Bone Fracture Detection Using YOLOv8

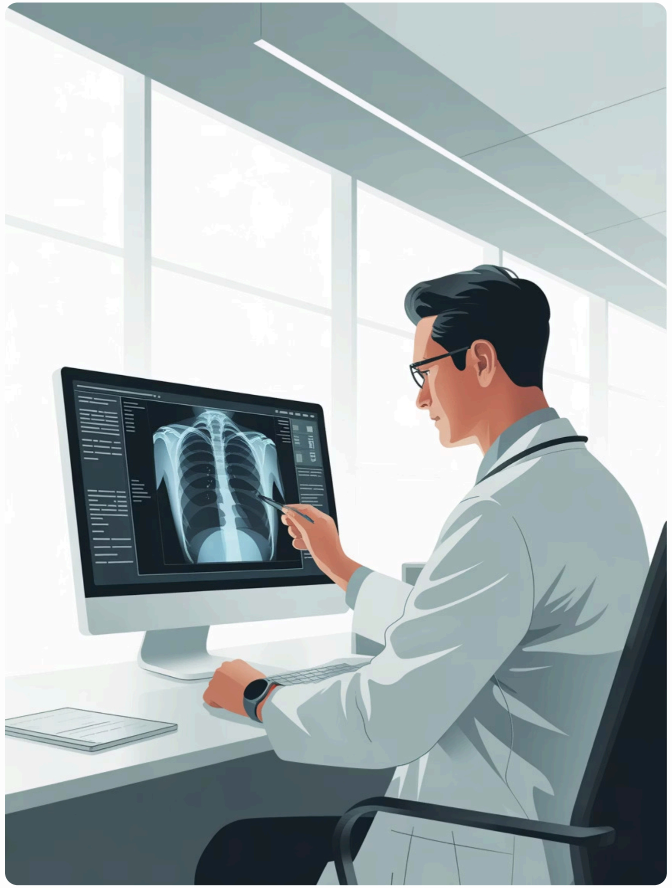
Computer vision project demonstrating automated fracture detection in medical imaging

Introduction

Bone fractures represent one of the most frequently diagnosed injuries in medical practice, requiring accurate and timely detection for optimal patient outcomes. Traditional manual analysis of X-ray images by radiologists, while highly skilled, presents inherent challenges including time consumption and variability in human judgment.

Recent breakthroughs in **Artificial Intelligence** and **Deep Learning** have revolutionized medical image analysis capabilities. Object detection frameworks like **YOLO (You Only Look Once)** now enable efficient identification and localization of fractures within X-ray imagery with remarkable precision.

This project presents a comprehensive **bone fracture detection system** leveraging the **YOLOv8 deep learning architecture**, trained on diverse fracture detection datasets and deployed through an intuitive **Gradio web interface** for practical clinical application.



Problem Statement

Expert Dependency

High reliance on trained radiologists limits accessibility in resource-constrained settings

Human Variability

Fatigue and subjective judgment introduce diagnostic inconsistencies

Subtle Detection

Small or complex fractures often evade detection during manual review

Resource Limitations

Limited medical infrastructure in rural and emergency environments

Project Objective

Develop an **automated, accurate, and rapid bone fracture detection system** that identifies fracture regions in X-ray images, functions on unseen medical data, provides visual bounding box localization, and operates through an intuitive web interface for broad clinical accessibility.

Project Objectives

01

Deep Learning Model Development

Build robust fracture detection architecture using state-of-the-art computer vision techniques

02

Dataset Integration

Merge multiple fracture datasets into unified, standardized format

03

YOLOv8 Training

Train optimized object detection model on comprehensive fracture dataset

04

Performance Evaluation

Validate model accuracy using standard computer vision metrics

05

Gradio Deployment

Deploy model through interactive web interface for end-user accessibility

06

End-to-End Solution

Provide complete medical AI pipeline from data to deployment

Dataset Description

This project utilizes **fracture detection datasets exclusively**, excluding classification-only datasets to maintain focus on localization capabilities.

FracAtlas Dataset

- X-ray images of fractured bones
- JSON format annotations
- Bounding box coordinates
- Train/validation/test splits

Bone Fracture Detection Dataset

- YOLO-formatted structure
- .txt label files
- Multiple fracture cases
- Complete dataset splits

Strategic Multi-Dataset Approach

- **Data diversity** enhances model robustness
- **Generalization** across fracture patterns
- **Overfitting reduction** through varied examples
- **Pattern coverage** of fracture variations

Data Preprocessing

Rigorous preprocessing ensures training integrity and model performance through standardized data handling.

Format Conversion

Transform all annotations to standardized YOLO format

Normalization

Scale bounding boxes to [0,1] range for consistent input

Class Unification

Establish single fracture class label across datasets

Data Cleaning

Remove images lacking valid annotation data

Dataset Merging

Combine sources into unified training structure

Final Dataset Structure

```
combined_bone/
├── images/
│   ├── train
│   ├── val
│   └── test
└── labels/
    ├── train
    ├── val
    └── test
```

Model Architecture: YOLOv8

Why YOLOv8?

High Speed

Real-time inference capabilities for rapid diagnosis

High Accuracy

State-of-the-art detection precision

Single-Stage

Efficient single-network detection

Real-Time

Production-ready performance

Model Specification

- **YOLOv8n (Nano)** architecture variant
- Pretrained on **COCO dataset**
- Fine-tuned on medical fracture imagery

Architecture Components

- **Backbone:** Feature extraction
- **Neck:** Feature fusion
- **Head:** Box regression and classification

Model Training

Model	Image Size
yolov8n.pt	640 × 640 pixels
Epochs	**Batch Size**
50 training iterations	16 images per batch

Training Command

```
model.train(
    data="combined.yaml",
    epochs=50,
    imgsz=640,
    batch=16
)
```

Loss Functions

- Box loss for localization accuracy
- Classification loss for detection confidence
- Distribution Focal Loss (DFL) for improved precision

Training Observations

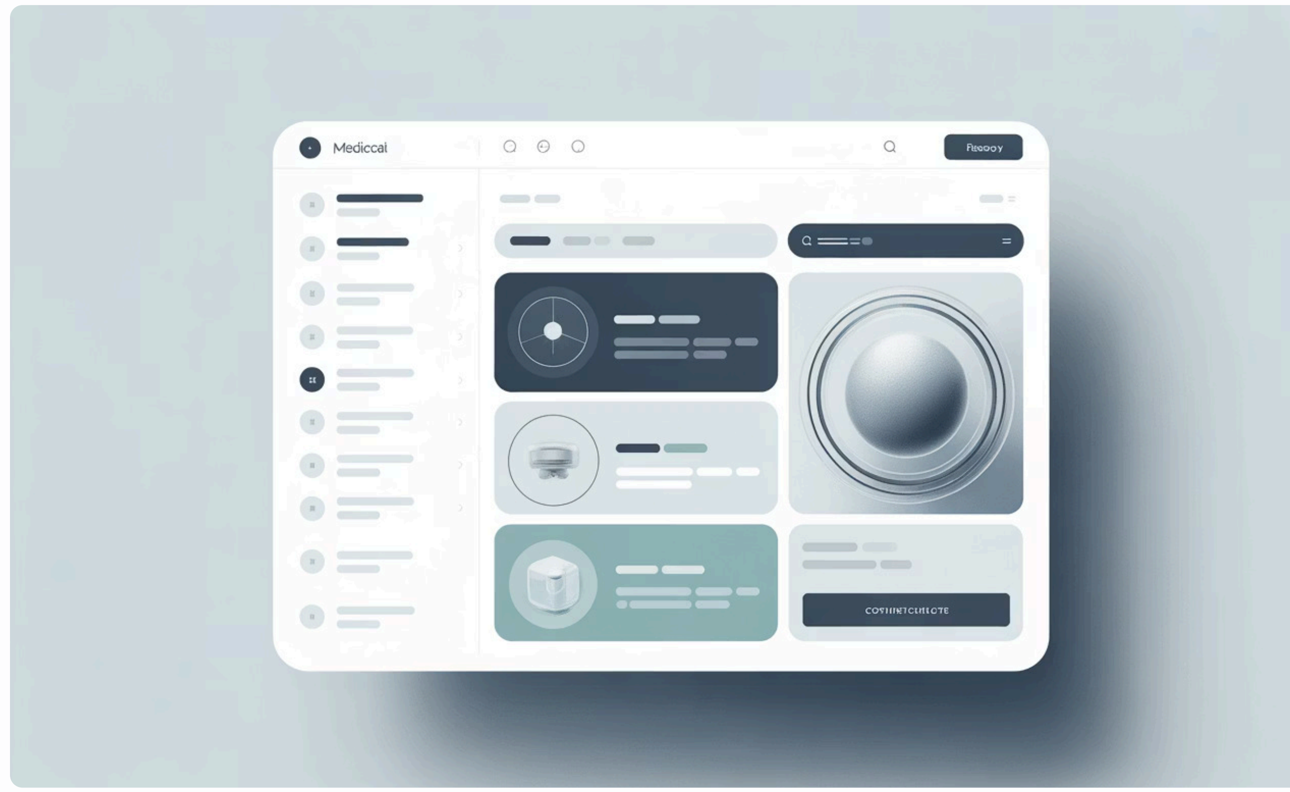
Training demonstrated **gradual loss reduction** across iterations, with **continuous mAP improvement** indicating enhanced detection capability. Model achieved **stable convergence** after multiple epochs, validating training stability and generalization potential.

Deployment Using Gradio

A user-friendly **Gradio web interface** enables practical clinical application without technical expertise.

Interface Features

- Drag-and-drop X-ray image upload
- Adjustable confidence threshold slider
- Visual bounding box overlay on detection
- Browser-based operation



No Coding Required

End users operate without programming knowledge

Rapid Inference

Real-time detection for immediate results

Clinical Demonstration

Suitable for education and research contexts

Clinical Applications

- Medical Education

  Teaching tool for radiology training programs

- Research Assistance

  Automated screening for clinical studies

- Clinical Decision Support

  Second-opinion tool for practicing physicians

Results and Conclusion

Project Success

This project demonstrates **deep learning and object detection** effectiveness in medical imaging. Using **YOLOv8**, we built an automated bone fracture detection system identifying fractures in X-ray images with **high accuracy**.

The system integrates data preprocessing, model training, evaluation, and deployment into a **complete AI pipeline**, highlighting AI-assisted healthcare potential.

Key Findings

Accurate Localization

Precise fracture region identification with visual bounding boxes

Rapid Inference

Real-time detection enables clinical workflow integration

Generalization

Effective performance on previously unseen medical data

User-Friendly

Intuitive interface accessible to non-technical users

Important Considerations

Clinical Note: This system serves as an **assistance tool only**. Final diagnosis must be made by qualified medical professionals. Results should inform, not replace, expert clinical judgment.

This work represents a significant step toward **AI-enhanced medical diagnostics**, demonstrating practical applications of computer vision in healthcare while maintaining appropriate ethical boundaries and professional oversight.