DEVICE-INDUCED ERRORS IN IMAGING AI: MECHANISMS, CLINICAL IMPACT, AND MITIGATION STRATEGIES IN DIAGNOSTIC RADIOLOGY

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Introduction

- Artificial Intelligence (AI) has achieved high diagnostic accuracy on curated datasets, but performance degrades sharply in real clinical environments where medical devices are ubiquitous.
- Implants, catheters, surgical clips, casts, and monitoring equipment introduce high-density interfaces, linear projections, and repetitive patterns that distort AI pixel-based analysis
- Unlike radiologists, convolutional networks process each study in isolation, without depth perception, temporal memory, or clinical context
- The result is predictable: false alerts near hardware, missed pathology behind artifacts, and postoperative changes flagged as new disease
- Most benchmark datasets exclude device-laden cases, producing accuracy claims that do not reflect real-world deployment

Purpose:
To establish a mechanistic framework explaining how medical devices, implants, and extrinsic materials induce predictable AI diagnostic failures in clinical radiology, and to propose targeted mitigation strategies

Methods

Study Design: Comprehensive review of peer-reviewed literature examining AI performance in device-rich radiological environments.

Synthesis:
Studies were analyzed to identify recurrent failure patterns, computational limitations, and downstream clinical consequences.

Taxonomy Development:
A mechanistic classification was built categorizing device-induced errors by visual and algorithmic characteristics, illustrated with representative clinical cases.

Results

High-Attenuation & Metallic Interfaces

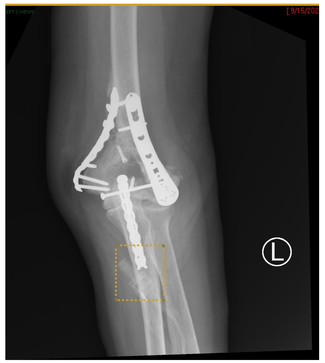

Figure 1. *Postoperative elbow with fixation plates, AI erroneously flags peri-hardware region as fracture*

Linear & Tubular Confounders

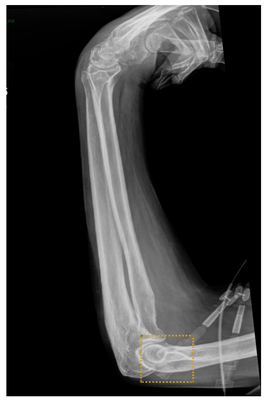

Figure 2. *External fixation and tubing at the elbow joint, AI misinterprets external hardware lines as intra-articular abnormality.*

Periodic / Clustered Objects

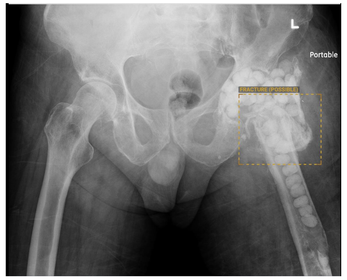

Figure 3. *AP pelvis after femoral head resection, antibiotic beads aligned along operative bed flagged as possible fracture.*

Surgical clips, brachytherapy seeds, and antibiotic bead strings form evenly-spaced bright foci that trigger shortcut learning, equating repetitive patterns with multifocal disease.

Extrinsic Overlays & Occlusion

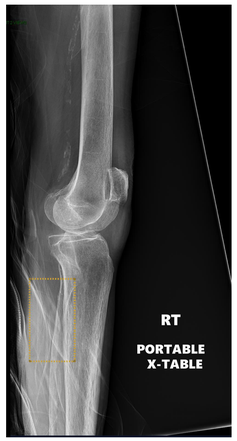

Figure 4: *Blanket folds misinterpreted as cortical fracture (dashed box) , 97F with leg trauma.*

Post-operative changes, and Context & Metadata Blindness

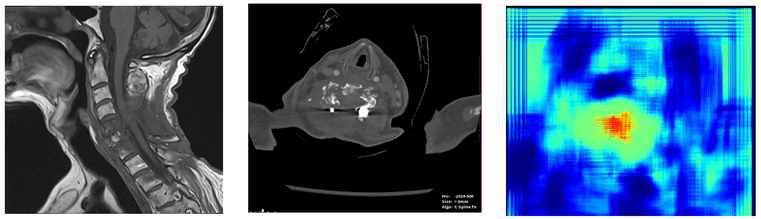

Figure 6: *Cervical spine MRI + CT with posterior hardware (A, B), AI heatmap erroneously highlights postoperative changes as fracture (C).*

Surgical hardware, grafts, drains, and operative remodeling create imaging patterns absent from most training sets. AI lacks temporal reasoning and misflags expected healing, ablation zones, or fibrosis as new pathology.

Most AI systems process imaging data in isolation, no surgical history, no operative notes, no prior studies, no clinical metadata. Routine postoperative findings are flagged as new pathology; expected device appearances trigger unnecessary consultations

Mitigation Strategies

- **Developers:** Train on device-rich datasets; integrate physics-aware algorithms; add uncertainty flags near hardware
- **Technologists:** Remove extrinsic objects before scanning; optimize positioning; document device type in DICOM metadata
- **Radiologists:** Scrutinize AI alerts near hardware; avoid automation bias; contextualize with clinical history
- **Institutions & Regulators:** Mandate device-stratified performance reporting; require pre-market validation on device-rich cohorts
- Consequences of device induced errors, include unnecessary imaging, missed pathology, automation bias, and medico-legal exposure, and solutions require coordinated action: physics-aware development, acquisition safeguards, radiologist oversight, and regulatory reform

Clinical Cases Descriptions

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