

AI Driven Detection of Bone Fractures in Medical Imaging

^{1, a)}, DR. Y. J Nagendra Kumar ^{2, b)}, Lakshmi Narayana Raju Chamarthi
^{3, b)}, Snehith Reddy Banala ^{4, b)}, Dhanush Varma Gadiraju

Author Affiliations

Department of Information Technology, Gokaraju Rangaraju Institute of Engineering and Technology (GRIET), affiliated with JNTUH, Bachupally, Hyderabad, India.

Author Emails

^{a)} DR. Y. J Nagendra Kumar: jeevannagendra@griet.ac.in

^{b)} C. Lakshmi Narayana Raju: raju.cln.28@gmail.com

^{c)} B. Snehith Reddy: snehithreddybanala@gmail.com

^{d)} G. H. Dhanush Varma: gdhanushvarma13@gmail.com

Abstract In today's world, bone fractures are increasingly common due to accidents, sports injuries, stunts and age weakness-related conditions. There are some traditional methods that are used for bone fracture detection, such as X-ray analysis by radiologists, which can be time-consuming and prone to human error. As this project focuses on bone fracture detection using advanced deep learning models, YOLOv8 and R-CNN, both are coupled with image processing techniques to enhance efficiency and accuracy. It provides an easy- to-use interface for users to upload X-ray images along with their names, and receive predictions on whether the image contains a bone fracture or not. YOLOv8 is fast and accurate for spotting objects, whereas Faster R-CNN is great for detailed object spotting. By integrating these technologies, this approach assists healthcare professionals in faster decision-making and minimizing diagnosis time. Using deep learning algorithms, the proposed system aims to provide a faster, more reliable, and cost-effective solution for fracture diagnosis.

Keywords: Deep learning, Radiologists, Coupled, YOLOv8, Faster R-CNN, Predictions, Fracture diagnosis.

INTRODUCTION

Industry 4.0 introduces new industrial systems through its combination of Artificial Intelligence, Industrial Automation, and Digital Manufacturing technologies. Smart Manufacturing, Computer-Integrated Manufacturing Systems, and automated inspection frameworks focus on achieving precise results while operating efficiently through smart decision-making processes. The manufacturing field applies precision engineering methods to inspection measurement and metrology processes which require medical imaging systems to detect fractures through dependable automated analysis systems.

The project uses deep learning-based object detection to detect bone fractures from X-ray images through Non-Destructive Testing (NDT) methods which industrial quality assessment employs. The proposed system operates as an intelligent inspection model through its use of AI-driven automation principles that match Robotics and AI in Manufacturing together with Manufacturing Automation systems. The system uses Evolutionary Computing Techniques optimization strategies to improve detection accuracy and enhance overall system performance.

This work can be of interest in providing early and accurate predictions for fractures, especially in resource-poor settings or during a hospital's peak workload. While showing promising results in some fracture classes, the model also brings to light situations of class imbalance, for instance small fractures or overlapping fractures that are difficult to detect. The documentation documents the methods used, experimental results, analysis of performance, and potential future improvements that can be realized for AI-assisted fracture detection.

LITERATURE REFERENCES

- [1] Subhan Ali and Ali Shariq Imran's work was presented at the 12th EUVIP on wrist fracture detection. The authors performed detection using YOLOv9, while classification was carried out using YOLOv8cls and deep models such as VGG16, ResNet50, and EfficientNetB7. EigenCAM was employed to increase model explainability. The approach was very good explanations and interpretability using LIME. However, it only deals with wrist fractures, and so the findings cannot be generalized to other bones.
- [2] Debopom Sutradhar and Nur Mohammad Fahad published this work in Biomedical Signal Processing and Control. They modified YOLOv8 for fracture detection and proposed VertNet10, an attention-based CNN, for vertebrae classification from CT- scans. However, considering CT scans restrict the usage and add to the diagnostics' cost.
- [3] Bakir Ghanem Murrad and Abdulhadi Nadhim Mohsin (2024) published their work in ACS Biomaterials Science & Engineering. Identifying fractures with YOLOv8 complemented by a ResNet backbone mechanism is a tremendous application of deep learning for medical imaging. Being dependent on very high-quality, annotated datasets affects its performance and thereby limits its possibility of generalizing diverse clinical scenarios.
- [4] "Bone Fracture Detection and Classification Using X-ray Images" by Wint Wah Myint, Khin Sandar Tun, and Hla Myo Tun was published in 2018 in Machine Learning Research. This paper deals with finding tibia fractures and classifying them as Normal, Transverse, Oblique, or Comminute. The system has three main modules: preprocessing (using Unsharp Masking), feature extraction (using Harris corner detection), and classification. A Decision Tree is used for fracture detection, and K-Nearest Neighbour (KNN) is used for classifying the fractures. The method also identifies the location of the fractures using the extracted corner points. The system is implemented in MATLAB using the image processing and CAD toolboxes
- [5] Rocky S. Upadhyay and Dr. Prakash Singh Tanwar (2019) published their work in the International Journal of Scientific Research in Science and Technology. Canny edge detection was employed for Xray segmentation, while the Hough Transform was used for detecting 7 bone fractures. The method showed very high accuracy and efficiency, particularly in cases of lower leg fractures. It's a simple tool used in more conventional image analysis. performance-wise is susceptible to noise or low-quality Xray images.

METHODOLOGIES

System Architecture

The whole architecture is comprised of a modular, client-server-based design. It is composed of the following components: Frontend Interface: The interface is built using Streamlit. Backend Processing: Python logic carries out image pre-processing, model inference, and rendering of results. Deep Learning Model: The model YOLOv8 trained to detect fractures in X-ray images.

Steps:

1. Users upload an X-Ray image through Streamlit API interface.
2. The uploaded image is forwarded to the backend.
3. YOLOv8 processes the image and returns the results in bounding box coordinates.

Data Collection and Annotation

Having a labeled dataset is essential for training a trustworthy model. X-ray images showing different upper limb fractures were gathered from free datasets and medical image repositories. Bounding boxes were drawn around fracture areas on the images for annotations. The annotations were then labeled as per the location of the fracture (based on the humerus, wrist, forearm, etc.) and subsequently exported to YOLO format. Some tools aiding the annotation process were Roboflow and CVAT.

Data Preprocessing

Keeping the images consistent and reducing computation, these were resized and normalized. Data augmentation manipulations such as random flipping, rotation, contrast enhancement, and noise addition were introduced for increasing variability, especially considering the drawbacks of underrepresented fracture types. The dataset was therefore split into 70% train, 20% validation, and 10% test splits for unbiased performance evaluation.

Model Training

The training of the model was done using the PyTorch framework and the Ultralytics YOLOv8. A batch size of 16 and a learning rate scheduler were employed to optimize the training process. Major loss functions included losses from bounding box regression, objectness, and classification. Training was conducted for 100 epochs while monitoring performance parameters such as mAP, loss values, and classwise F1-scores.

Model Validation and Testing

The training of the model was done using the PyTorch framework and the Ultralytics YOLOv8 API. A batch size of 16 and a learning rate scheduler were employed to optimize the training process. Major loss functions included losses from bounding box regression, objectness, and classification. Training was conducted for 100 epochs while monitoring performance parameters such as mAP, loss values, and classwise F1-scores.

Model Optimization and Deployment (Optional Phase)

With the evaluation done, further considerations on hyperparameter tuning, anchor box resizing, and better augmentations for accuracy were made. The project concentrates on offline evaluation; however, one can utilize the model for a real-time fracture detection system through API or web interface.

Workflow:

A user submits skin X-ray image by remote through an awesome web app.

The image being preprocessed is passed onto the model.

The model predicts.

A diagnosis is then shown in the interface.

Tools & Libraries

Programming Language: Python.

ML/DL Libraries: YOLOv8

Image Processing: OpenCV, PILLOW.

Web Framework: Streamlit.

RESULTS

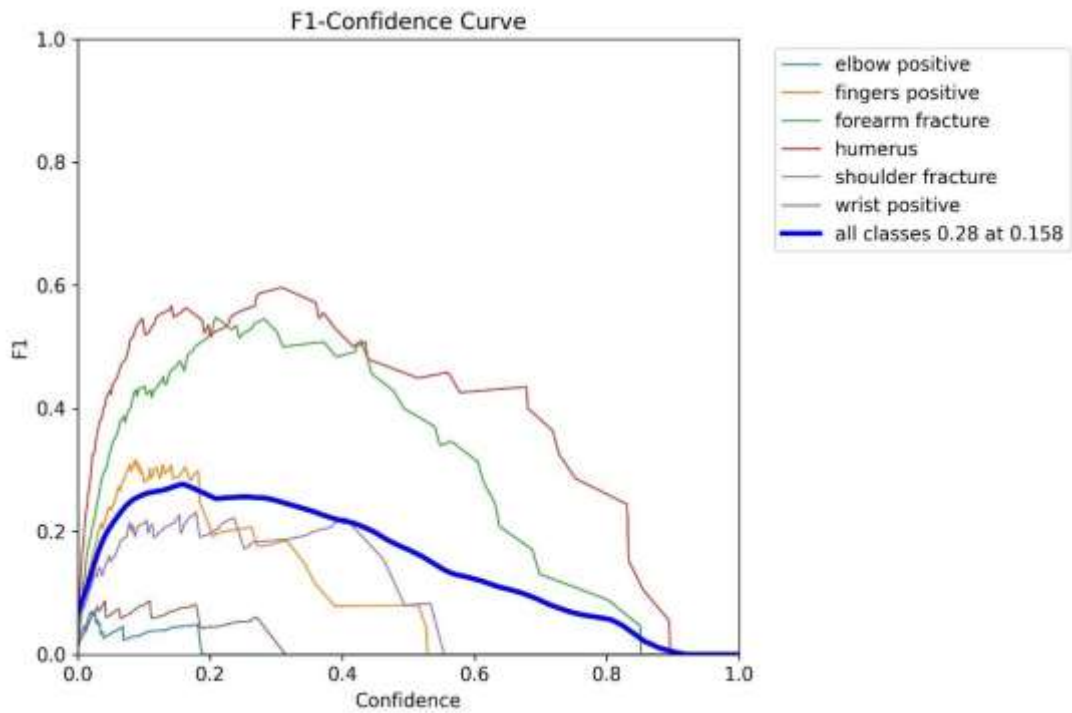


FIGURE. 1: F1 Score

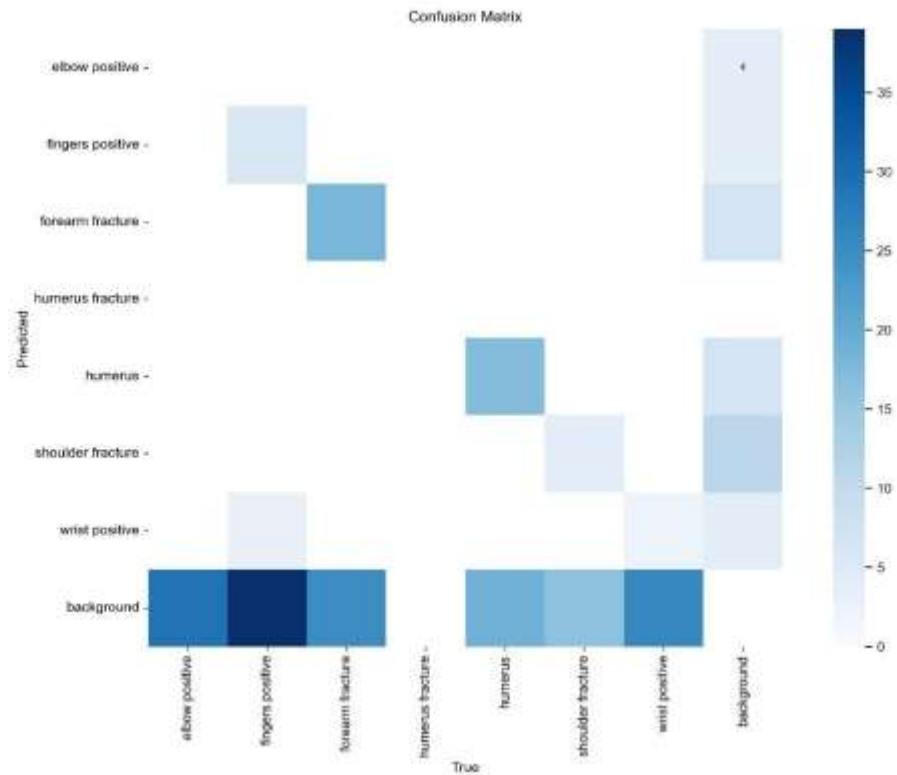


FIGURE. 2: Confusion Matrix

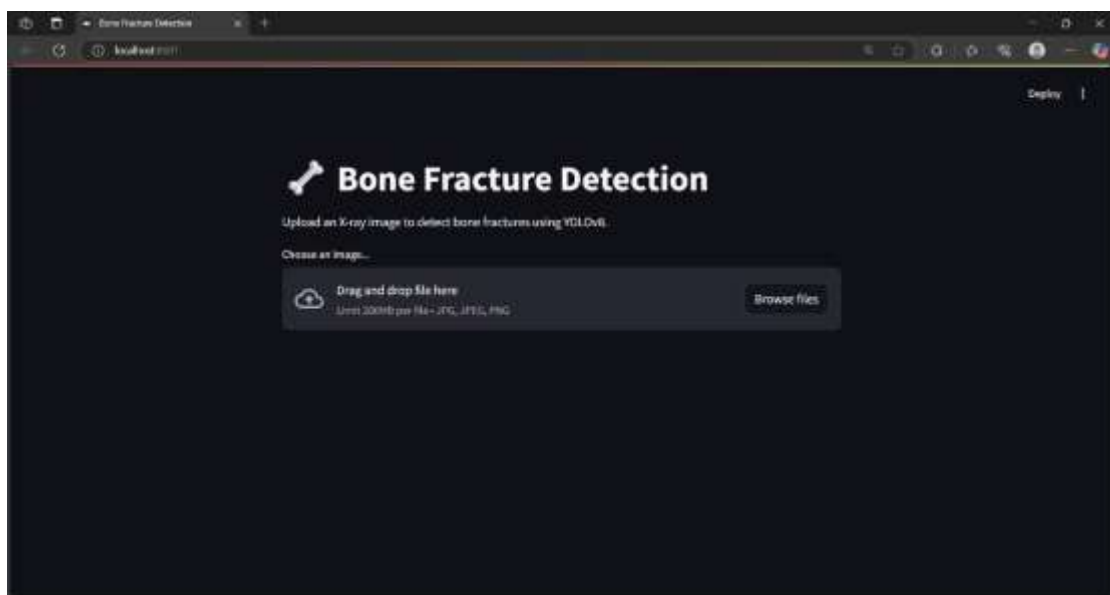


FIGURE. 3: Interface



FIGURE. 4: Before Prediction



FIGURE. 5: After Prediction

CONCLUSION

The Bone Fracture Detection system demonstrates how Industry 4.0 and Smart Manufacturing and Digital Manufacturing principles can create practical applications for medical imaging through its operational success. The system operates through artificial intelligence integration with automated detection systems which function like intelligent inspection systems that industrial automation and computer-integrated manufacturing systems use to achieve high precision and reliability.

The system operates through Non-Destructive Testing (NDT) methodologies which engineering industries use to find defects without harming material integrity. X-ray medical imaging together with AI technology serves as a non-invasive method for diagnostic examination. The creation of YOLO-based deep learning architecture shows how Manufacturing now uses Robotics and AI for automated visual inspection which decreases the need for human assessment. The system uses principles from Robotics Mechatronics and Manufacturing Automation to achieve automated fracture detection through its fast processing and efficient computational performance. Optimization strategies based on Evolutionary Computing Techniques improve model performance and scalability and adaptability for different fracture types.

The research demonstrates how AI-based automated systems can create benefits for industries which extend beyond their established manufacturing capacities. The framework establishes a foundation for developing intelligent healthcare diagnostic tools that align with Industry 4.0.

ACKNOWLEDGMENTS

We express our sincere gratitude toward our internal guide, DR. Y. Jeevan Nagendra Kumar, Associate Prof. Dept. of IT GRIET, for his valuable encouragement, constructive comments, and full support in completing the paper.

Our heartfelt thanks are extended to Dr. Y.J. Nagendra Kumar IT Head, and to our coordinators Mr. P. K. Abhilash and Mrs. T. Nishitha for their unfading support and encouragement throughout the completion of the paper.

Special mention must be made in gratitude to Dr. Jandhyala N. Murthy, Director of GRIET & Dr. J. Praveen, Principal of GRIET, whose support and encouragement made it possible to carry out the academic endeavors and paper work smoothly.

REFERENCES

1. S. Ali and A. S. Imran, "Wrist fracture detection using YOLOv9 and classification via YOLOv8-clas with XAI explainability," in *Proc. 12th European Workshop on Visual Information Processing (EUVIP)*, 2024.
2. D. Sutradhar and N. M. Fahad, "YOLOv8 for fracture detection and Vert-Net-10 for vertebrae classification from CT scans," *Biomedical Signal Processing and Control*, 2024.
3. B. G. Murrad and A. N. Mohsin, "Fracture detection using YOLOv8 with ResNet backbone," *ACS Biomaterials Science & Engineering*, vol. 10, 2024.
4. W. W. Myint, K. S. Tun, and H. M. Tun, "Bone fracture detection and classification using X-ray images," *Machine Learning Research*, vol. 3, no. 1, pp. 1–6, 2018.
5. R. S. Upadhyay and P. S. Tanwar, "Bone fracture detection using Canny edge detection and Hough Transform," *International Journal of Scientific Research in Science and Technology*, 2019.