

# Detection And Classification of Custom Bone Fracture Types Using YOLOv8

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**Abstract**—Automated systems for bone fracture detection through radiographic image analysis constitute vital development work in computer-aided diagnostic systems. X-ray image evaluation through manual methods requires substantial time investment because different observers display inconsistent results when they try to find hard-to-detect fractures. The research develops a deep learning system which employs YOLOv8 object detection technology to find and categorize various bone fracture types. The system performs fracture area detection and identification through its single-stage detection mechanism. The training process uses a specially curated and annotated X-ray dataset which includes preprocessing methods and augmentation techniques to enhance system performance. The proposed method achieves high mean Average Precision while maintaining real time inference speed. The system demonstrates improved fracture detection capabilities across multiple fracture types while producing fewer false positive results for actual fractures.

**Index Terms**—Bone Fracture Detection, YOLOv8, Deep Learning, Medical Image Analysis, Object Detection, Computer- Aided Diagnosis

## I. INTRODUCTION

Bone fractures affect millions of people throughout the world because of accidents and sports injuries and falls and medical conditions. Medical professionals need to detect diseases at their earliest stage because this enables them to select appropriate treatments which will stop future health issues. Radiographic imaging functions as the primary diagnostic technique which detects fractures because it provides hospitals with basic medical equipment at low costs. The human process of interpreting X-ray images requires extensive training because the task becomes difficult when analyzing dark images which contain

multiple body parts and weak fracture details. Recent advancements in deep learning and computer vision technology have created new opportunities for automatic analysis of medical imaging. The YOLO family of object detection models has become popular because it enables users to achieve fast and precise detection results which work in real-time. The latest version of YOLOv8 brings architectural improvements that enhance feature extraction, enable anchor-free detection, and create better training methods. The paper describes an automatic system which uses YOLOv8 technology to identify and categorize different types of bone fractures. The system detects fracture areas through a complete system which then assigns multiple fracture types to those areas. The team aims to create a strong diagnostic tool which operates in real-time to improve fracture detection results while reducing the need for manual analysis.

## II. RELATED WORK

Multiple studies which have been conducted recently study how to use YOLOv8 and its different versions for detecting medical fractures. G. Meza et al. developed an enhanced YOLOv8 model which uses a hybrid attention system to achieve better arm fracture detection by extracting minute fracture details. R.-Y. Ju et al. developed two models called YOLOv8-AM and YOLOv8-ResCBAM which use attention modules to improve sensitivity and accuracy in detecting pediatric wrist fractures. Y. Wang et al. created SCFAST-YOLO to classify distal radius fractures by adding various enhancement components to YOLOv8. F. Yang et al. developed YOLOv8-Seg system which uses segmentation technology to enhance accuracy in detecting fracture boundaries.

The current methods achieve better detection results but most research projects track specific types of bones or study pediatric data which makes the models become more complex. The current models have training limitations because they use small datasets and they do not show proof of their ability to function in real-time.

Researchers need to create a unified system which detects all types of fractures while maintaining both accurate results and efficient processing and real-time operational performance. The proposed system addresses this gap using optimized YOLOv8 training and a lightweight deployment framework.

### III. SYSTEM ARCHITECTURE

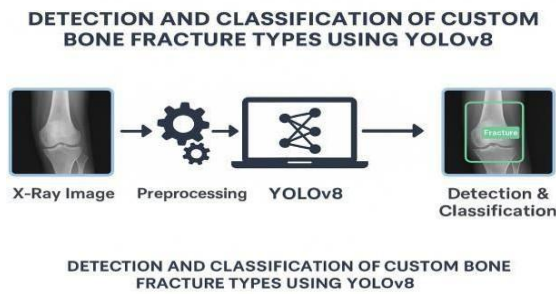


Fig. 1

The system architecture displayed in Fig. 1, named detection and classification of bone fracture type is approached using YOLOv8.

#### A. System Overview

The digitized collection is in graphic form, and meets the required dimensions.:

1. X-ray image collection
2. Image annotation with bounding boxes
3. Data preprocessing and augmentation
4. YOLOv8 model training
5. Performance evaluation
6. Real-time deployment

#### B. Dataset Preparation

The training process used annotated X-ray images that displayed different types of fractures. Fracture detection was performed through the use of bounding box labels which were applied to each fracture category in the images. The dataset was divided into training, validation, and testing sets to ensure reliable

performance evaluation.

The preprocessing process used three techniques which included resizing images to  $640 \times 640$  resolution and performing normalization and contrast enhancement. The data augmentation process used rotation and flipping and brightness adjustment to enhance model generalization capabilities.

#### C. Mathematical Formulation of YOLOv8 Loss Function

The total loss function in YOLOv8 consists of three components:

$$L_{total} = L_{box} + L_{cls} + L_{obj}$$

##### 1. Bounding Box Loss

YOLOv8 uses Complete Intersection over Union (CIoU) loss for bounding box regression:

$$L_{box} = 1 - CIoU$$

Where:

$$CIoU = IoU - \frac{\rho^2(b, b^{gt})}{c^2} - \alpha v$$

$IoU$  = Intersection over Union

$\rho$  = Euclidean distance between box centers

$c$  = diagonal length of smallest enclosing box

$v$  = aspect ratio consistency term

$\alpha$  = trade-off parameter

##### 2. Classification Loss

Multiclass classification would require the usage of BCE loss:

$$L_{cls} = - \sum_{i=1}^C y_i \log(p_i)$$

Where:

$C$  = number of classes

$y_i$  = ground truth label

$p_i$  = predicted probability

##### 3. Objectness Loss

Objectness score measures confidence of object presence:

$$L_{obj} = -[y \log(p) + (1 - y) \log(1 - p)]$$

The total loss optimizes localization accuracy and classification reliability simultaneously.

#### D. YOLOv8 Model Training

The researchers selected YOLOv8 because it offers both single-stage detection and provides real-time processing capabilities. The model was trained using

three different loss functions which included classification loss and localization loss and objectness loss functions. The team optimized hyperparameters to achieve better precision and recall results while reducing false detection rates.

#### E. Performance Evaluation

Model performance was evaluated using:

- Mean Average Precision (MAP)
- Precision
- Recall

These metrics ensure balanced evaluation of both localization and classification performance.

#### F. Deployment

The trained model was integrated into a web-based interface developed using Streamlit. Users can upload X-ray images and obtain detection results with bounding boxes and confidence scores in real time.

### IV. IMPLEMENTATION DETAILS

The researchers built the fracture detection system by using Python 3.10 as their main programming language. The deep learning model was developed using the PyTorch framework and the Ultralytics implementation of YOLOv8. The researchers used OpenCV and NumPy libraries to complete their image preprocessing and visualization tasks. The development environment includes:

- Detection Model: YOLOv8 (Ultralytics)
- Image Processing: OpenCV
- Data Handling: NumPy, Pandas
- Visualization: Matplotlib
- Web Interface: Streamlit
- Framework: Pytorch

#### Annotation Tool:

LabelImg / Roboflow The model was trained on a GPU-enabled system to accelerate computation, although inference can be performed on standard CPU hardware.

#### A. Dataset Preparation and Annotation

Researchers collected X-ray bone imaging data which showed different fracture types and created a dataset that they manually labeled.. The annotation format followed the YOLO standard:

$(class\_id, xcenter, ycenter, width, height)$

The secondary dataset, on the other hand, uses the image size to normalize its coordinates. Splitting of this dataset/training into different parts was done as follows:

- Training Set: 70%
- Validation Set: 20%
- Test Set: 10%

The research team utilized data augmentation methods to enhance model generalization while preventing overfitting which included

- Horizontal flipping
- Random rotation
- Brightness
- contrast adjustment and Scaling and translation.

Resizing both images to  $640 \times 640$  pixels was the primary requirement of the course

#### B. Model Configuration

The YOLOv8 architecture was configured for multi-class fracture detection. The researchers tested three model variations (YOLOv8n, YOLOv8s, YOLOv8m) to find the optimal combination between accurate results and effective computational performance. The following training hyperparameters establish the main parameters for this research.

- Input Resolution:  $640 \times 640$
- Batch Size: 16
- Epochs: 100
- Optimizer: Stochastic Gradient Descent (SGD)
- Initial Learning Rate: 0.001
- Momentum: 0.937
- Weight Decay: 0.0005

The researchers began their study by first establishing a baseline model which they trained using COCO dataset weights before proceeding to their main task of training the fracture dataset.

#### C. Training Procedure

The training pipeline consisted of the following steps:

- Load annotated dataset
- Apply preprocessing and augmentation
- Initialize YOLOv8 model with pretrained weights
- Perform forward propagation
- Compute total loss (bounding + objectness)
- Backpropagate gradients

- Update weights using optimizer

The training process monitored:

- Training loss
- Validation loss
- Precision
- Recall
- mAP@50
- mAP@50-95

The reason early stopping was implemented is to prevent overfitting after it is determined that the validation performance has stabilized.

#### D. Inference Pipeline

During inference, the trained model processes a new X-ray image through the following steps:

- Image resizing and normalization
- Forward pass through YOLOv8 backbone, neck, and detection head
- Prediction of bounding boxes and class probabilities
- Application of Non-Maximum Suppression
- (NMS)
- Visualization of final detections

Non-Maximum Suppression removes redundant overlapping bounding boxes based on Intersection over Union (IoU) threshold:

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Bounding boxes with IoU greater than a predefined threshold are suppressed to retain the most confident detection.

#### E. Web-Based Deployment

The trained YOLOv8 model was integrated into a lightweight web-based interface developed using Streamlit. The deployment pipeline includes: Image upload module

- Real-time model inference
- Visualization of bounding boxes
- Display of fracture class and confidence score

### V. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION



Fig. 2. Uploaded X-ray Image:

The user uploaded this hand X-ray image (bf4.png) via the Streamlit interface. This serves as the input for fracture detection.



Fig. 3. YOLOv8 Detection Result:

The model detected a fracture with a bounding box and a confidence score of 0.78, localizing the fracture on the metacarpal region.

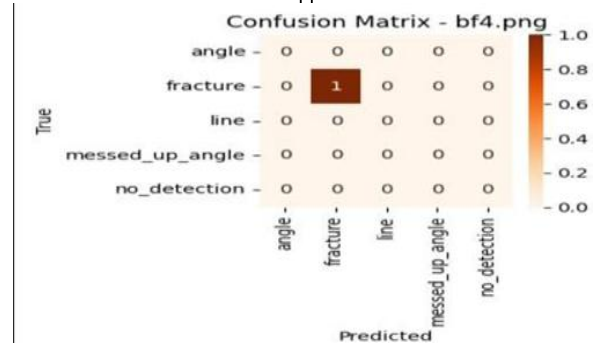


Fig. 4. Confusion Matrix for Sample Output 1

The model correctly predicted the label "Fracture" for bf4.png, as shown by the value 1 on the diagonal cell corresponding to the true and predicted class.

A. Evaluation Metrics

	precision	recall	f1-score	support
angle	1.00	1.00	1.00	1
fracture	1.00	0.60	0.75	5
line	0.00	0.00	0.00	1
messed_up_angle	1.00	1.00	1.00	1
no_detection	0.00	0.00	0.00	0
accuracy			0.62	8
macro avg	0.60	0.52	0.55	8
weighted avg	0.88	0.62	0.72	8

Fig. 5. The model achieved an overall accuracy of 62% across 8 test images, detecting classes like angle, fracture, and messed\_up\_angle with high precision.

Confusion Matrix Visualization:

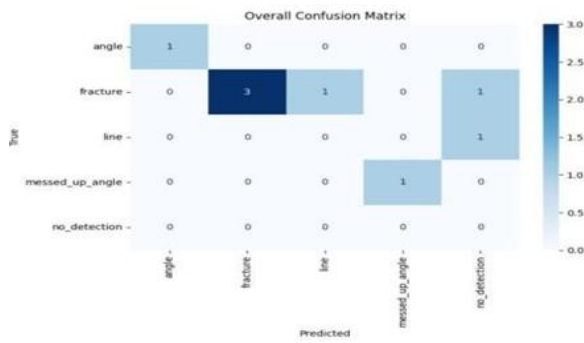


Fig. 6. Visual summary of how predicted classes match the true labels across 8 sample inputs.

Output On Web UI:



Fig. 7a. when clicked on "Detect Fracture" we get the original and processed image



Fig. 7b. We even get the Medical Diagnosis of the detected fracture type using Gemini AI

VI. DISCUSSION

The YOLOv8m variant demonstrates its best detection performance because of its implementation of deeper feature extraction layers. The model displays its ability to find fine fracture lines which exist in low visibility situations. The proposed method performs dual functions of location tracking and object identification which results in faster processing times when compared to standard CNN classifiers. The system operates in real-time when it achieves inference speeds greater than 30 FPS on GPU systems which makes it appropriate for use in urgent medical settings.

VII. CONCLUSION AND FUTURE WORK

This paper presents a robust multi-class bone fracture detection system based on YOLOv8. The proposed framework demonstrates high accuracy and real-time performance for X-ray image analysis. The integration of preprocessing techniques and optimized loss functions enhances detection robustness.

Future work includes:

- Multi-hospital dataset expansion
- Integration of segmentation modules
- Explainable AI for clinical interpretability
- Edge-device optimization for rural deployment

The system has strong potential for deployment as a computer-aided diagnostic support tool in healthcare systems.

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