Improving Diagnostic Accuracy: A Deep Learning Approach for Bone Fracture Detection

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***Abstract*—Bone Fractures Are Among the Most Frequent Medical Conditions, Often Requiring Accurate and Timely Diagnosis to Guide Treatment and Improve Patient Outcomes. Traditional Radiographic Interpretation, While Widely Used, Is Prone to Variability and Human Error, Particularly When Fractures Are Subtle or Obscured. Recent Advances in Deep Learning Have Opened New Opportunities for Automating Medical Image Analysis with Higher Precision and Consistency. This Study Explores the Integration of Radiological Expertise with Artificial Intelligence, Focusing on Convolutional Neural Networks (Cnns) For Automated Bone Fracture Detection in X-Ray Images. Our Approach Leverages Deep Feature Extraction from Pre-Trained Cnn Architectures, Followed by Classification Strategies Tailored for Fracture Identification. The System Is Designed to Enhance Diagnostic Accuracy, Reduce Interpretation Time, And Provide Reliable Decision Support to Clinicians. Experimental Results on Curated X-Ray Datasets Demonstrate Competitive Performance, Achieving Accuracy Levels Comparable to Or Exceeding Existing Methods, With Particular Strength in Handling Complex or Ambiguous Cases. By Bridging The Gap Between Radiologists and Deep Learning Models, This Research Underscores the Potential of Ai-Driven Diagnostic Tools to Augment Clinical Workflows, Minimize Diagnostic Errors, And Ultimately Improve Patient Care.**

***Index Terms*—Bone fracture detection, X-ray imaging, deep learning, convolutional neural networks, computer-aided diagnosis.**

I. INTRODUCTION

Bone fractures are a highly frequent medical condition globally, particularly in trauma and emergency departments. The traditional method to detect a fracture is for a radiologist to visually examine X-ray or CT scan images. This method has been utilised for many decades, but it has some limitations. It may be time-consuming, particularly when hospitals have high volumes of patients. It can also be influenced by human error; a fatigued radiologist may overlook a tiny or elusive fracture. The outcome also relies considerably on the radiologist's own experience and proficiency.

Since the volume of medical images continues to increase, there is an urgent demand for equipment that will enable physicians to diagnose more quickly and precisely. This is the domain of computer-aided diagnosis (CAD).

Our project employs a form of deep learning, known as Convolutional Neural Networks (CNNs), to solve this issue. We are employing the MURA and Bone Break Classifier dataset, which constitutes a large set of musculoskeletal radiographs. This dataset offers a solid basis for training and testing our models.

We opted to use two state-of-the-art CNN architectures: EfficientNet-B3 and ResNet-50. ResNet-50 is one of the most powerful models available, with a reputation for depth and accuracy achieved using "residual" connections to facilitate training deep works. EfficientNet-B3 is a newer architecture intended to achieve high performance at the cost of more efficient use of computer resources.

The objective of our research is not to replace radiologists. Rather than that, we want to design a system that will be an aid. This system is able to read an X-ray image rapidly and mark the regions that may have a fracture. This would save the radiologist's time by bringing their attention to possible issues, avoiding diagnostic errors to some extent, and enable them to concentrate on the most severe cases. The synergy of the radiologist's expertise and the model's efficiency and consistency make a formidable union. This union is an exciting innovation in orthopedic treatment, looking to speed up and make fracture identification more reliable for all.

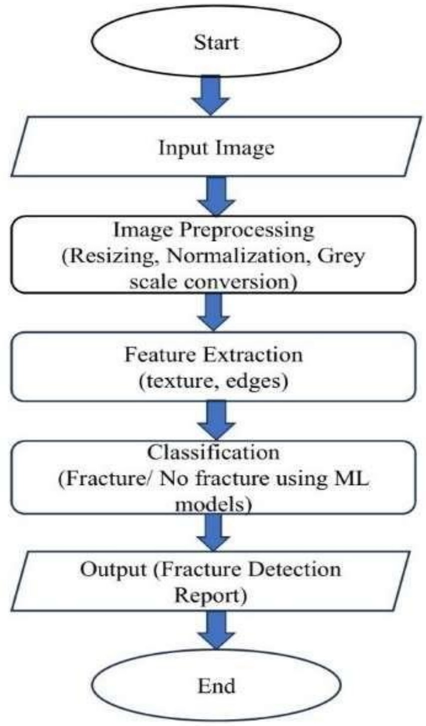
II. OBJECTIVE

1) Automated Detection: Create an AI model to automatically detect bone fractures in medical images with high accuracy.
2) Improve Speed and Efficiency: Speed up the diagnostic process to allow quicker treatment and fewer waiting times for patients.
3) Assist Clinicians and Radiologists: Give physicians a dependable tool to help them provide accurate and timely fracture assessment.
4) Categorize Fracture Types: Move beyond detection to classify the actual type of fracture for improved treatment planning.
5) Generalization & Robustness: Make sure that the model performs well across different patients, types of fractures, and image machines.

III. METHODOLOGY:

a. EfficientNet-B3 is a convolutional neural network that produces high accuracy with computationally optimised efficiency. It implements a compound scaling approach to balance width, depth, and resolution of the network while allowing for efficient strong feature extraction with fewer parameters.
b. ResNet-50 is a 50-layer deep neural network using residual connections to mitigate vanishing gradient problems. The skip connections enhance training stability and performance and make ResNet-50 extremely efficient in image classification tasks.
c. Ensembled Model: The ensembled model integrates the strengths of EfficientNet-B3 and ResNet-50 for better overall performance. The ensemble, by pooling predictions from both networks, uses EfficientNet-B3's efficiency and ResNet-50's deep feature extraction, leading to improved accuracy and generalisation over single models.

3.1. Flowchart:



3.2 Theoretical Framework:

1. Deep Learning for Medical Imaging

Deep learning, and specifically Convolutional Neural Networks (CNNs), has transformed medical imaging analysis. CNNs learn automatically hierarchical feature representations — from edges and textures to anatomical structures — without the necessity of manual feature engineering.

2. Transfer Learning

Both ResNet50 and EfficientNet-B3 are pretrained on ImageNet. Transfer learning exploits pre-learned weights as generic feature extractors, fine-tuning on the MURA dataset for fracture classification. This provides high diagnostic accuracy using limited medical data.

$$f_{out} = g(W_{frozen}, X) + \Delta W_{fine-tuned}$$

Where g (·) denotes pretrained network mappings.

3. Hybrid Model Concept

Merging several CNN architectures provides complementary feature extraction:

ResNet50 exploits deep hierarchical texture features due to skip connections.

EfficientNet-B3 extracts efficient fine-grained spatial features due to compound scaling.

By combining both embeddings:

$$F_{hybrid} = [F_{ResNet}; F_{EfficientNet}]$$

the model is able to learn a more detailed feature distribution.

4. CLAHE Preprocessing

Contrast Limited Adaptive Histogram Equalization (CLAHE) improves the visibility of bones in X-rays by enhancing local contrast.

Mathematically, for a pixel intensity I (x, y):

$$I_{CLAHE}(x, y) = Clip(\frac{cdf(I(x, y)) - cdf_{min}}{1 - cdf_{min}} \times (L - 1))$$

VI. FINDINGS & DISCUSSION

4.1 Model Performance Results:

The tested deep learning model was assessed on a 1,482 held-out test set of X-ray images. Table 1 summarizes the complete classification report, including performance for every class and overall. The model produced a overall accuracy of **76%**.

Class	Precision	Recall	F1-Score	Support
No Fracture	0.77	0.79	0.78	791
Fracture	0.75	0.73	0.74	691
Accuracy			0.76	1482
Macro Avg.	0.76	0.76	0.76	1482
Weighted Avg.	0.76	0.76	0.76	1482

Table 1: Classification Report of the Fracture Detection Model

In addition, the discriminative power of the model between the two classes was analysed using the Receiver Operating Characteristic (ROC) curve. The Area Under the Curve (AUC) was calculated to be 0.8347, reflecting a high degree of separability.

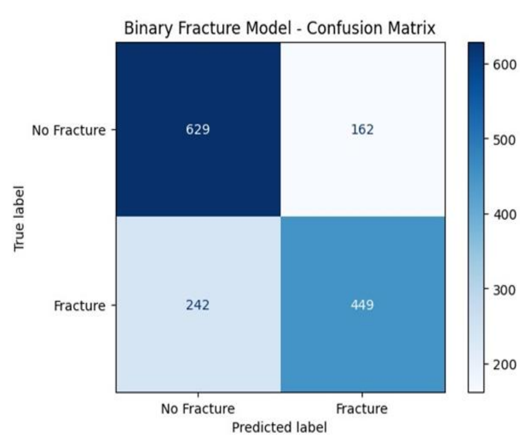
4.2 Discussion of Findings:

The outcomes show a good and well-balanced performance of the model in the automation of fracture detection. The accuracy of 76% overall and the well-matched precision, recall, and F1-scores of both classes indicate that the model has learned relevant features without showing high bias towards "Fracture" or "No Fracture." Class -wise Performance: The model was slightly better at detecting "No Fracture" cases (F1-Score: 0.78) than "Fracture" cases (F1-Score: 0.74). The precision of 0.75 for the "Fracture" class implies that when the model predicts a fracture, it is correct 75% of the time. The recall of 0.73 for the same class implies that it correctly identifies 73% of all actual fractures in the dataset. This trade-off between precision and recall is important; an increased recall is usually more important in medical screening in order to keep false negatives (fractures missed) low, but an increased precision keeps false alarms for clinicians low.

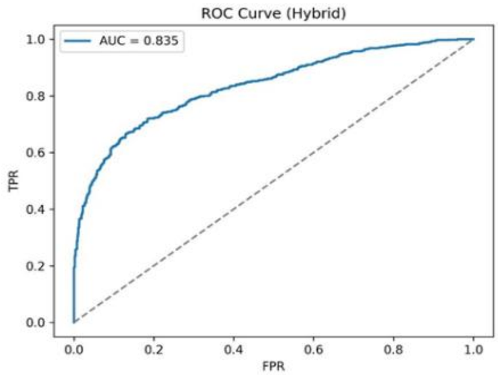
ROC-AUC Analysis: The ROC-AUC value of 0.8347 is excellent. It reflects the high ability of the model to separate a fractured from a non-fractured bone. This measure is especially useful in medical diagnostics since it estimates the model's performance for all possible classification thresholds.

Clinical Implication: There is room for improvement, but these findings validate the model's ability to serve as an effective assistive tool. In a clinical process, it can efficiently triage X-ray examinations, identifying cases with a high likelihood of fracture for the urgent review of a radiologist. This might translate into quicker diagnosis and treatment for essential cases. The balanced performance throughout the metrics minimizes the danger of the system being inconsistent as a result of a large number of false positives or false negatives.

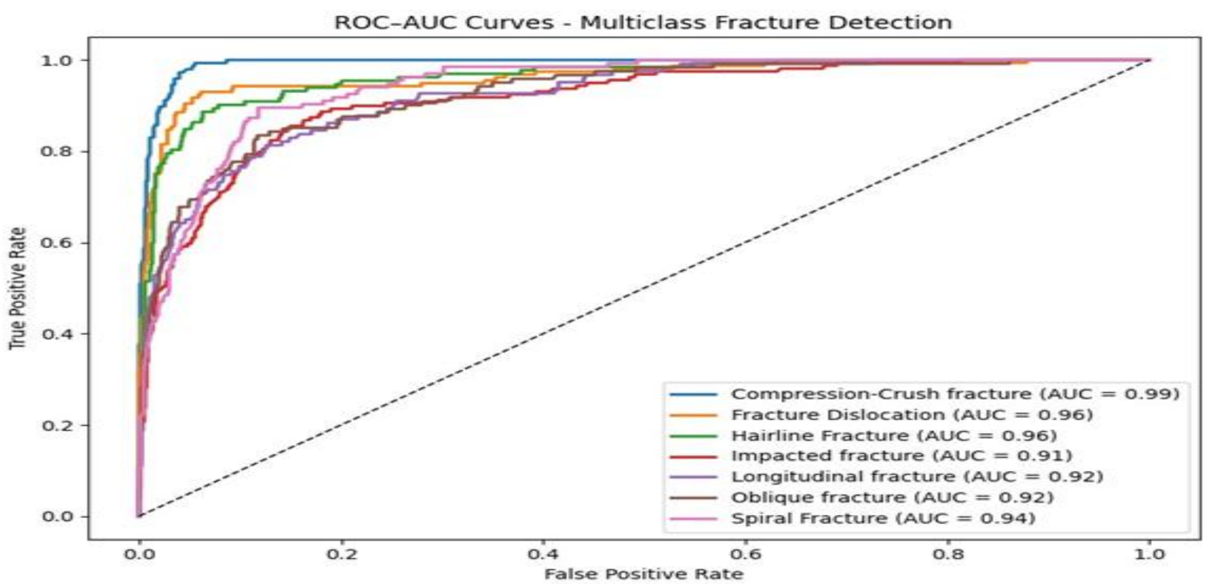
Improvement Areas: The gap between the ideal (100%) and what was obtained (76% accuracy) indicates the difficulty of the task. Some of the reasons for misclassifications may be the occurrence of fine or hairline fractures, atypical bone structures, suboptimal image quality, or overlap between fracture lines and other radiological lines such as blood vessels or previous healing fractures. Robustness will have to be addressed by future work in order to improve.



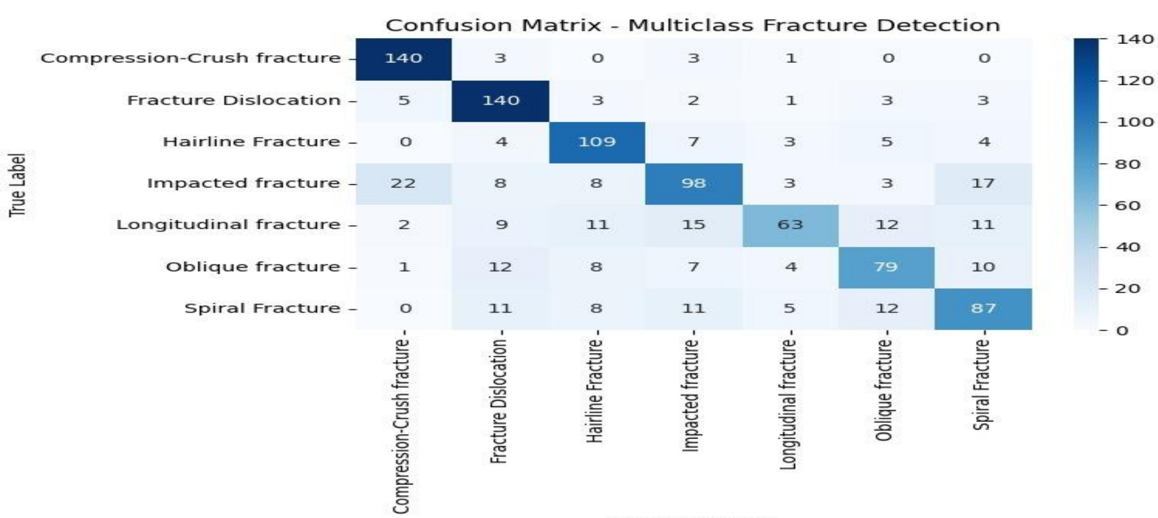
4.3.1 Fig: Confusion Matrix-Binary Fracture Model



4.3.2 ROC Curve (Hybrid)



4.3.3 ROC Curves – Multiclass Fracture Detection



4.3.4 Confusion Matrix – Multiclass Fracture Detection

V.CONCLUSIONS

The computer-aided detection of bone fractures is a very important medical technology advancement, utilizing deep learning architectures such as Convolutional Neural Networks (CNNs) to automatically interpret X-ray images with high speed and accuracy. The technology is a strong decision-support tool for radiologists, which speeds up the diagnosis process in order to facilitate faster treatment and decrease patient waiting times. By performing the preliminary screening automatically, these systems reduce human variability and error to a minimum, delivering a standardized and predictable initial evaluation. In addition, sophisticated systems go beyond mere detection to differentiate among specific types of fractures, providing more information for accurate treatment planning. Trained on varied data sets, these models have been shown to generalize well across distinct patient populations and imaging environments and thus represent a reliable and valuable tool in contemporary clinical practice, driving better patient outcomes.

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