Automated Detection of Bone Fractures Using ResNet18 on X-ray Images: A Deep Learning Approach

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# Abstract

Advancements in artificial intelligence (AI) and deep learning are transforming medical diagnostics, particularly in radiographic image analysis. This study explores the use of a ResNet18 convolutional neural network (CNN) for automated bone fracture detection in X-ray images. Using a custom dataset of 4,159 labeled X-rays, the model was trained and tested using both scratch training and transfer learning methods. Transfer learning yielded an accuracy of 81.4%, a precision of 0.99, and an F1-score of 0.88. The research addresses challenges of small, imbalanced datasets and introduces a web interface for clinical usability. This work highlights the potential of lightweight AI tools for improving diagnostic accuracy, especially in low-resource settings.

Keywords: deep learning, bone fracture, ResNet18, X-ray, CNN, transfer learning, medical imaging

# Introduction

Bone fractures are a significant clinical concern, often resulting from trauma, falls, or pathological conditions like osteoporosis. Traditional diagnosis relies heavily on expert interpretation of radiographic images, a process that can be time-consuming and error-prone. Artificial intelligence, particularly deep learning using convolutional neural networks (CNNs), has shown considerable promise in automating fracture detection (Choi et al., 2020; Litjens et al., 2017). This paper presents the development and evaluation of an AI-powered diagnostic tool using ResNet18 for accurate classification of fractures from X-ray images.

# Literature Review

Recent studies have demonstrated CNNs’ effectiveness in fracture detection tasks. Models like ResNet, VGG, and EfficientNet have shown over 90% accuracy in certain orthopedic datasets (Shinawar Naeem et al., 2023). Transfer learning, using pretrained models such as ImageNet, is especially effective with limited labeled data (Eze & Thompson, 2024). Explainable AI (XAI) tools like Grad-CAM have improved interpretability in clinical contexts (Sundararajan et al., 2024). Despite these advancements, challenges remain in dataset diversity, generalizability, and clinical integration.

# Methodology

This study utilized a custom dataset sourced from the MURA and RSNA repositories, comprising 4,159 X-ray images across five anatomical regions. Data preprocessing included resizing images to 224x224 pixels, normalization, and augmentation using the Albumentations library. The model architecture was ResNet18, evaluated using both scratch training and transfer learning approaches. The training setup employed cross-entropy loss and the Adam optimizer, with evaluation metrics including accuracy, precision, recall, F1-score, and Intersection over Union (IoU). All experiments were conducted using PyTorch, OpenCV, and Scikit-learn.

# Results and Discussion

The transfer learning model achieved an accuracy of 81.4%, outperforming the scratch-trained model at 76.6%. Precision was recorded at 0.99, with a recall of 0.79 and F1-score of 0.88. IoU improved from 0.68 in scratch training to 0.72 using transfer learning. A confusion matrix and ROC curve supported these findings. The inclusion of saliency maps enhanced the interpretability of predictions. A front-end interface built with HTML, CSS, and JavaScript allowed users to upload X-ray images and receive classification results in real-time.

# Conclusion and Future Work

This research demonstrates the viability of a lightweight, interpretable AI system for bone fracture detection using ResNet18. Despite dataset limitations, the model performed reliably and showed strong potential for deployment in resource-limited settings. Future work should focus on integrating textual radiology reports to enable multimodal analysis, expanding datasets, and deploying mobile-ready real-time diagnostic tools.

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