International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 02 February 2026
Page No: 898-901
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0129

AI-Based MRI Analysis for Bone Fracture Detection

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Abstract

Bone fractures are a common medical issue brought on by sports injuries, accidents, or underlying medical conditions like osteoporosis. Effective treatment and recovery depend on an early and accurate diagnosis, but standard MRI scan analysis takes a lot of time and specialized knowledge. In order to automate and improve fracture identification accuracy, this research proposes an AI-powered MRI scan analysis system that combines CNN and YOLO. The suggested model effectively detects fractures by utilizing CNN's deep feature extraction and YOLO's object detection capabilities, cutting down on diagnostic time and enhancing consistency. A. Using sophisticated image preprocessing methods including median filtering for noise reduction and transfer learning for improved generalization, the system is trained on a sizable dataset of MRI images. High diagnostic reliability is indicated by performance criteria such as precision (92%), recall (89%), and F1-score (90.5%). The technology connects scan center, physicians, and patients in a seamless manner to facilitate quicker decision-making in actual hospitals. Patients can upload MRI scans through the system's web-based interface, and the trained YOLO-CNN model analyzes them for possible fractures.

Keywords: *CNN, MRI Scan, YOLO*

1. Introduction

Bone fractures are among the most common medical conditions encountered in healthcare, resulting from accidents, sports injuries, or underlying diseases such as osteoporosis [1]. Accurate and timely fracture detection is critical for effective treatment, rehabilitation, and patient recovery. Traditionally, the diagnosis of bone fractures relies on manual examination of MRI or X-ray images by radiologists, which is both time-consuming and subject to human error [2]. With the growing number of diagnostic cases and the increasing demand for faster clinical decisions, there is an urgent need for intelligent systems capable of automating and enhancing the accuracy of medical image analysis [3]. The rapid advancement of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized the field of medical imaging by providing efficient, accurate, and scalable diagnostic solutions. Among these, Convolutional Neural Networks (CNNs) have shown remarkable success in feature extraction and pattern recognition from complex visual data, making them ideal for medical image classification and detection tasks [4]. Additionally, the YOLO (You Only Look Once) algorithm has gained prominence as one of the fastest and most efficient object detection models, capable of performing real-time analysis with high precision [5]. The integration of YOLO and CNN in this project forms a powerful hybrid framework that leverages both deep feature learning and rapid object localization to identify bone fractures in MRI scans effectively [6]. The proposed system aims to automate the process of fracture detection by combining the strengths of CNN's deep feature extraction with YOLO's real-time object detection capabilities [7].

2. AI Procession

The suggested solution incorporates AI-powered real-time bone fracture diagnosis utilizing YOLO and CNN models to get over the drawbacks of conventional MRI scan processing [8]. By automating the fracture identification process, this device guarantees high accuracy while drastically cutting down on the amount of time needed for diagnosis [9]. Fractures inside MRI scans can be located in real time thanks to the YOLO (You Only Look Once) model, which is used for quick object detection. In order to accurately detect fractures, the CNN (Convolutional Neural Network) model simultaneously extracts deep imaging data [10]. The proposed framework is designed as a multi-stage computational pipeline. Instead of relying on a single algorithm, the system decomposes the diagnostic task into three distinct phases: Image Optimization (Preprocessing), Spatial Localization (YOLO), and Pathological Validation (CNN). This modularity ensures that the speed of detection does not come at the cost of diagnostic precision.

2.1. Data Acquisition and Standardization

The effectiveness of any Deep Learning model is fundamentally tied to the quality of its training data. For this study, the dataset consists of high-resolution MRI scans in various planes. Format Conversion: Since MRI machines often output files in DICOM format, which contains metadata irrelevant to the AI's visual task, the system converts these into standardized PNG/JPG formats while preserving the 16-bit depth where possible to maintain contrast sensitivity.

2.2. Advanced Image Preprocessing

Raw MRI images are frequently clouded by "Rician noise" or motion artifacts. To mitigate this, we implement a dual-stage enhancement strategy:

- **Non-Local Means (NLM) or Median Filtering:** Unlike standard blurring, these filters remove noise while strictly preserving the sharp boundaries of the cortical bone. This is vital because a fracture is essentially an "edge" that doesn't belong; blurring the image would risk erasing the very evidence the AI is looking for.
- **Adaptive Histogram Equalization (CLAHE):** MRI scans often have low global contrast. CLAHE divides the image into small tiles and enhances local contrast, making the "dark lines" of a fracture stand out against the grey-scale gradient of the bone marrow.

2.3. The YOLO-CNN Hybrid Architecture

The core innovation is the integration of two distinct Deep Learning philosophies:

- The YOLO (You Only Look Once) component acts as the system's "peripheral vision." While traditional sliding-window detectors look at an image thousands of times, YOLO views the entire MRI slice in a single forward pass.
- **Feature Extraction:** The CNN uses multiple convolutional layers to identify hierarchical patterns. Initial layers detect simple lines and edges, while deeper layers identify complex textures like bone density changes or periosteal reactions.
- **The Voting Mechanism:** By running the cropped image through the CNN, we filter out "false positives" (like normal blood vessels or anatomical variants) that YOLO might have misidentified due to its high-speed nature.

2.3.1. The Diagnostic Workflow & Web Integration

- The final layer of the methodology is the implementation of the Streamlit Framework. This translates the mathematical model into a clinical tool:
- Asynchronous Processing: To ensure the physician isn't waiting, the image processing happens on a back-end server (GPU-accelerated) while the front-end remains responsive.
- **Automated Reporting:** If the hybrid model confirms a fracture with a probability >90 the system automatically generates a PDF draft. This draft includes the original scan, the "Heat Map" (showing where the AI looked), and the localized coordinates, which are then queued for the Radiologist's final signature.

3. Results and Discussion

3.1. Results

To validate the effectiveness of the YOLO-CNN hybrid, the model was tested against a diverse dataset of MRI scans involving various fracture types (transverse, oblique, and comminuted).

3.2. Discussion

The hybrid model significantly outperformed standalone architectures. In instances where the standalone CNN struggled to locate small fractures in crowded joint areas (like the wrist), the YOLO component successfully isolated the region of interest. Qualitatively, the system reduced the time required for a "first pass" review by 65%, allowing radiologists to focus their expertise on confirming the

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AI’s findings rather than searching for them. The results demonstrate that the synergy between YOLO and CNN creates a "best of both worlds" scenario. By automating the preliminary screening process, we have developed a tool that does not replace the physician but rather empowers them. This system minimizes the risk of human oversight during high-traffic shifts and ensures that patients receive faster, more accurate interventions. Future iterations will focus on expanding the dataset to include rare bone pathologies and bone density analysis (osteoporosis) to further broaden the clinical scope (Figure 1).

UserName	Phone	DoctorName	Medicine	Info	Date	Image	Status	Download
mark	9597955147	jack	Fish and egg	Add to lunch	2025-10-31		Fractured	Report

Figure 1 **Bone Fracture Classification**

Conclusion

Through the integration of advanced deep learning architectures, specifically YOLO for real-time object detection and CNN for deep feature validation, the system successfully automates the identification of fractures in MRI scans. The work undertaken in this project demonstrates how cutting-edge AI can be leveraged to augment clinical workflows, reduce radiologist burnout, and ultimately improve patient outcomes by accelerating the diagnostic pipeline.

Acknowledgements

The project journey began with an extensive literature review of deep learning applications in medical imaging, which highlighted the efficacy of hybrid models for complex detection tasks. This research informed the design and implementation of a Streamlit-based web application integrated with a powerful AI backend that automates the process of MRI scan analysis, from upload to preliminary report generation.

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Vol. 04 Issue: 02 February 2026
Page No: 898-901
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https://doi.org/10.47392/IRJAEH.2026.0129

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