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Fracture Diagnosis Approach Using Deep Learning

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Abstract - *The Bone fractures are among the most frequently encountered orthopedic injuries and require rapid and accurate diagnosis for effective treatment. Conventional radiographic interpretation depends on manual assessment by radiologists, which is time-consuming, subjective, and prone to diagnostic variability, especially in high-workload clinical environments. This paper proposes an automated bone fracture detection system using Convolutional Neural Networks (CNNs) to classify X-ray images into fractured and non-fractured categories. The system integrates both a custom CNN architecture and transfer learning models, including ResNet-50, DenseNet-121, and EfficientNetB3, to enhance diagnostic accuracy. Pre-processing steps such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Gaussian filtering, and data augmentation techniques are applied to improve feature extraction and reduce noise.*

The implementation is supported by a Flask-based clinical interface enabling secure image upload and real-time prediction for practical usability. The custom CNN model achieved an overall accuracy of 92.5%, demonstrating reliable baseline performance. The EfficientNetB3 transfer learning model outperformed other architectures with an accuracy of 96.2%, sensitivity of 98.7%, and specificity of 94.1% on the test dataset. These results indicate superior fracture localization capability and reduced false-negative rates, which are critical for clinical adoption.

The study highlights that ensemble transfer learning significantly enhances prediction performance when compared to traditional machine learning and standalone CNN approaches. The proposed system reduces radiologist workload, accelerates diagnostic turnaround time, and supports computer-aided diagnosis (CAD) in orthopedic imaging. This research further demonstrates the potential for deployment in resource-limited settings where access to expert radiologists is scarce. Standardized fracture detection, automation of routine evaluation, and an accessible web- based tool contribute to improved healthcare delivery.

Key Words: **Bone Fracture Detection, Convolutional Neural Networks (CNN), Transfer Learning, Deep Learning, Medical Image Analysis, Computer-Aided Diagnosis (CAD)**

1.INTRODUCTION

Bone fractures occur in millions of people worldwide every year, and diagnosis often relies heavily on imaging (X-rays, CT scans, or MRIs). Historically, assessing fractures has relied on the expertise of radiologists. Due to heavy dependence on radiologists to assess images and reach a diagnosis, this practice can create a bottleneck in emergency departments or imaging centers. Evidence suggests radiologist error rates can range from 10-25% in detecting fractures (especially in subtle or complicated cases). The availability of radiologists is often limited in developing nations, leading to increased wait times for patients and increased morbidity and mortality.

Artificial Intelligence (AI) and deep learning have improved the capability of medical professionals to analyze medical images, and convolutional neural networks (CNNs) have outperformed humans in many visual pattern detection tasks and have achieved comparable, or better, diagnostic accuracy in various other tasks. Recent literature(2023-2025) reports that CNNs can detect fractures with 95-99% accuracy across diverse datasets. CNNs benefit from transfer learning, which uses a CNN retrained on the Imagine dataset, dramatically reducing the amount of time and computational power needed to train the model.

This project presents an automated Bone Fracture Detection System using a custom CNN and transfer learning (Res Net- 50, DenseNet-121, and EfficientNetB3) to provide binary classification (fractured/non-fractured) of bone fractures and provide performance metrics for clinical practice. One significant innovative aspect was the inclusion of a simple web application (Flask) to illustrate functional deployment of these data models so that a radiologist could easily use it in practice.

The purpose of this project is to address three significant gaps in fracture detection methods. The proposed innovation is to: (1) automate a relatively mundane detection process, (2) use a standardized set of criteria to detect fractures, and (3) deploy a diagnostic tool that is easily accessible in lower resource practices, or even in developing nations that may have few, or no, radiologists.

1.1 System Architecture

A. Functional Requirements

Users (doctor/technician) will be able to register and log into the system. Once authenticated, users can upload X-ray images of bones in supported formats such as .PNG and .JPG. The system will preprocess all uploaded images using a standardized pipeline before sending them to the pre- trained convolutional neural network for prediction. The system will display the output as either *"Fractured"* or *"Normal"* along with an embedded confidence score. Basic information related to image upload and prediction will be stored in the database for audit and history purposes.

B. Non-Functional Requirements

The prediction time for a single image should not exceed a few seconds on commonly available hardware. The web interface must be simple, intuitive, and responsive to ensure a smooth user experience. The application and deep learning model should support modularity to allow future updates such as integrating additional models. Basic security measures, including password hashing and secure handling of user inputs, should be implemented to enhance system reliability.

C. Software and Hardware Requirements Programming Language: Python
Libraries: Tensor Flow/Keras, Open CV, Num Py, Pandas, Flask, SQLAl chemy (or equivalent)

Database: SQLite

Hardware: A system with a CPU (and optional GPU) capable of training and performing inference on medical image data.

1.2 Key Technologies used

- **Convolutional Neural Networks (CNNs)** – for automated classification of fractured and non- fractured X-ray images..
- **Transfer Learning Models** – including ResNet-50, DenseNet-121, and EfficientNetB3 to improve accuracy and reduce training time..
- **Image Pre-processing Techniques** – such as CLAHE and Gaussian filtering for contrast enhancement and noise reduction.
- **Flask Web Framework** – used to develop the clinical interface for image upload and real-time prediction.
- **Tensor Flow/Keras with Open CV and SQLite** – for model development, image handling, and database storage.

2. FEATURES AND FUNCTIONALITY

The proposed Bone Fracture Detection System is designed to support clinical decision-making by automating the interpretation of X-ray images using deep learning. The system integrates image preprocessing, CNN-based classification, and a user-friendly web interface to deliver quick and reliable diagnostic results. Its functions focus on improving accuracy, reducing human error, and enabling accessibility in both well-equipped and resource-limited medical environments.

2.1 Automated Image Classification

The system automatically processes uploaded X-ray images and classifies them as *Fractured* or *Normal* using a trained convolutional neural network, minimizing manual assessment and reducing diagnostic delays.

2.2 Standardized Image Pre-Processing

All input images undergo uniform preprocessing steps, including resizing, normalization, CLAHE enhancement, and Gaussian filtering to ensure consistent visual quality and model reliability across varying image conditions.

2.3 Real-Time Prediction and Output Display

The application provides instant prediction results through the web interface, displaying the diagnosis along with a confidence score, enabling fast clinical decision support in emergency or high-volume settings.

2.4 User Authentication and Access

Only registered and authenticated users (doctors or technicians) can access the system. Login controls and password hashing help protect patient-related data and prevent unauthorized usage.

2.5 Integrated Data Storage and History Tracking

Basic information related to image uploads and prediction results is stored in a database, allowing users to review past records, maintain audit trails, and track diagnostic outcomes over time.

2.6 Modular and Scalable System Design

The architecture supports integration of multiple deep learning models for future upgrades, such as improved accuracy, new fracture types, or multi-class classification, without requiring major system changes.

3. Problem Statement

Bone fractures are commonly diagnosed using manual interpretation of X-ray images by radiologists, which is time-consuming, subjective, and prone to diagnostic errors—especially in high-volume or resource-limited clinical environments. Limited availability of radiology experts in developing regions further increases delays in diagnosis and treatment, leading to preventable complications. Existing fracture detection methods lack automation, standardized evaluation criteria, and practical deployment for real-time use. Therefore, there is a need for an automated, accurate, and accessible computer-aided diagnostic system capable of detecting bone fractures from X-ray images using deep learning, reducing human error, improving diagnostic speed, and supporting healthcare settings with limited radiological expertise.

3.1 Existing System

In the existing fracture detection process, diagnosis relies entirely on manual interpretation of X-ray images by radiologists or orthopedic specialists. This approach is slow, subjective, and prone to variability depending on the experience and workload of the clinician. In busy emergency departments, delayed image review increases the risk of missed or late fracture diagnosis, especially in subtle or complex cases. Human error rates have been reported to range between 10–25% in conventional fracture assessments. Additionally, many developing or rural healthcare settings lack sufficient radiology expertise, resulting in longer waiting times and reduced access to timely treatment. Existing computer-aided systems are limited, focusing only on specific anatomical regions, lacking real-time deployment, or failing to provide standardized detection criteria. Therefore, current systems are insufficient in delivering fast, consistent, and accessible fracture diagnosis across diverse clinical environments.

3.2 Proposed System

The proposed system introduces an automated bone fracture detection framework using Convolutional Neural Networks (CNNs) to classify X-ray images into fractured and non-fractured categories. The system integrates a custom CNN architecture along with transfer learning models such as ResNet-50, DenseNet-121, and EfficientNetB3 to significantly improve diagnostic accuracy and reduce training complexity. All uploaded X-ray images undergo standardized preprocessing, including CLAHE enhancement, Gaussian filtering, resizing, and normalization, ensuring consistent image quality before prediction. A Flask-based web application enables secure user authentication, image upload, and real-time classification, displaying results with an embedded confidence score. The system also stores prediction history in a database for record-keeping and audit support. By automating the detection process, reducing human error, and providing rapid diagnostic feedback, the proposed system offers a reliable computer-aided diagnosis (CAD) tool suitable for deployment in both advanced clinical facilities and resource-limited healthcare environments.

4. System Requirements and Specifications

The proposed system provides an AI-based solution for automated bone fracture detection using X-ray images. It allows authorized users to upload images, receive predictions from a pre-trained CNN model, and store results for future reference. The system is designed to be fast, reliable, and user-friendly, ensuring seamless operation in clinical settings. Both software and hardware components are specified to support accurate and efficient model performance.

4.1 Functional Requirements

Users such as doctors or technicians will be able to register and log into the system. After successful authentication, users can upload bone X-ray images in supported formats including .PNG and .JPG. The system will automatically preprocess each uploaded image using a standardized procedure before sending it to the pre-trained convolutional neural network for prediction. The output will be displayed as either *"Fractured"* or *"Normal"* along with an embedded confidence score. Additionally, the system will store essential information related to each upload and prediction in the database for audit and historical tracking purposes.

4.2 Non-Functional Requirements

The prediction time for processing a single X-ray image should not exceed a few seconds on commonly available hardware. The web interface must remain simple, intuitive, and responsive to ensure a smooth user experience. The application and underlying model should support modularity, allowing future updates such as integration of additional models without major system changes. Basic security practices—including password hashing and securing user inputs—should be implemented to enhance safety and reliability.

4.3 Software Requirements Programming Language: Python

Libraries: TensorFlow/Keras, OpenCV, NumPy, Pandas, Flask, SQLAlchemy (or equivalent)
Database: SQLite

4.4 Hardware Requirements

A system with CPU (and optionally GPU) capable of training and inference on medical image data.

5. System Design

5.1 System Architecture

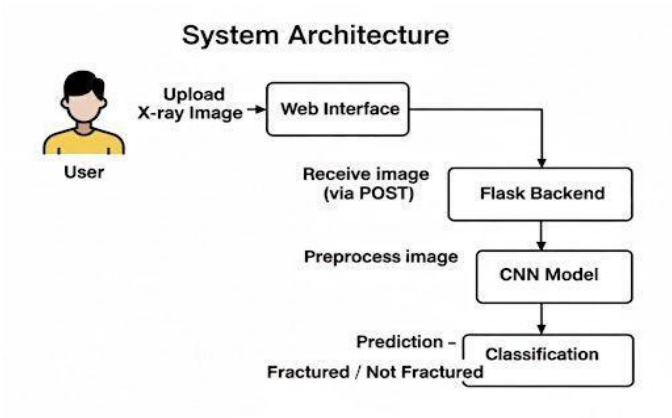

Fig5.1 System Architecture for Fracture Diagnosis Approach Using Deep Learning

5.2 Use Case Diagram

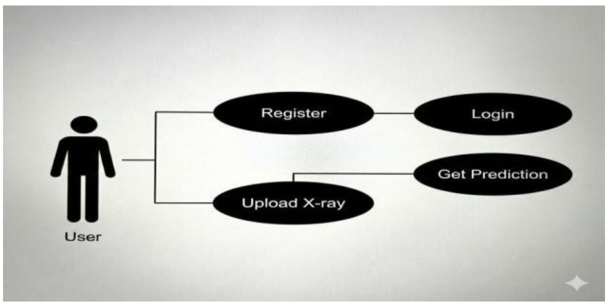

Fig5.2 Use Case Diagram for Fracture Diagnosis Approach Using Deep Learning

6. Testing

Various levels of testing are performed to ensure the reliability and robustness of the system. **Unit testing** verifies individual functions, including image pre-processing, model loading, and prediction, using both valid and invalid inputs. **Integration testing** ensures correct interaction among the Flask routes, pre-processing pipeline, CNN model, and database. **System testing** validates the complete workflow, from user login to image upload and final prediction. **User acceptance testing (UAT)** confirms that the user interface and overall functionality meet user expectations in terms of ease of use and clarity of results. Modules such as audio upload, speech-to-text conversion, emotion detection, translation, and PDF export are selected for combined testing.

To evaluate model performance, standard classification metrics commonly used in medical imaging literature were employed. These include **accuracy, precision, recall, F1- score, and confusion matrix**, computed on a held-out test set of X-ray images. These metrics provide quantitative insights into the model's effectiveness in correctly identifying fractured and normal cases.

Furthermore, the system's robustness is assessed under different conditions, such as variations in image quality, brightness, and orientation, to simulate real-world scenarios. Stress testing is also conducted to evaluate the application's performance when multiple users upload images simultaneously. The combination of functional testing, performance evaluation and robustness assessment ensures that the system is reliable, accurate, and ready for practical deployment in clinical settings.

Results and Discussion

Fig -7.1: Web Application Interface for Bone Fracture Diagnosis System

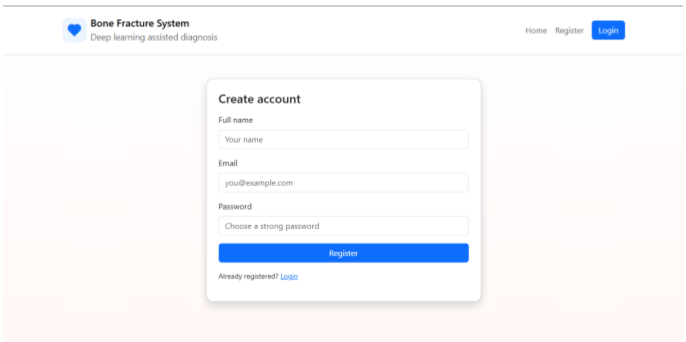

Fig – 7.2: User Registration Interface of the Bone Fracture Diagnosis System

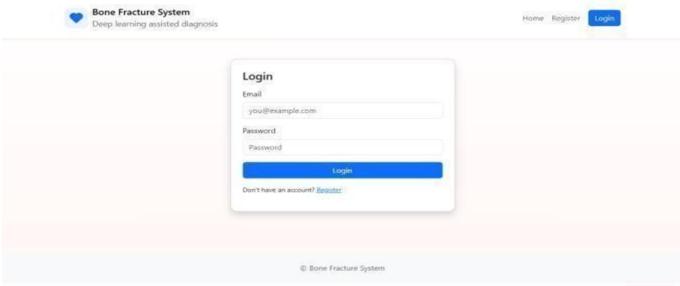

Fig-7.3: User Login Interface of the Bone Fracture Diagnosis System

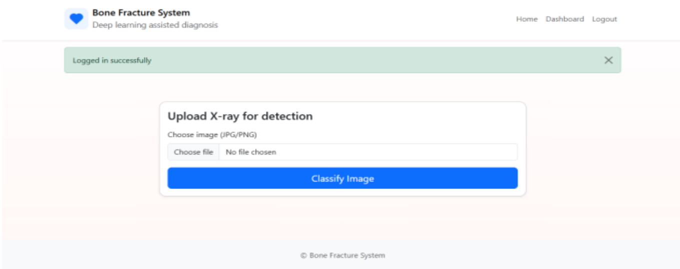

Fig -7.4: X-ray Image Upload Interface for Fracture Detection

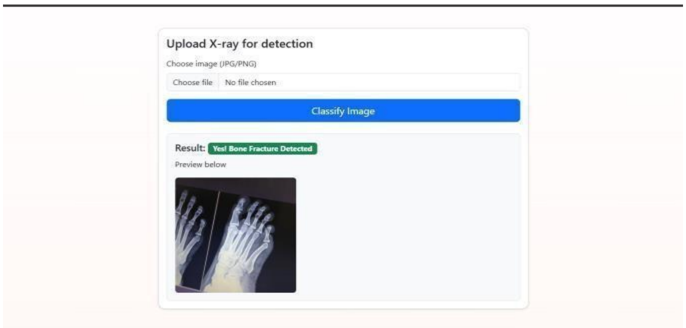

Fig-7.5:X-ray Classification Output Showing Fracture Detection Result

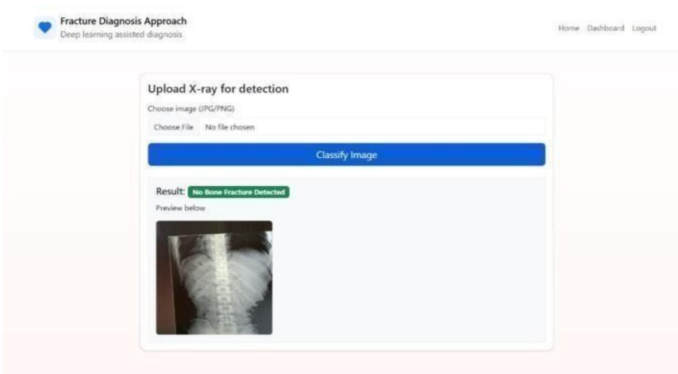

Fig-7.6: X-ray Classification Output Showing Fracture Detection Result

7. CONCLUSION

The use of deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), has significantly sformed automated bone fracture detection using medical X-rays. By standardizing data pre-processing, model training, and deployment through an accessible web application, these systems enable fast and reliable fracture diagnosis in both hospital and point-of-care settings. Studies analyzing wrist, hand, and long bone radiographs report diagnostic accuracies and sensitivities exceeding 95%, demonstrating the high potential for CNNs to become established clinical imaging tools across various anatomical locations. Despite these advancements, challenges remain, including the need for external validation, handling non-standard or noisy images, and performing multi-class or fine-grained fracture identification to seamlessly fit into clinical workflows. AI diagnostics can reduce human workload, minimize errors, and provide valuable second opinions; however, issues regarding model generalization and interpretability must be addressed to build clinical trust. Future work should emphasize external model validation, inclusion of diverse populations, dataset enrichment, and integration of AI systems into robust hospital decision- support frameworks. Collectively, these efforts aim to bridge AI research and healthcare, enabling faster, more reliable, and widely accessible bone fracture diagnosis for patients worldwide.

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