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Non-Radioactive Infrared Thermal Imaging and AI Applications: Across Medical Imaging Modalities for Fracture Diagnosis

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Abstract:

Fracture diagnosis is a critical task in emergency and orthopedic medicine, yet traditional X-ray imaging has notable limitations, including the risk of misdiagnosis in occult or subtle fractures and unnecessary radiation exposure to healthy tissues. In recent years, two technological advancements, IRT and AI, have shown considerable promise in addressing these challenges. IRT offers a non-invasive and radiation-free method for detecting localized inflammation related to fractures, while AI algorithms, particularly deep learning models, have demonstrated high accuracy in automated fracture detection from radiographic images. However, current literature review on the combined applications of these three techniques are limited. As a result, this review systematically examines the current progress in integrating IRT and AI algorithms into intelligent X-ray systems for fracture diagnosis. The principles, clinical applications, and recent innovations in these technologies are outlined, including AI-guided fracture localization, thermal image analysis, and intelligent radiation collimation. Particular attention is given to the emerging concept of multimodal systems that combine radiographs, thermal data, and AI to enhance diagnostic efficiency and reduce patient radiation burden. Furthermore, critical limitations, and future research directions in this multidisciplinary field are established and debated. This review provides an overview scope to enable the development and clinical implementation of smart imaging systems in fracture treatment.

Keywords: Infrared Thermal Imaging; Artificial Intelligence; X-ray Imaging; Fracture Diagnosis; Radiation Control

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1. Introduction

Diagnosis of fractures is an everyday and important task in clinical practice, particularly in emergency medicine, orthopedics, sport medicine, and geriatric medicine. Compared with other imaging techniques, traditional X-ray imaging is still the first choice for its low costs, its easy accessibility, and the rapid imaging that it permits [1].

The one of the significant limitations of conventional X-ray imaging is the indiscriminate radiation exposure to surrounding healthy tissues [2]. Standard imaging protocols apply a broad field of radiation to image the affected area, causing unwanted exposure, especially in vulnerable populations such as children, pregnant females, and patients who require repeated imaging [2,3]. Cumulative radiation can cause long-term deleterious health consequences [4]. For instance, a large cohort study of 680,000 children and adolescents exposed to CT scans has reported a statistically significant increase in cancer incidence later in life, pointing towards the risks of multiple low-dose exposure [4]. Another highly reported risk is misdiagnosis [1].

Slight fractures, like occult fractures, hairline fractures, and slight joint trauma, are usually not diagnosed due to the low contrast resolution of X-rays and problems with ideal positioning [1]. Studies have confirmed that emergency doctors and radiologists may overlook up to 20% of scaphoid fractures in initial X-ray reports [1]. Diagnostic risk is also increased by human limitations including reader fatigue, clinical time pressure, and inter-observer variability [1]. Because of these constraints, there is growing clinical need for advanced diagnostic approaches that promise efficiency as well as diagnostic accuracy. Specifically, technologies for the rapid localization of suspected fracture, minimization of radiation dose, and computer-aided decision support are of particular interest.

Infrared thermal imaging (IRT), a non-radiative and non-invasive technique that detects localized temperature abnormalities associated with inflammation, is finding potential for early screening of fractures [5]. Artificial intelligence (AI), in the form of deep learning algorithms such as convolutional neural networks (CNNs) and object detection frameworks, has also been found to excel over others in computerized fracture detection and classification from radiographic images [6]. The convergence of IRT and AI technologies provides new avenues for the development of intelligent X-ray systems. The systems are envisioned to incorporate multi-modal data, thermal imaging and radiographs—along with AI-driven analysis for maximizing diagnostic procedures [7]. Intelligent collimation systems also yield avenues to minimize radiation exposure by focusing the X-ray beam selectively on the areas of probable fracture [7]. This review attempts to critically review the progress in integration of infrared thermal imaging and artificial intelligence algorithms in smart X-ray systems for fracture diagnosis. This review addresses technical underpinning, clinical application, present limitations, and future perspectives of such techniques. The goal is to give clinicians and scientists an updated perspective on how smart imaging systems might improve diagnostic effectiveness and patient safety in fracture care.

2. Infrared Thermal Imaging in Medical Diagnostics

2.1 Fundamental Principles of Infrared Thermal Imaging

IRT is a non-contact, non-invasive technique which captures and displays surface temperature distributions by measuring emitted infrared radiation from biological tissue [8]. According to Planck's law, all objects at a temperature greater than absolute zero emit infrared radiation in proportion to their temperature. In medicine, IRT delivers real-time thermal maps of the skin surface, the temperature change can reflect intrinsic pathological or physiological events [8].

IRT differs from other imaging modalities such as ultrasound, optical imaging, and MRI. Unlike ultrasound, which relies on the reflection of sound waves, or MRI, which detects nuclear magnetic signals from hydrogen atoms, IRT passively detects electromagnetic radiation in the 8– 12 μm range [8]. While optical imaging systems require external light sources, IRT do not need that, it naturally emitted heat [9]. This unique sensing mechanism makes IRT particularly useful for identifying localized inflammation, vascular changes, or metabolic abnormalities on or near the skin surface [8].

2.2 Pathophysiology of Thermal Patterns in Fractures

In the context of fracture diagnosis, infrared thermal imaging provides valuable physiological insights by capturing inflammation-induced thermal changes at the skin surface. Bone fractures initiate an acute inflammatory cascade that involves vasodilation, increased vascular permeability, and enhanced metabolic activity in the affected region [8]. These physiological responses collectively lead to elevated localized temperatures near the fracture site [8]. The heat generated by this inflammation is conducted to the surface of the skin, resulting in thermal asymmetry when compared to the contralateral limb [8]. Clinical investigations have reported that this temperature difference typically ranges from 0.8°C to 2.0°C during the acute phase of a fracture [10]. This thermal anomaly may diminish as the inflammatory response subsides during the healing process, suggesting that thermal imaging is also useful in monitoring the progress of recovery [8].

2.3 Clinical Applications in Fracture Detection

Although infrared thermal imaging has been traditionally utilized in vascular and oncological diagnostics, it also application in musculoskeletal trauma is gaining attention. In pediatric emergency settings, infrared thermography has been tested as a non-invasive way to help identify suspected long bone fractures before ordering confirmatory X-rays [11]. This approach valuable in reducing radiation exposure for young patients while expediting triage workflows [11]. In sports medicine, IRT has been employed to evaluate acute injuries, overuse, and rehabilitation progress by identifying abnormal thermal distributions in joints and extremities [12]. Additionally, several studies have demonstrated the feasibility of using handheld or smartphone-based infrared cameras in prehospital and resource-limited settings to perform preliminary fracture screening [11]. Although still investigational, these use cases indicate the potential of IRT to serve as an adjunct to traditional imaging in specific clinical contexts.

2.4 Ultrasound (US) and AI in Fracture Diagnosis

Ultrasound imaging is an ionizing, non-invasive modality that uses high-frequency sound waves to create real-time images of musculoskeletal tissues [13]. It is useful in the assessment of superficial bones, joints, and adjacent soft tissues and is appropriate in pediatric patients and pregnant women where the use of radiation needs to be avoided [13].

Recent advances in AI, especially convolutional neural networks (CNNs), have enabled fracture detection and localization automatically from ultrasound scans [14]. AI algorithms can identify hypoechoic gaps, cortical discontinuity, and associate soft tissue swelling with the same reliability as skilled sonographers [14]. Additionally, AI-augmented speckle reduction noise and image enhancement have improved diagnostic quality of ultrasound, especially for less skilled hands [15].

However, ultrasound effectiveness remains operator-specific, and bone visualization is also suboptimal in deep anatomical regions [13,15]. To address this, AI-guided management systems are in the making to direct probe placement and scan protocols and reduce inter-operator variability [15].

2.5 Optical Imaging and AI in Fracture-Related Applications

Near-infrared (NIR) and visible light optical imaging is used for the assessment of superficial wounds, surgical wounds, and open fractures. Optical imaging is unable to visualize internal bone structures but provides valuable surface information that may be additional to other modalities [16].

Applications of AI in optical imaging focus on automated wound assessment, surgical navigation, and postoperative monitoring [17]. As an example, AI algorithms can assess wound size, detect signs of infection through colorimetry, and integrate intraoperative optical imaging with preoperative imaging to enhance surgical precision [18]. NIR imaging combined with AI-guided pattern analysis has also been explored as a means of detecting changes in microvascular perfusion near fractures, it can be potentially used as a healing progress biomarker [19].

Limitations include shallow penetration depth, sensitivity to lighting conditions, and the inability to directly assess closed fractures [20]. Nevertheless, when integrated with other non-radioactive modalities, optical imaging enriched by AI can provide contextual information for comprehensive fracture management [19].

2.6 MRI and AI in Musculoskeletal Assessment

MRI has long been valued in musculoskeletal assessment for its superior softtissue contrast and its ability to detect bone marrow edema, occult fractures, and associated ligamentous injuries without exposing patients to ionizing radiation [21]. Recent advances in AI, especially deep learning, have further amplified MRI's diagnostic capabilities. A key innovation lies in automated segmentation of bones, cartilage, and ligaments, enabling accurate threedimensional reconstructions that support presurgical planning [22]. Lesion detection has also benefitted from DL: models trained on MRI data can identify subtle marrow signal changes indicative of microfractures or ligamentous tears with promising accuracy [23].

Another frontier is accelerated imaging through AIbased reconstruction, which can significantly reduce scan times while preserving—or even enhancing—diagnostic image quality [24]. These synergistic innovations have expanded MRI's role in fracture and complex musculoskeletal assessments, particularly in cases where traditional Xray or ultrasound findings are inconclusive. Nonetheless, several challenges hinder broader clinical adoption: high MRI examination costs, limited access in resourceconstrained settings, and the necessity for large, wellannotated datasets to train robust AI models [25].

3. Discussion

The collective evidence across imaging modalities demonstrates both the promise and the challenges of integrating

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non-radioactive techniques with AI in fracture diagnosis. IRT offers unique advantages as a radiationfree, contactless, and rapid screening tool that can reveal physiological changes related to inflammation and perfusion [8–11]. Its portability and low cost make it particularly suitable for pediatric patients, sports medicine, and prehospital care [11,12]. Similarly, ultrasound provides a non-ionizing, real-time method for visualizing superficial fractures and adjacent soft tissues, while AI algorithms enhance its diagnostic accuracy and help reduce operator dependence [14,15,26]. Optical imaging contributes valuable surface-level information for open fractures and surgical monitoring, and when enriched by AI it facilitates wound assessment and perfusion tracking [15–18]. MRI, by contrast, remains the gold standard for soft-tissue and occult fracture evaluation, and its diagnostic capabilities have been expanded by AI through improved segmentation, lesion detection, and accelerated image reconstruction [20–23].

Despite these strengths, each modality is constrained by notable limitations. IRT is restricted to superficial assessments, highly sensitive to environmental conditions, and often lacks specificity when differentiating fractures from other inflammatory conditions [8,25]. Ultrasound remains strongly operator-dependent and is less effective for deep anatomical structures, even when AI support is integrated [13,14]. Optical imaging cannot visualize closed fractures and is limited by shallow penetration and sensitivity to external lighting conditions [19]. MRI, while powerful, is hindered by high costs, limited accessibility, and the need for large, annotated datasets [24]. On a broader level, the integration of AI across all these modalities faces persistent challenges, including the scarcity of standardized multi-modal datasets, insufficient interpretability of algorithms, and the limited availability of large-scale clinical validation studies [27–29].

Taken together, these findings suggest that no single modality is sufficient to address the complex demands of fracture diagnosis. Instead, multi-modal integration, guided by AI-driven analysis, emerges as the most promising strategy for balancing diagnostic precision with patient safety [7,27]. By consolidating the unique advantages of each imaging technique and mitigating their individual shortcomings, future intelligent imaging systems may fundamentally improve fracture care.

4. Challenges and Future Directions

Although the integration of IRT and AI into fracture diagnosis shows considerable potential, several important challenges remain before these technologies can be translated into routine clinical practice. A major obstacle lies in the scarcity of standardized, multi-modal datasets. Without such resources, it is difficult to train robust AI models that can generalize across diverse patient populations and clinical environments [27]. Closely related to this is the issue of algorithmic transparency and interpretability: current AI models often function as "black boxes," which undermines clinician trust and complicates regulatory approval [28].

Another critical barrier is the limited evidence from large-scale, prospective clinical trials. Most existing studies are small, single-center investigations, making it difficult to assess the real-world effectiveness of AI- and IRT-enhanced diagnostic workflows [24,29]. There is little evidence on whether these systems can reduce repeat imaging, minimize cumulative radiation exposure, or improve patient outcomes over time. Addressing this evidence gap through multi-center randomized trials will be essential for clinical adoption [29].

From a technical perspective, real-time deployment of AI on portable or point-of-care devices remains constrained by computational limitations. Developing lightweight models that can deliver reliable predictions under variable conditions is therefore a priority [7,28]. Furthermore, future research should explore the concept of active radiation dose reduction through AI-guided collimation and closed-loop exposure control. By dynamically adjusting the size, shape, and intensity of the X-ray beam, such systems could irradiate only the necessary anatomical regions, thereby minimizing unnecessary exposure without compromising diagnostic accuracy [30,31].

Finally, the successful translation of these innovations into practice will require the establishment of standardized acquisition protocols, performance benchmarks, and regulatory frameworks. International collaboration will be critical in this regard, not only to harmonize methodologies but also to ensure equitable access to these technologies across healthcare systems with differing levels of resources [29,32]. If these challenges can be addressed, the next generation of intelligent imaging systems has the potential to significantly improve both diagnostic precision and patient safety in fracture management.

5. Conclusion

Fracture diagnosis continues to face challenges in terms of radiation safety, diagnostic accuracy, and workflow efficiency. This review highlights how IRT and AI provide promising solutions by offering noninvasive, radiation-free screening and automated decision support. When integrated into intelligent X-ray systems, these technologies not only enhance fracture detection but also hold the potential to minimize unnecessary exposure through

AI-guided collimation and multi-modal analysis. Nevertheless, significant barriers remain, including the scarcity of standardized multi-modal datasets, variability in IRT measurements, and the lack of large-scale prospective clinical trials. Future research should therefore focus on establishing robust clinical evidence, advancing real-time AI-guided imaging protocols, and developing frameworks for multimodal data fusion. By addressing these gaps, IRT- and AI-enhanced diagnostic systems could transform fracture care, advancing both patient safety and diagnostic precision.

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