

AI-Powered Bone Fracture Detection and Depth Measurement: A Review

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Abstract: Bone fractures are a prevalent clinical condition, and classical diagnosis based on X-rays, MRI, and CT scans is time-consuming, expensive, and error-prone. To overcome this drawback, deep learning-based approaches have been investigated for automatic fracture detection and classification. In this work, we propose a light-weight system with Convolutional Neural Networks (CNNs) and light-weight models such as MobileNet and EfficientNet for accurate classification of fractures in X-ray images. Data augmentation and training with optimal configurations enhance performance with up to 98 accuracy. Furthermore, VGG16-based a model is embedded within a Flask-based web application for classifying fracture severity into mild, moderate, and severe classes. The system also suggests diet and exercise for recovery, with an effective and precise tool for the guidance of healthcare providers and patients in fracture management.

Keywords: Bone fracture, Deep learning, CNN, MobileNet, VGG16, Medical image classification, Flask application

I. INTRODUCTION

X-ray imaging is a standard diagnostic instrument used extensively to diagnose or rule out fractures due to its ability to give clear images of bone structures. Its interpretation may be difficult at times for medical professionals, causing delay in diagnosis, as well as some false positives or false negatives. Advances in computer vision and deep learning over the past decade have held much promise in automated fracture detection. In contrast to conventional machine learning methods, which involve hand-crafted feature extraction, deep learning models like Convolutional Neural Networks (CNNs) and MobileNet can automatically learn hierarchical features from X-ray sets in order to enhance accuracy and efficiency. MobileNet, for instance, is particularly suitable for real-time applications as a result of its reduced computational complexity. Utilizing such models allows smart classification systems to identify and classify fractures with high efficiency, particularly when they are trained on large labeled datasets including the datasets found on websites like Kaggle. There are many different kinds of bones within the body, and severe car crashes or falls will tend to fracture them. Because their bone structures are less solid, older people are particularly vulnerable. Timely diagnosis and successful treatment—most commonly done via X-ray or MRI scans—are necessary to heal fractures. But small fractures are hard to test manually, resulting in a lengthy and error-prone process. Computerized diagnostic systems have been created to overcome such constraints by minimizing the probability of error and time. Medical imaging, such as the detection of fractures, is increasingly making use of sophisticated machine learning technologies. Bone images in these systems are preprocessed to sharpen edges and eliminate noise before feature extraction. Machine learning algorithms are then trained using such features to facilitate accurate diagnosis and classification. Various techniques have been created in the past for bone fracture detection and classification. Artificial Neural Networks (ANN) were employed by Dimililer and Kamil [7], but they could not differentiate between healthy bones and broken bones. Although Chai et al. [9] employed Gray-Level Co-occurrence Matrix (GLCM) to extract features from texture with an accuracy of 86.67



II. PROBLEM STATEMENT

Bone fractures, particularly the fracture of hand and leg, are common injuries that need to be diagnosed early and as early as possible to guide the treatment. With hectic clinic practice, radiologists will face most of the X-ray images where millimeter fractures are not detected due to fatigue or limiting knowledge. Hand reading not only takes time but is also susceptible to human error and bias. Besides, current diagnostic tests do not provide customized recovery advice, e.g., exercise protocols or diet planning. Therefore, there is a pressing need for an intelligent system classifying fracture severity (Mild, Moderate, Severe) using machine learning and providing customized recovery advice, enhancing the diagnostic accuracy, making the clinical process more efficient, and enhancing patient care.

III. METHODOLOGY

The methodology for developing the Bone Fracture Classification System involves several key stages, from data collection and preprocessing to model training and web application development. Below is a step-by-step breakdown of the process:

1. Data Collection and Preprocessing :

- Dataset Collection : X-ray images of hand and leg fractures are collected from various medical sources. The images are manually labeled into three categories based on fracture severity: Mild , Moderate , and Severe .
- Image Preprocessing : The collected images are resized to a uniform dimension suitable for the VGG16 input (e.g., 224x224 pixels). Preprocessing steps such as normalization, grayscale conversion, and image augmentation (rotations, flips, and zooms) are applied to enhance model robustness and handle limited dataset size.

2. Model Architecture and Training :

- VGG16 Model : The VGG16 architecture, pre-trained on ImageNet, is used as the base model for feature extraction. The model's final layers are fine-tuned to suit the bone fracture classification task.
- Transfer Learning : The top layers of the pre-trained VGG16 model are removed and replaced with custom fully connected layers for classification. The model is trained on the fracture dataset using transfer learning, which leverages the pre-trained weights to speed up training and improve accuracy with a relatively small dataset.
- Training and Validation : The dataset is split into training and validation sets, with a portion reserved for testing the model's performance. The model is trained using a categorical cross-entropy loss function and an optimizer like Adam or SGD, and performance is evaluated using accuracy metrics.
- Model Evaluation : The model is evaluated on the validation set to monitor overfitting and underfitting. Techniques like dropout and early stopping are applied to optimize the model's generalization capabilities.

3. Development of Flask Web Application

- User Interface : A Flask-based web application is developed to allow users to upload X-ray images. The front-end of the web application is designed using HTML, CSS, and JavaScript to ensure a simple, user-friendly experience.
- Model Integration : The trained VGG16 model is integrated into the Flask application. Upon image upload, the model processes the X-ray and classifies the fracture as Mild , Moderate , or Severe .

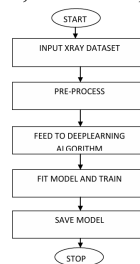


Fig. 1. Flow Chart Training



- Exercise and Diet Recommendations : Once the classification is completed, the system displays a set of tailored recommendations. These include exercises to aid in fracture recovery (e.g., range-of-motion exercises for mild fractures) and dietary suggestions for promoting bone healing (e.g., calcium-rich foods for severe fractures).

IV. LITERATURE SURVEY

Deep learning has emerged as a powerful tool for automated bone fracture detection in radiographic images, offering significant improvements over traditional computer-aided diagnosis systems. Early work by Olczak et al. [1] demonstrated the feasibility of convolutional neural networks (CNNs) for fracture classification. Their study showed that CNN-based models could achieve performance comparable to radiologists, establishing a strong foundation for subsequent research. Similarly, Kim et al. [2] employed deep-learning methods on diverse radiographic images and reported improved diagnostic accuracy across various anatomical regions, emphasizing the clinical potential of these models.

Building upon these pioneering efforts, later studies focused on refining deep-learning architectures and enhancing detection accuracy. Awan et al. [3] designed CNN-based models specifically optimized for bone fracture detection, incorporating preprocessing techniques such as contrast normalization to adapt to the grayscale characteristics of radiographs. Bar et al.

[4] conducted a comparative study of multiple deep-learning models, highlighting the impact of architectural choices and preprocessing pipelines on fracture detection performance. Al-Ani et al. [5] proposed an efficient framework that integrated preprocessing, feature extraction, and ensemble learning. Their approach achieved high accuracy while reducing computational complexity, thereby addressing scalability and deployment issues in real-world healthcare environments.

Beyond image-level classification, object detection methods have been explored to provide more clinically actionable results. Yadav and Shrivastava [6] employed Faster R-CNN, a two-stage object detection framework, to not only identify the presence of fractures but also localize them with bounding boxes. This shift from classification to detection significantly improved clinical interpretability, as localization aligns with the way radiologists analyze images. Similarly, Cheng et al. [7] developed advanced CNN-based models capable of improved localization and reduced false positives, further bridging the gap between automated systems and human-level diagnostic performance.

A common methodological trend across these works is the reliance on transfer learning. Models such as VGG [8], ResNet [9], and AlexNet [10], originally developed for large-scale natural image recognition, have been widely adopted as backbone networks. By leveraging pretrained weights from ImageNet, researchers effectively mitigated the challenge of limited annotated medical datasets and achieved robust feature extraction on radiographs. These architectures introduced key innovations—VGG's deep layered design, ResNet's residual connections enabling very deep models, and AlexNet's pioneering success in large-scale image classification—which continue to serve as benchmarks in medical imaging research. Overall, existing studies clearly demonstrate that CNNs and object detection frameworks can achieve reliable and accurate bone fracture detection in X-rays. However, several challenges remain. First, dataset scarcity and the high cost of annotation limit the availability of large, standardized benchmarks. Second, domain adaptation issues persist, as models trained on data from one hospital or imaging device often underperform when deployed in different clinical settings. Third, most approaches operate as "black-box" systems, raising concerns about explainability and trust in clinical practice. Addressing these challenges is essential for translating deep-learning models from research prototypes into practical diagnostic tools used by radiologists. [11] Iyer, Sankaran, et al. "A novel approach to vertebral compression fracture detection using imitation learning and patch based convolutional neural network." 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI). IEEE, 2020. [12] El-Saadawy, Hadeer, et al. "A two-stage method for bone X-rays abnormality detection using mobileNet network." Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020). Springer International Publishing, 2020. [13] Karanam, Santoshachandra Rao, Y. Srinivas, and S. Chakravarty. "A systematic review on approach and analysis of bone fracture classification." Materials Today: Proceedings 80 (2023): 2557-2562. [14] Ma, Yangling, and Yixin Luo. "Bone fracture detection through the twostage system of crack-sensitive convolutional neural network." Informatics in Medicine Unlocked 22 (2021): 100452. [15] Bagaria, Rinisha, Sulochana Wadhwani, and A.



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V. CHALLENGES

Despite advancements, several challenges remain: lack of large annotated datasets, limited generalization across imaging devices, black-box nature of deep learning models, regulatory concerns, and integration issues with hospital systems. Addressing these issues is critical for clinical adoption.

VI. FUTURE DIRECTIONS

Future research should focus on explainable AI (XAI) for clinical trust, integration of multimodal imaging, edge AI and IoT-enabled diagnostic devices, and AR/VR tools for real-time visualization of fracture severity.

VII. CONCLUSION

AI-powered bone fracture detection and depth measurement represent transformative steps in medical diagnostics. With deep learning and computer vision, these systems promise enhanced accuracy, speed, and scalability. Overcoming challenges related to data quality and clinical integration will be key to widespread adoption.

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