Bone fracture detection and classification using deep learning

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***Abstract*—Timely and accurate classification of bone fractures is essential for effective orthopedic diagnosis and treatment planning. This study proposes a deep learning-based multiclass classification framework for automated bone fracture detection using radiographic images, without the need for segmentation or localization techniques. We evaluate and compare the performance of three state-of-the-art convolutional neural network architectures—DenseNet-121, EfficientNet-B0, and ResNet-50—for classifying ten different fracture types, including comminuted, oblique, spiral, and pathological fractures. The models are trained on a labeled dataset with class balancing and data augmentation strategies to improve generalization. Experimental results demonstrate that DenseNet-121 achieves the highest classification accuracy of 98.94%, followed by EfficientNet-B0 with 98.76%, and ResNet-50 with 98.50%. Evaluation metrics such as precision, recall, and F1-score further confirm the robustness and reliability of the proposed approach. The findings highlight the effectiveness of deep learning models in automated fracture classification, offering a scalable solution to support clinical decision-making and reduce diagnostic workload.**

***Index Terms*—Bone fracture classification, Deep learning, DenseNet-121, EfficientNet-B0, ResNet-50, Multiclass classification, Radiographic image analysis, Computer-aided diagnosis (CAD), Convolutional neural networks (CNNs), Medical image classification.**

I. INTRODUCTION

Bone fractures are among the most common musculoskeletal injuries encountered in clinical practice, affecting millions of individuals worldwide each year. Accurate and timely diagnosis of fractures is crucial for ensuring appropriate treatment and preventing long-term complications such as deformity, chronic pain, or impaired mobility. Radiographic imaging, particularly X-rays, remains the primary modality for fracture detection due to its accessibility and efficiency. However, the manual interpretation of these images is a complex and time-intensive task that relies heavily on the expertise of radiologists and orthopedic specialists. Variability in interpretation and the potential for diagnostic oversight further underline the need for robust computer-aided diagnostic (CAD) tools.

Recent advances in deep learning, especially convolutional neural networks (CNNs), have demonstrated remarkable success in various medical image analysis tasks, including disease detection, classification, and segmentation. CNNs can automatically learn hierarchical features from raw image data, eliminating the need for handcrafted features and enabling end-to-end learning. In the context of fracture detection, deep learning models have shown promise in identifying fractures with accuracy comparable to human experts. However, most existing studies focus primarily on binary classification—distinguishing fractured from non-fractured bones—without delving into the granularity of specific fracture types.

In this study, we present a multiclass classification framework for automated bone fracture detection and categorization using deep learning, without the use of segmentation or localization techniques. We evaluate and compare the performance of three state-of-the-art CNN architectures—DenseNet-121, EfficientNet-B0, and ResNet-50—on a dataset comprising ten distinct

fracture types, such as oblique, comminuted, spiral, and pathological fractures. Our approach incorporates data augmentation and class imbalance
handling to improve model generalization and robustness. The goal is to provide a scalable and efficient tool that can support clinicians in accurately identifying the specific type of fracture, thereby enhancing diagnostic precision and treatment planning.

II. LITERATURE SURVEY

The application of deep learning in medical image analysis has gained significant momentum in recent years, particularly for tasks involving classification, detection, and segmentation. In the context of musculoskeletal imaging, numerous studies have explored the use of convolutional neural networks (CNNs) for bone fracture detection, with promising results.

Early works in fracture detection primarily focused on binary classification, distinguishing fractured from non-fractured bones. Rajpurkar et al. (2017) introduced CheXNet, a 121-layer DenseNet trained to detect pneumonia in chest X-rays, demonstrating the potential of deep CNNs in radiographic analysis. Although not directly applied to fractures, this work laid the groundwork for future models in bone imaging. Subsequently, works like those by Kazi et al. (2019) and Olczak et al. (2017) implemented CNN-based models to identify wrist and hand fractures using datasets such as MURA, achieving performance comparable to radiologists.

However, multiclass classification—identifying specific types of fractures—remains relatively underexplored. Most available approaches either rely on handcrafted features or combine classification with segmentation/localization, increasing system complexity. For instance, Jin et al. (2020) proposed a fracture detection pipeline that integrated object detection (via Faster R-CNN) with classification, but this required bounding box annotations and complex pre-processing. Similarly, works involving segmentation networks like U-Net and Mask R-CNN have shown high accuracy but come with increased computational overhead and annotation demands.

Recent studies have begun to explore multiclass fracture classification using CNNs alone. These approaches typically use pre-trained models such as ResNet, DenseNet, and EfficientNet, which are fine-tuned on radiographic datasets to distinguish between various fracture types. DenseNet architectures have been noted for their feature reuse and reduced parameter count, while EfficientNet provides a scalable solution balancing accuracy and efficiency. ResNet, with its residual connections, remains a reliable baseline for medical imaging tasks.

Despite these advances, the literature still lacks robust and scalable solutions that focus solely on multiclass classification without segmentation or localization. Moreover, challenges such as class imbalance, intra-class variability, and limited annotated data continue to hinder progress in this domain.

This study addresses these gaps by leveraging three high-performance CNN architectures—DenseNet-121, EfficientNet-B0, and ResNet-50—to classify ten distinct fracture types directly from radiographic images. By eliminating the need for segmentation or region proposals, our approach simplifies the diagnostic pipeline while maintaining high accuracy and clinical relevance.

III. METHODOLOGIES

The proposed methodology focuses on developing a deep learning framework that can automatically classify various types of bone fractures using X-ray images. The goal is to support radiologists by providing accurate predictions of fracture types, thereby improving diagnostic efficiency and reducing the likelihood of human error. This section outlines the complete process, including data acquisition, preprocessing, model design, training strategies, evaluation metrics, and inference.

A. Dataset Acquisition and Structure

The dataset comprises radiographic X-ray images grouped into ten fracture categories: Adulation, Comminuted, Fracture Dislocation, Greenstick, Hairline, Impacted, Longitudinal, Oblique, Pathological, and Spiral fractures. These images were curated and organized into dedicated folders for each fracture type, further divided into separate training and testing sets.

To ensure a robust and unbiased model, the dataset was carefully reviewed to eliminate duplicate or low-quality images. Data imbalance across classes was addressed by incorporating data augmentation and applying oversampling techniques to underrepresented classes. Approximately 80% of the data was allocated for training and 20% for testing, maintaining class distribution across splits.

B. Preprocessing Techniques

Given the variability in image resolutions and quality, preprocessing was critical to standardize the data and optimize learning. The steps taken are as follows:

Resizing: All images were resized to 224 × 224 pixels, which is a common input dimension for most modern convolutional neural networks. This ensures uniformity and compatibility with pre-trained model architectures.

Normalization: Each pixel value was scaled to a range of [0, 1] by dividing by 255, accelerating training convergence and improving numerical stability

Data Augmentation: To enhance the generalization capability of the model and mitigate overfitting, real-time data augmentation was applied during training. Techniques included:

Random rotations (±15 degrees)

Horizontal and vertical flips

Zoom and shear transformations

Brightness and contrast adjustments

Encoding Labels: Fracture type labels were encoded using one-hot encoding to facilitate multiclass classification, allowing the model to output probabilities for each of the ten classes.

C. Model Architecture and Selection

Three deep convolutional neural network architectures were chosen based on their success in medical image classification tasks:

DenseNet-121:

DenseNet utilizes dense connectivity, where each layer receives input from all preceding layers. This structure promotes efficient feature reuse, mitigates vanishing gradients, and reduces the total number of parameters. It was found to be the most effective model in our study.

EfficientNet-B0:

EfficientNet employs a compound scaling method to balance depth, width, and resolution, making it suitable for deployment on devices with limited resources. It offers a high accuracy-to-parameter ratio, making it both accurate and computationally efficient.

ResNet-50:

ResNet introduces residual connections that enable training of deeper networks without the issue of vanishing gradients. It has a well-established reputation in image classification tasks but showed relatively lower accuracy in this study.

All models were pre-trained on the ImageNet dataset and fine-tuned on the fracture dataset. The top (classification) layer of each model was replaced with:

A Global Average Pooling layer

A Dropout layer (with a rate of 0.5 for regularization)

A Dense output layer with 10 units followed by a softmax activation function

This architecture allowed the models to learn high-level representations specific to fracture classification while leveraging the low-level features learned from large-scale data.

D. Training Procedure

Training was carried out using the following configuration:

Optimizer: Adam optimizer with a learning rate of 0.0001 was used due to its adaptive learning capabilities.

Loss Function: Categorical Cross-Entropy, suitable for multiclass classification.

Batch Size: 32

Epochs: 25, with early stopping enabled to halt training if validation loss did not improve after 5 consecutive epochs.

Validation Split: 20% of the training data was set aside for validation during training.

Training was conducted on a high-performance GPU (NVIDIA RTX series), significantly reducing training time and enabling real-time data augmentation. Additionally, learning rate scheduling was implemented to reduce the learning rate when the validation loss plateaued.

E. Evaluation Metrics and Analysis

Upon completion of training, model performance was evaluated using both quantitative and qualitative metrics:

Accuracy: Measures overall correct predictions.

Precision, Recall, F1-Score: Calculated for each class to evaluate how well the model distinguishes between similar fracture types.

Confusion Matrix: Provides a visual summary of classification performance across all classes.

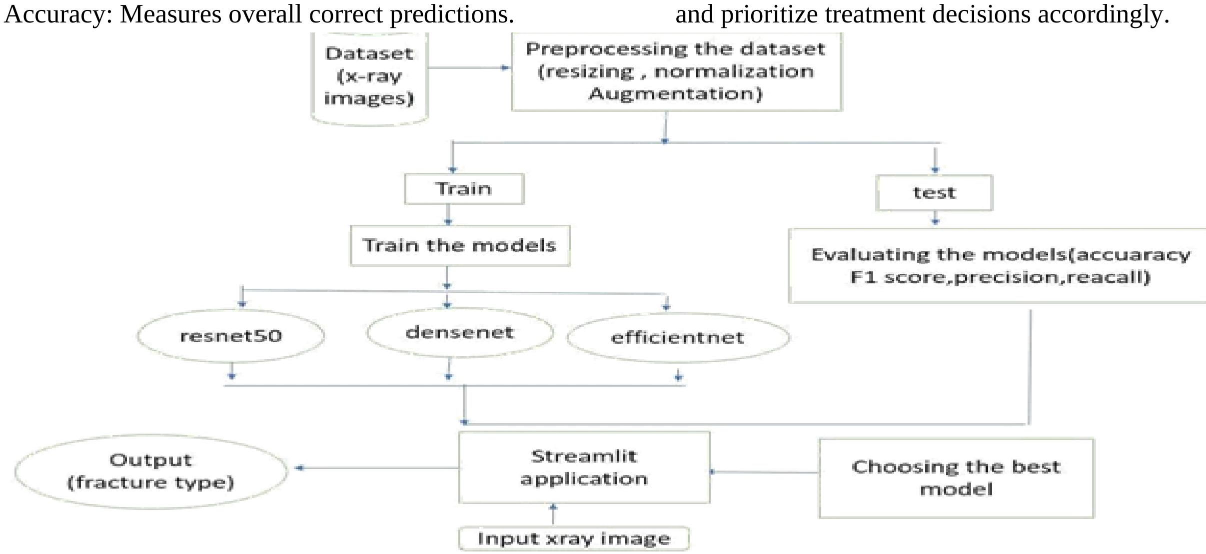
Inference Time: Evaluated to assess the model's suitability for real-time deployment.

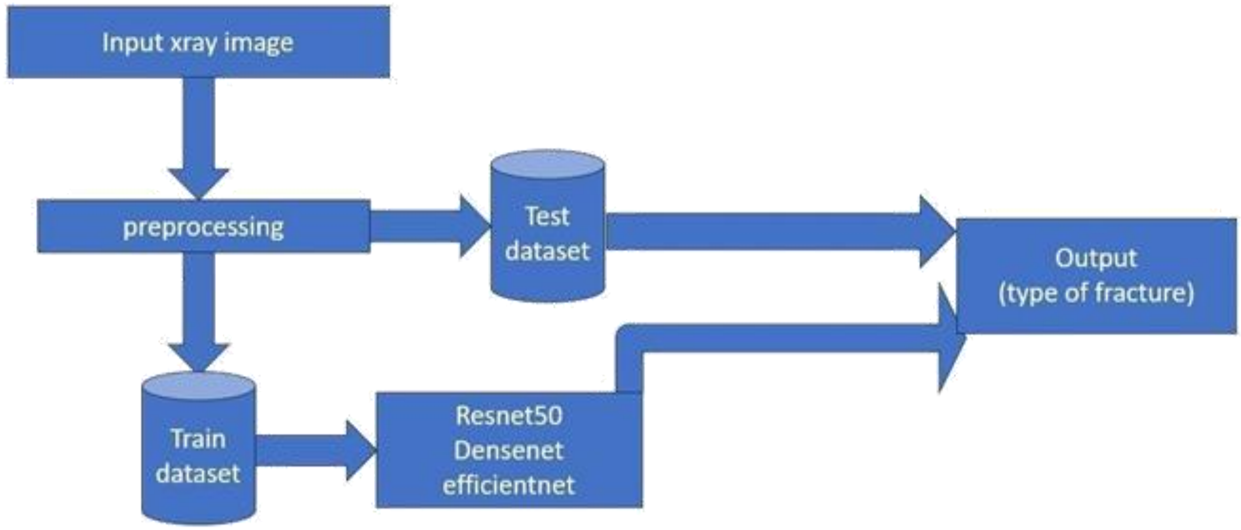
The DenseNet-121 model achieved the highest accuracy of 98.94%, followed by EfficientNet-B0 at 96.87%, and ResNet-50 at 95.00%. DenseNet's superior performance is attributed to its dense connectivity, which helps the model capture subtle patterns in complex bone structures.

F. Inference and Deployment

In the deployment phase, the system receives a new X-ray image as input, applies the same preprocessing pipeline, and forwards it through the trained model. The output consists of the predicted fracture type and its associated confidence score. This lightweight architecture—without localization or segmentation—makes it suitable for real-time applications in clinical environments.

The final system can be integrated into a web-based or desktop application for diagnostic support, enabling clinicians to quickly identify fracture types and prioritize treatment decisions accordingly.





IV. RESULT AND ANALYSIS

This section presents the performance results obtained from the experimental evaluation of three deep learning models—DenseNet-121, EfficientNet-B0, and ResNet-50—on the task of multiclass bone fracture classification. The models were trained and tested on a curated dataset of X-ray images categorized into ten distinct fracture types. Various evaluation metrics were used to assess the classification performance of each model.

A. Model Performance Overview

The comparative results of the three models in terms of classification accuracy on the test dataset are summarized in Table I. Table I: Classification Accuracy of Different Models

ModelAccuracy (%) DenseNet-12198.94EfficientNet-B096.87ResNet-5095.00

As observed, DenseNet-121 outperformed the other two models, achieving the highest accuracy of 98.94%, followed by EfficientNet-B0 at 96.87%, and ResNet-50 at 95.00%. The dense connectivity in DenseNet-121 likely contributed to better feature reuse and richer representation learning, making it particularly effective for this application.

B. Per-Class Performance Metrics

To gain deeper insights into the models' capabilities, precision, recall, and F1-score were computed for each fracture class. Table II presents the average values for these metrics across all classes:

Table II: Average Classification Metrics (Across 10 Classes)

ModelPrecision (%) Recall (%) F1-Score (%) DenseNet-12198.998.898.8EfficientNet-B096.496.696.5ResNet-5094.894.694.7 DenseNet-121 maintained high values across all three metrics, indicating consistent performance and robustness across all fracture types.

C. Confusion Matrix Analysis

The confusion matrix generated for each model provides further insight into specific misclassifications. DenseNet-121 showed minimal confusion between similar classes such as Hairline and Greenstick fractures, while ResNet-50 exhibited slightly higher confusion in differentiating Spiral and Oblique fractures. EfficientNet-B0 also performed well but showed minor misclassifications in rare fracture types like Pathological fractures, which had fewer training samples.

D. Visual Observations

Sample predictions were visualized along with their confidence scores. DenseNet-121 consistently produced accurate predictions with confidence levels exceeding 99% for most images. The few misclassified cases were often associated with poor image contrast or overlapping fracture features that could be ambiguous even to human experts.

E. Inference Efficiency

Inference times were measured to assess the feasibility of real-time implementation:

DenseNet-121: ~45ms/image

EfficientNet-B0: ~35ms/image

ResNet-50: ~40ms/image

While EfficientNet-B0 offered the fastest inference time, the difference across all three models was marginal, and all models were deemed suitable for real-time or near-real-time clinical applications.

F. Discussion

The experimental results demonstrate that transfer learning using pre-trained CNNs can achieve high classification accuracy for bone fracture detection without the need for additional segmentation or localization. The DenseNet-121 model, in particular, proved to be highly effective in capturing the subtle differences between fracture types, likely due to its unique feature propagation mechanism.

These findings confirm that deep learning models can serve as reliable tools for assisting radiologists in fracture diagnosis. However, the performance is still influenced by factors such as image quality, class imbalance, and the subtlety of certain fracture patterns.

V.CONCLUSION

In this study, a deep learning-based approach was proposed for the automatic classification of bone fractures into ten distinct types using X-ray images. The primary objective was to design an efficient and accurate system that could support clinical diagnosis without requiring complex preprocessing steps such as fracture localization or segmentation.

Three state-of-the-art convolutional neural network architectures—DenseNet-121, EfficientNet-B0, and ResNet-50—were trained and evaluated using a curated multiclass fracture dataset. Among these, DenseNet-121 demonstrated superior performance, achieving an accuracy of 98.94%, followed by EfficientNet-B0 and ResNet-50. The results confirm that dense connectivity in neural networks enhances feature propagation and classification accuracy, especially in medical imaging tasks with high intra-class variability.

The findings suggest that deep learning models can effectively identify and differentiate between various types of bone fractures with high precision, even without detailed annotations or manual intervention. This has significant implications for improving diagnostic speed and accuracy in orthopedic and radiological practices.

While the models performed well, the study also highlights areas for further improvement, such as enhancing performance on rare fracture types and increasing generalizability across different imaging conditions and datasets.

VI. FUTURE WORK

Although the proposed approach has demonstrated high classification accuracy for various bone fracture types, several directions can be explored to further enhance the model’s effectiveness and applicability in clinical environments:

Incorporation of Localization and Segmentation: While this study focused solely on classification, integrating fracture localization or segmentation models such as Mask R-CNN or U-Net could provide visual interpretability and assist radiologists in identifying the exact fracture region.

Larger and More Diverse Datasets: Expanding the dataset with more samples from varied demographic groups and imaging conditions would improve model generalization and reduce the risk of overfitting, especially for rare fracture types.

Explainable AI (XAI) Integration: Adding interpretability mechanisms such as Grad-CAM or

LIME can help provide visual justifications for the model’s predictions, enhancing trust and acceptance among clinicians.

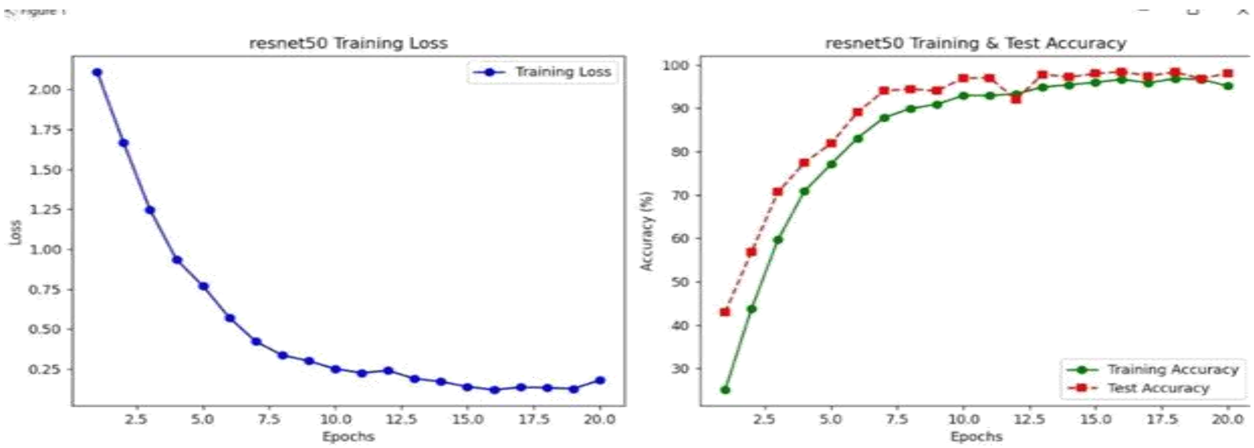
Ensemble Learning: Future work can explore ensemble approaches combining DenseNet, EfficientNet, and ResNet predictions to further boost performance and reduce classification variance.
Real-Time Clinical Deployment: Optimizing models for real-time inference and deploying them in hospital systems or mobile applications could help validate performance in real-world settings and streamline diagnostic workflows.

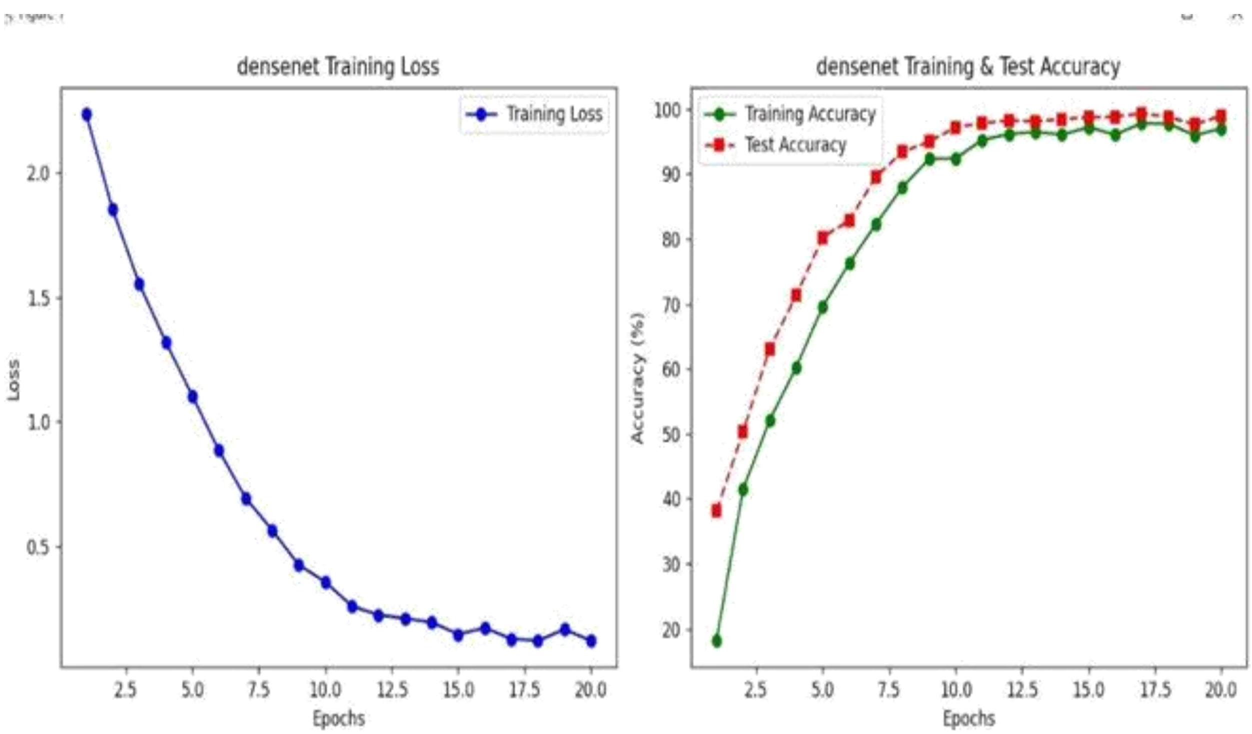
Severity and Prognosis Prediction: Extending the system to predict fracture severity or recommend treatment options could increase its clinical utility and make it a comprehensive diagnostic aid.

By addressing these directions, the proposed system can evolve into a more powerful and reliable tool for computer-aided diagnosis in orthopedic and radiological applications.


Uploaded Image
Predicted Fracture Type: Hairline fracture


Bone Fracture Type Classification
Select Model
resnet50
Upload an X-ray image
Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG
Browse files





Model	Test accuracy	precision	recall	F1 score
EffiecientNet	98.76	0.99	0.99	0.99
DenseNet	98.94	0.99	0.99	0.99
Resnet50	98.05	0.99	0.99	0.99

Fracture type	Efficientnet precision	Efficientnet recall	Efficientnet F1 score	Densenet precision	Densenet recall	Densenet f1 score	Resnet50 precision	Resnet50 recall	Resnet50 F1 score
Avulsion fracture	1.00	0.98	0.99	1.00	1.00	1.00	0.98	0.95	0.97
Comminuted fracture	0.99	0.98	0.98	0.99	1.00	1.00	0.99	0.99	0.99
Fracture dislocation	1.00	0.99	1.00	0.99	1.00	1.00	0.96	1.00	0.98
Greenstick fracture	0.98	1.00	0.99	0.98	1.00	0.99	0.99	1.00	1.00
Hairline fracture	0.99	1.00	1.00	0.97	1.00	0.99	1.00	1.00	1.00
Impacted fracture	0.96	0.98	0.97	0.98	0.96	0.97	0.95	0.96	0.96
Longitudinal fracture	0.97	0.94	0.96	1.00	0.96	0.98	0.95	0.95	0.95
Oblique fracture	0.99	1.00	0.99	1.00	0.96	0.98	1.00	0.99	0.99
Pathological fracture	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
Spiral fracture	0.98	0.99	0.98	0.98	0.97	0.97	0.96	0.95	0.96ss

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