly where the model sees a possible fracture, allowing quick verification.

4.8 Clinical Review Layer

Results are displayed in the radiology viewer. High-probability cases are prioritized in the worklist. The clinician confirms or rejects each finding, and the decision is stored for audit and model improvement.

V. Working Methodology

The working process is shown in Fig. 3. Localization quality is measured by the Intersection over Union between a predicted box B_p and the ground truth box B_g:

$$IoU = |B_p \cap B_g| / |B_p \cup B_g| \quad (1)$$

A detection is counted as correct if IoU exceeds a threshold, typically 0.5. Diagnostic performance is reported with sensitivity, specificity and AUC, and for detectors with mean average precision. Because fractures are a minority of images, focal loss down-weights easy negatives:

$$FL(p_t) = -\alpha_t (1 - p_t)^{\gamma} \cdot \log(p_t) \quad (2)$$

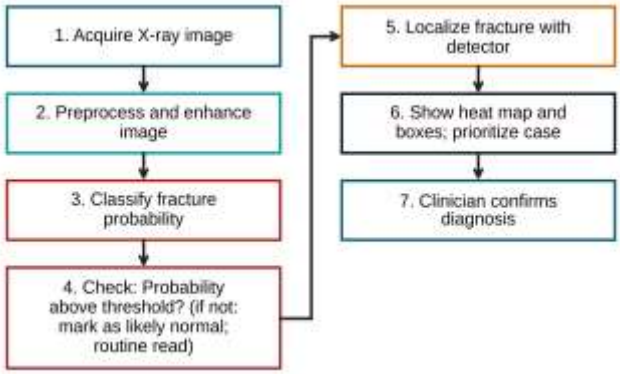


Fig. 3. Workflow of AI-assisted fracture detection.

VI. Discussion

6.1 Comparison of Approaches

Table II compares model families. Classification CNNs are simple and accurate for normal versus abnormal decisions; detectors add localization at higher computational cost; and segmentation networks provide the most detail but require pixel-level annotations.

Model	Output	Annotation Need	Compute
CNN classifier (ResNet, DenseNet)	Fracture yes / no	Image labels	Low–Medium
Faster R-CNN	Boxes + labels	Bounding boxes	High
YOLO	Boxes + labels	Bounding boxes	Medium (real time)
U-Net	Pixel masks	Pixel masks	Medium
Ensemble	Combined	Mixed	High

TABLE II Comparison of Model Families

Applications include emergency triage, screening in rural clinics with tele-radiology, training of junior doctors and quality assurance in radiology departments.

6.2 Open Challenges and Future Work

Table III summarizes the main challenges. Future work should include multi-centre datasets from Indian hospitals, models that cover all body parts and paediatric cases, analysis of CT for complex fractures, integration with portable X-ray machines in remote areas, and prospective trials that measure clinical outcomes.

Challenge	Mitigation
Image quality	Preprocessing; quality checks
Dataset diversity	Multi-centre and paediatric data
Subtle fractures	Higher resolution; focal loss; multiple views
Clinical validation	Prospective studies; outcome measures
Over-reliance on AI	Clinician remains final decision-maker

TABLE III Challenges and Mitigation

VII. Conclusion and Future Work

AI-based bone fracture detection has progressed rapidly, with deep learning models reaching performance comparable to experienced clinicians on specific tasks and improving clinicians' accuracy when used as an aid. The reviewed literature shows that transfer learning, object detection and visual explanation together create practical tools for highlighting suspicious regions and prioritizing urgent cases. Performance depends on image quality, dataset diversity and fracture type, so careful validation is essential. Used as a second reader under professional supervision, AI can improve diagnostic efficiency and reduce missed fractures.

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