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# Pediatric Fracture Detection with X-ray Images Using yolov8

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**Abstract:**
Accurate and timely diagnosis of bone fractures is crucial for effective medical intervention and patient care. In this paper, we propose a novel approach for automated bone fracture detection using YOLOv8, a state-of-the-art object detection framework. By training the YOLOv8 model on a dataset of radiographic images containing both fractured and intact bones, we demonstrate its capability to accurately localize and classify fractures with high precision and recall. Our experimental results showcase the effectiveness of YOLOv8 in detecting fractures across various anatomical regions and fracture types, achieving competitive performance compared to existing methods. Furthermore, we explore the impact of dataset size, augmentation techniques, and model architecture variations on detection accuracy and robustness. The proposed system offers a promising solution for streamlining fracture diagnosis workflows, potentially reducing the burden on healthcare professionals and improving patient outcomes. Through comprehensive evaluation and comparison with traditional approaches, we validate the efficacy and practical utility of our proposed YOLOv8-based bone fracture detection system.

**Keywords:** Fracture Detection, Deep Learning, Yolov8, OpenCV.

## 1.INTRODUCTION:

Pediatric Fractures present unique challenges in clinincal diagnosis due to the intricacies of bone development and the need for timely and accurate detection to ensure proper treatment and recovery. Traditional methods of fracture detection relay heavily on manual examination and intrepretation of X-ray images leading to subjectivity and potential oversight. However, with the advent of deep learning techniques, particularly YOLOv8, there exists a promising evenue for automating and enhancing fracture detection process. This paper explores the application of YOLOv8 , a state-of - the-art object detection model, in the realm of Pediatric fracture detection through X-ray imaging. By leveraging the capabilities of YOLOv8, this study aims to improve the efficiency and accuracy of fracture diagnosis, ultimately enhancing clinical outcomes for pediatric patients.

### 1.1.Object Detection:

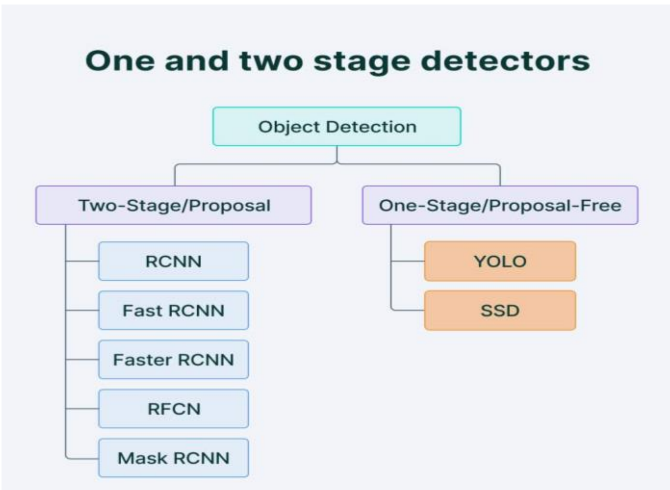


Fig. 1 Object Detection Classification

Object detection is a computer vision task that involves identifying and locating objects within an image or a video sequence. It has numerous real-world applications like ranging from sevurity surveillance and autonomous driving to augmented reality and medical imaging.Object detection is the process of locating and classifying objects within in an images or videos. Unlike image classification, which only identifies the dominant object in an image, object detection algorithm provides information about the presence, location, and category of multiple objects in an image.

## 2. LITERATURE REVIEW:

The use of artificial intelligence (AI) and deep learning (DL) in bone imaging is gaining momentum, particularly for helping radiologists detect fractures and other bone issues. Recent studies show that DL can accurately identify bone abnormalities from radiographs, which is vital as musculoskeletal conditions are expected to double in the next 30 years. DL's ability to quickly and accurately analyze complex images can reduce the high rate of missed fractures in emergency settings, improving patient care. However, challenges remain, such as the need for large, annotated datasets and integrating DL systems into healthcare workflows. Despite these hurdles, DL has great potential to enhance the accuracy and efficiency of bone imaging in medical practice, as noted by Tanushree Meena and Sudipta Roy [1].

Detecting vertical root fractures (VRFs) early is crucial. Masume Johari et al. [2] developed a probabilistic neural network (PNN) to diagnose VRFs in intact and endodontically treated teeth using periapical and CBCT radiographs. Using 240 radiographs, the PNN was trained and tested with image analysis techniques. Results showed CBCT images were more effective, with accuracy, sensitivity, and specificity values of 96.6%, 93.3%, and 100%, respectively, compared to periapical radiographs. The study highlights the PNN's effectiveness, especially with CBCT images, though further research with more comprehensive simulations is recommended.

Bone fractures are common and typically diagnosed using X-ray imaging, but manual detection is slow and error-prone. D. P. Yadav and Sandeep Rathor [3] developed a deep neural network (DNN) to automate this process, classifying healthy and fractured bones. To address overfitting on small datasets, they used data augmentation. Their model achieved a 92.44% accuracy with 5-fold cross-validation, and over 95% and 93% accuracy on 10% and 20% of the test data, respectively, outperforming previous models with accuracies of 84.7% and 86%.

4. PROPOSED SYSYTEM:

Image Acquisition Pre-processing Image Enhnacement Single Neural Network Prediction

Fig. 2 proposed system

Unlike traditional two-step approaches (regional proposal + classification), YOLO performs both object localization and classification in a single forward pass through the neural network. This unified approach makes YOLO extremely fast and efficient.

### 4.1. Processing Pipeline:

YOLOv8 processes images by

- **Resizing Input Image:** It resizes the input image into a fixed size (In the dataset we have resized the image into 237x237 pixels).
- **Single Convolutional Neural Network**: YOLOv8 runs a single convolutional neural network on the resized input image.
- **Thresholding Detections**: The results which are being detected are thresholded based on the model's confidence scores.
- **Bounding Boxes**: This will return theb bounding boxes (coordinates) of detected objects along with their class labels.
- **Output Format:** For each detected object, YOLOv8 provied class label, confidence score, bounding box coordinates.

## 5. Methodologies:

The dataset we have used contains of total 3404 x-ray images. As YOLOv8 is a pre-trained model here 3161 X-ray images has been taken for training, 160 images for valid and 83 for testing. For preprocessing we have used Auto-oriented and done the resize stretch to 640X640 pixels. As for the augmentations we have used Flip-horizontal.

### 5.1. YOLOv8 Architecture:

YOLOv8 Architecture consists of three parts which are head, neck and backbone each is specified for a specific task.

- **Backbone:** This is the Convolutional Neural Network(CNN) responsible for extracting features from input image. YOLOv8 uses custom CSPDarknet53 backbone, which employs cross-stage partial connections to improve information flow between layers and boast accuracy.
- **Neck:** The neck also known as feature extractor, merges feature maps from different stages of backbone to capture information of various scales. YOLOv8 utilizes a novel c2f module instead of the traditional Feature Pyramid Network (FPN). This module combines high-level semantic features with low-level spatial information, leading to improved detection accuracy, especially for small objects.
- **Head:** Head is responsible for making predictions. YOLOv8 employs multiple detection modules that predict bounding boxes, objectness scores & class probabilities for each grid cell in feature map. These predictions are then aggregated to obtain the final detections.

**i) Optimizer:** YOLOv8 uses AdamW optimizer during training. The AdamW optimizer is an extension of the popular Adam optimizer, which incorporates weight decay(L2 regularization) to prevent overfitting. It combines adaptive learning rates with weight decay, making it effective for training deep neural networks like YOLOv8. If we want to change the optimizer to something other than SGD, we can adjust the training configuration file(usually a .yaml file) to specify the desired optimizer(e.g., Adam or RMSprop).

**ii) Forward Pass:** In the forward pass the YOLO model process an input image and predicts bounding boxes for objects within that image. Here the input image is divided into a grid of cells, each cell is responsible for predicting bounding boxes for ibjects that fall within it. For each cell, the model predicts object categories(using softmax activation). The bounding box coordinates(center coordinates, width, and height) relative to the cell. The final output is a tensor containing class probabilities and bounding box coordinates of all cells.

**iii) Loss Claculation:** YOLOv8 uses a combination of loss functions to optimize its predictions

- Classification Loss measures how well the model predicts object classes.
- Localization Loss penalizes the discrepancy between predicted bounding box coordinates and ground truth coordinates.
- Confidence Loss reflects the confidence score(objectness) for each bounding box.
- The total YOLOv8 loss is weighted sum of these individual losses:

$$\text{YOLOv8Loss} = \lambda_{Cls}.\,Classification\ Loss + \lambda_{loc}\,.Localization\ Loss + \lambda_{conf}\,.Confidence\ Loss$$

**iv) Distribution Focal Loss (DFL):**

An improved version of focal loss that focuses on hard-to-classify examples. It adjusts focal loss based on class distribution to make the model more sensitive to minority classes. DFL is used to improve bounding box regression, especially for objects with unclear boundaries.

**v) Backpropagation and Weight Update:** After calculating loss, gradients are computed with respect to the model's parameters(weights). Backpropagate these gradients through the network to update the model weights using optimization algorithms like stochastic gradient descent(SGD) or Adam.

The weight update rule for parameter(w) is

$$w_{\text{new}} = w_{\text{old}} - \eta \cdot \frac{\partial \text{Loss}}{\partial w}$$

**vi) Multi-GPU Training:** Uf you have multiple GPU's, you can distribute the trianing workload across them for faster convergence. YOLOv8 supports multi-GPU training out of the box. This method is efficient and speeds up training compared to using 1 GPU.

**vii) Validation and Early Stopping:** During trainig, the model is evaluated on a validation set. If the validation loss stops improving, early stopping is used to halt training. This helps prevent overfitting by stopping training when performance on the validation set deteriorates.

**viii) Fine-Tuning and Transfer Learning:** Fine-Tuning involves adjusting hyperparameters or modifying the architecture of the pre-trained model. Transfer learning is a process where a pre-trained model(e.g., trained on other dataset) is used as a starting point for training on a new task. This can accelerate convergence and improve performance when the new task is similar to the task the model was originally trained on.

**xi) Post-Processing:** After the model make predictions, post-processing steps are applied.Non-Maximum Suppresion(NMS) is used to remove redundant bounding boxes. Confidence score thresholds are set to filter out weak detections.

**x) Evaluation Metrics:** The trained model is evaluated on a test set using metrics like precision, recall, and F1-score. Average Precision(AP) at different Intersection over Union(IoU) thresholds is calculated. These metrics provide a comprehensive evaluation of the model's performance.

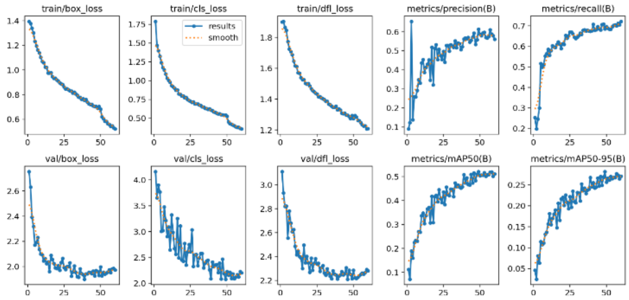


Fig. 3 The Graphs of Avg precision, losses

**xi) Deployment:** Finally, the trained YOLOv8 model weights are saved for future inference. The model can be deployed for real-time fracture detection in medical applications.

Fig.4 The predicted images

**6. Advantages:**

- High Accuracy and Speed: YOLOv8 can locate and classify objects in images with high accuracy and speed, making it suitable for detecting different types of fractures in various scenarios.
- Fast and Reliable Diagnosis: YOLOv8 can provide a fast and reliable diagnosis of bone fractures, which can improve treatment outcomes.
- Accurate Localization: YOLOv8 precisely locates the fracture site within the X-ray, aiding in accurate treatment planning2.

**7. Disadvantages:**

- Information Bottleneck: As the network becomes deeper, an information bottleneck may occur, leading to loss functions that fail to produce useful gradients.
- Slower Training Times: While YOLOv8 shows faster inference speed, some users report slower training times compared to previous versions.
- Misinterpretation of X-ray Images: The percentage of X-ray images misinterpreted have reached 26%5. This could lead to incorrect fracture detection.

**Conclusion:**

The implementation of YOLOv8 for bone fracture detection shows promising results in automating the process of identifying fractures in medical imaging. By leveraging state-of-the-art object detection techniques, the system achieves high accuracy and efficiency in detecting fractures, thus potentially aiding healthcare professionals in diagnosing injuries more effectively and swiftly. However, further validation on diverse datasets and rigorous evaluation against existing methods is necessary to establish its robustness and clinical applicability. Overall, the utilization of YOLOv8 presents a significant step towards enhancing fracture detection processes, offering potential benefits in patient care and medical workflow optimization.

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