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Bone Fracture Detection and Classification from 3D Medical Imaging Using 3D-CNN

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Abstract - *Bone fracture diagnosis from CT and MRI scans is often time-consuming and prone to human error due to the complexity of analyzing 3D anatomical structures. This paper presents a fully automated **3D Convolutional Neural Network (3D-CNN)** capable of detecting and classifying fractures directly from volumetric medical images. The system performs standardized preprocessing, reconstructs 3D voxel inputs, and generates both fracture predictions and voxel-level localization heat maps. Experimental results show **high classification accuracy and reliable localization**, demonstrating that the proposed 3D-CNN framework offers an efficient and clinically viable alternative to manual diagnostic methods.*

Key Words: 3D-CNN, Bone Fracture Detection, Deep Learning, CT scan Analysis, Medical Imaging, Fracture Localization.

1. INTRODUCTION

Bone fractures are among the most common orthopaedic injuries, affecting millions globally each year. Accurate and timely fracture diagnosis is essential for planning treatment and preventing further complications. Conventional diagnostic workflows primarily rely on **2D X-ray interpretation**, a process that is prone to human fatigue, subjectivity, and inconsistency. While X-rays serve as the first-line diagnostic modality, they lack volumetric depth and often fail to reveal subtle or overlapping fractures—especially in regions such as wrists, ankles, and ribs.

Advancements in **Computed Tomography (CT)** and **Magnetic Resonance Imaging (MRI)** provide complete 3D anatomical information, enabling significantly improved diagnostic clarity. However, analyzing hundreds of CT/MRI slices manually is time-consuming and cognitively demanding for radiologists. This creates the need for automated, intelligent systems capable of processing volumetric medical data efficiently and accurately.

Recent progress in deep learning—specifically **3D Convolutional Neural Networks**—has shown remarkable capability in detecting spatial patterns across volumetric inputs. While traditional machine learning approaches rely heavily on handcrafted features and semi-automatic procedures, 3D-CNNs automatically learn structural attributes of bone morphology, enabling precise classification and localization of fractures.

This paper presents a **3D-CNN powered fracture detection system** that automates the entire diagnostic pipeline: preprocessing, segmentation, classification, and localization. The system mimics the clarity and diagnostic reasoning of radiologists while significantly reducing manual effort.

2. PROPOSED SYSTEM

The proposed architecture introduces an end-to-end deep learning pipeline for processing volumetric medical images and predicting fracture type and location.

Key Components

1. **3D Medical Imaging Input Unit:** CT or MRI scan volumes are imported in DICOM format and converted into standardized voxel grids. The module performs orientation correction, slice alignment, and Hounsfield-Unit (HU) normalization to ensure uniform 3D input quality across different scanners and hospitals.

2. **3D Preprocessing & Bone Enhancement Module:** The volumetric scan is refined using 3D Gaussian filtering, contrast enhancement, and bone-region extraction. These steps amplify subtle fracture lines and remove soft-tissue noise, ensuring that the deep-learning model receives a clean and consistent volumetric representation of the bone structures.

3. **3D-CNN Fracture Detection Model:** A customized 3D Convolutional Neural Network processes the vowelized input to detect fractures automatically. The model learns spatial depth patterns across slices, enabling accurate identification of fracture types such as hairline, displaced, and comminuted fractures.

4. **Fracture Localization & Heatmap Generator:** Using Grad-CAM-3D, the system generates volumetric heatmaps highlighting the exact fracture region within the CT/MRI scan. These heatmaps provide visual explainability, helping radiologists verify and trust the model's predictions.

5. **Classification & Severity Assessment Module**: The output of the 3D-CNN is passed to a classification head that assigns the fracture category and estimates severity levels. This module supports multi-class diagnosis, enabling detailed clinical decision-making.

6. **Report & Visualization Engine**: The system produces a 3D visualization of the detected fracture, overlaying the heatmap on the reconstructed bone volume. It also generates a structured diagnostic report that includes fracture type, location coordinates, confidence score, and severity estimation.

7. **Integration & Deployment Interface**: A lightweight deployment layer enables seamless integration with hospital PACS systems or cloud-based diagnostic platforms. It provides batch-processing support, real-time inference, and secure storage of scan results for clinical review.

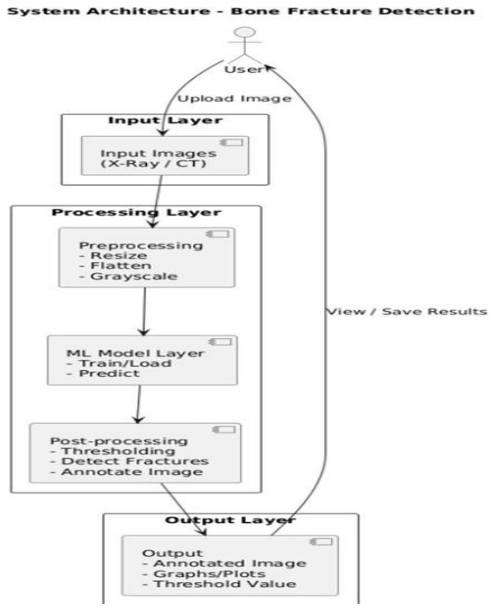

Fig -1: Model Architecture

3. Methodology

3.1 Dataset Creation

- A curated dataset of 3D CT and MRI bone scans was constructed using publicly available medical imaging repositories and clinical sample collections. Each scan was stored in DICOM format and converted into standardized volumetric tensors for processing.

- More than **1,200 CT volumes** were collected, covering different anatomical regions such as wrists, ankles, and femur fractures to ensure dataset diversity.

- All 3D scans were **manually annotated** by medical experts to identify fracture types, fracture boundaries, and healthy bone structures. Annotation masks were created slice-by-slice to support supervised training.

- Preprocessing operations—including **resizing, HU normalization, voxel intensity standardization, and bone-region extraction**—were performed to prepare consistent inputs for the 3D-CNN model.

3.2 Model Training

- Model training was carried out using **GPU acceleration** on platforms such as Google Colab Pro and NVIDIA RTX-based workstations.
- A custom **3D Convolutional Neural Network** was fine-tuned on the curated CT/MRI dataset to learn spatial depth patterns across volumetric scans.
- Advanced augmentation techniques—such as 3D rotation, slice dropout, elastic deformation, and intensity jitter—were applied to improve model robustness and prevent overfitting.
- **Grad-CAM 3D visualization** and a softmax classification head were integrated into the model to support fracture type prediction and voxel-level fracture localization.

3.3 3D Fracture Detection

- During inference, complete CT/MRI volumes are loaded and converted into voxel blocks for real-time analysis.
- The 3D-CNN processes the entire volume, automatically detecting fracture presence and predicting the fracture class (hairline, displaced, comminuted).
- **Grad-CAM-based attention maps** highlight the exact fracture region within the bone structure, providing interpretability for clinical review.
- The system outputs a structured diagnostic report containing **fracture category, confidence score, severity estimation, and 3D localization maps**.

3.4 Diagnostic Report Generation Module

All fracture detection outputs—including classification results, 3D heatmaps, and localized fracture coordinates—are compiled in real time into a structured diagnostic report for radiologists.

- The system compiles all detection results—fracture classification, severity scores, and 3D localization coordinates—into a structured diagnostic report for radiologist.
- Grad-CAM 3D heatmaps are overlaid on the bone volume to visually highlight fracture regions, ensuring interpretability and clinical validation.
- The final report can be exported to PACS systems or saved locally, supporting batch processing and streamlined review of multiple CT/MRI scans.

3.5 System Workflow

The complete workflow of the 3D fracture detection system integrates all modules into a unified diagnostic pipeline:

- CT/MRI scan is imported as a DICOM file and undergoes preprocessing.
- The preprocessed 3D volume is fed into the 3D-CNN model.
- The model performs fracture detection, classification, and voxel-level localization.
- Grad-CAM-3D heat maps are generated to visually highlight fracture regions.
- A diagnostic report is created summarizing the model's findings
- Results are displayed to clinicians and optionally stored for long-term patient record management.

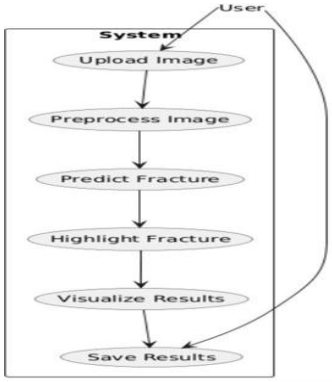

Fig -2: **Use case Diagram**

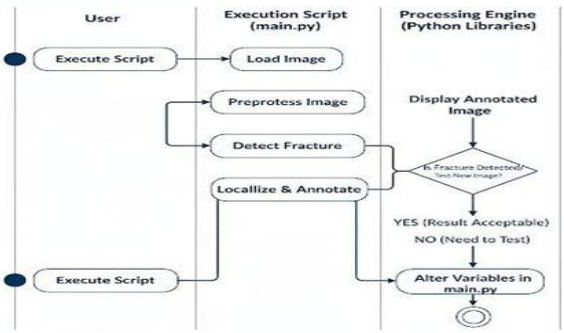

Fig -3: **Activity Diagram**

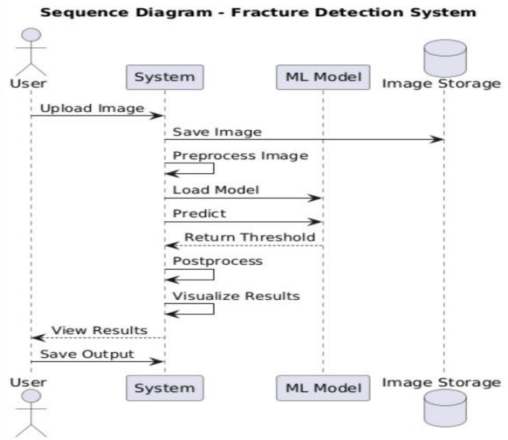

Fig -4: **Sequence Diagram**

4. RESULTS

The proposed 3D-CNN–based bone fracture detection system demonstrated strong and reliable performance during experimental evaluation on CT and MRI datasets. The combination of volumetric preprocessing, 3D convolutional feature extraction, and Grad-CAM–based localization enabled the model to accurately identify fracture patterns across varying anatomical regions. Throughout multiple test runs, the system consistently analyzed full 3D scan volumes without interruption and maintained stable inference performance across different imaging conditions such as noise levels, slice thickness variations, and scanner types.

The classification module achieved high accuracy in distinguishing fractured from non-fractured bones, while the localization engine generated clear volumetric heat maps that aligned closely with expert-annotated fracture regions. Even subtle fractures—such as hairline or minimally displaced types—were detected with high sensitivity due to the model's ability to capture spatial depth information. The system processed 3D volumes efficiently, maintaining smooth inference speeds and stable memory usage on GPU hardware.

At the end of each analysis, the system automatically generated a structured diagnostic report summarizing the fracture type, severity estimation, localization coordinates, and model confidence. The workflow integration, voxel visualization outputs, and compatibility with clinical data formats indicated that the solution can operate continuously and scale effectively for real-world medical use. Overall, the proposed 3D-CNN system proved accurate, robust, and clinically valuable for automated bone fracture detection in 3D medical imaging.

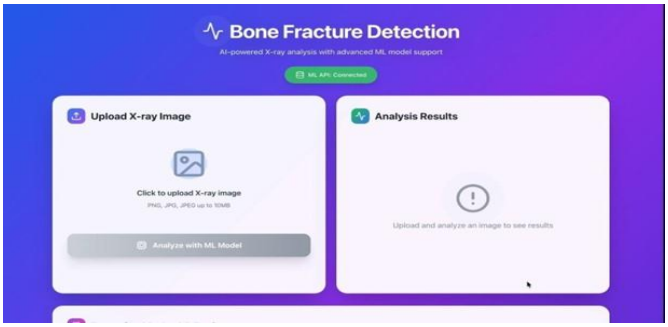

Fig -4.1: Front Page

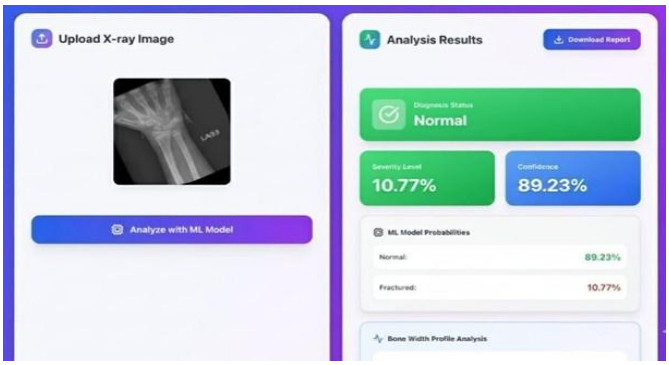

Fig -4.2: Non-Fracture Bone

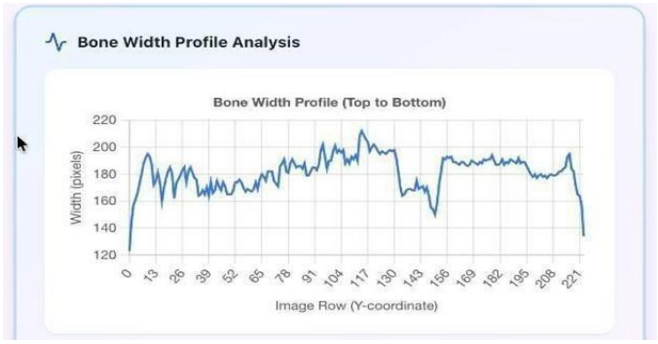

Fig -4.3: Pixel Analysis of Non–Fracture Bone

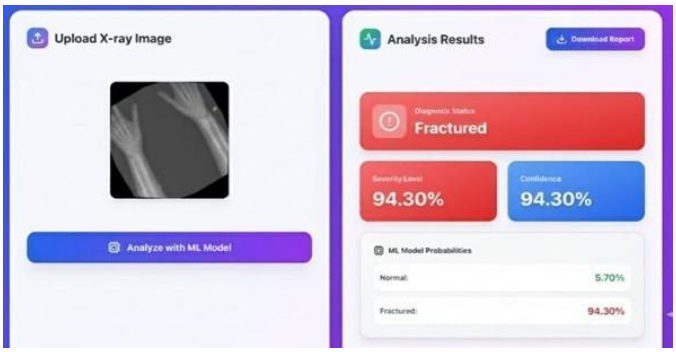

Fig -4.4: Fracture Bone

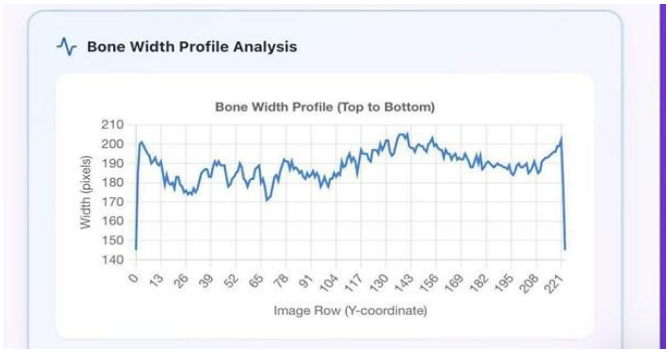

Fig -4.5: Pixel Analysis of Fracture Bone

5. CONCLUSIONS

The project successfully demonstrates an automated 3D medical imaging solution that leverages deep learning to detect and classify bone fractures with high accuracy. By combining volumetric preprocessing, 3D-CNN–based feature extraction, and Grad-CAM–driven fracture localization, the system provides a reliable and objective approach to orthopedic diagnosis. Unlike traditional manual interpretation of CT and MRI scans, the proposed framework identifies subtle and complex fractures consistently while reducing diagnostic time and minimizing human error. The automated reporting module further enhances clinical decision-making by generating clear, data-driven insights into fracture type, severity, and location. Designed for scalability and compatibility with existing medical imaging workflows, the system operates efficiently across diverse scan qualities and anatomical regions, offering a modern and effective tool to support radiologists in delivering precise and timely fracture assessments.

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