Automated Fracture Detection from CT Scans

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***Abstract*—Computed Tomography (CT) scans play a crucial role in modern medical imaging for detecting bone fractures. However, identifying the location and position of broken bones can be challenging, particularly in complex cases involving multiple extremities. In this paper, we propose a robust approach for enhancing fracture detection and localization in CT scans using the YOLO v7 model. By simultaneously predicting class probabilities and bounding boxes in a single iteration, the YOLO v7 model shows improved and consistent performance measures. We developed our approach on a dataset of 1217 CT cases, by training our model on combined extremities, resulting in improved and consistent performance metrics for detecting and localizing fractures. Our proposed method achieved a high precision rate of 99% for identifying broken bones in the lower right limb and 66% for the combined set of upper and lower extremities on both sides. Our findings highlight the potential of YOLO v7 as a powerful tool for enhancing medical imaging workflows, particularly for further treatment planning, by improving fracture detection and localization. Future studies could investigate the generalizability and scalability of our proposed method in larger datasets and different clinical settings.**

***Index Terms*—CT scans, YOLO v7, Fractured Bones, Pre-Trained Neural Network Model**

I. Introduction

Computed Tomography (CT) scans play a critical role in modern medicine, particularly in the assessment of bone injuries, providing valuable information for screening, diagnosis, and treatment planning. Developing robust artificial intelligence (AI) models to assist medical professionals in analyzing CT scans is contingent upon the availability of accurate training datasets [1]–[3]. Prompt and accurate detection and localization of fractures are crucial for timely treatment and positive patient outcomes, given that fractures commonly occur as a result of falls and road accidents [4]–[6].

Object detection and localization models, such as YOLO v7 [7], have shown promising results in medical image analysis [8], [9]. In this paper, we propose a novel approach for enhancing fracture detection and localization in CT scans using the YOLO v7 model. Our goal is to provide a more accurate and efficient method for identifying the location and position of broken bones, which can ultimately improve medical imaging workflows and patient outcomes.

II. Methodology

The YOLO v7 architecture employs convolutional layers to extract features from input images and uses fully connected layers to classify objects, generating detections through a detection layer [10]. We utilize this model to predict the precise location and position of a broken bone in our CT scan images. Our work aims to enhance medical imaging workflows by leveraging the YOLO v7 algorithm's accuracy in object detection and localization tasks to detect fractures in medical images. To accomplish this, we utilize a clinically annotated dataset [6] of 1217 cases of computed tomography (CT) scans of fractured limbs. The dataset includes upper and lower extremity fractures, divided into 4 classes: Right Lower Limb (RLL), comprised of 732 images, Right Upper Limb (RUL), comprised of 352 images, Left Lower Limb (LLL), comprised of 69 images, and Left Upper Limb (LUL), comprised of 64 images. We assume perfect classification accuracy to identify CT scans with broken bones. Fig. 1 shows the workflow for localizing fractures in limb CT scans using the YOLO v7 model. Through a series of sequential labeling and image training steps using diverse CT scan images of complex fractures, we train a YOLO v7 model for broken bone detection and diagnosis to improve patient care.

III. Experimentation

The YOLO v7 model was trained for 2000 epochs on a HPC cluster[1] using various sets of images that included images from all four fracture sites. The dataset

[1]Computations supporting this project were performed on High Performance Computing systems (Lawrence) at the University of South Dakota, funded by NSF Award OAC-1626516.

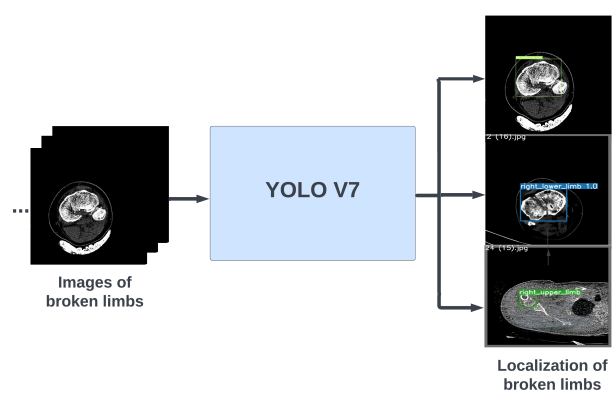

Fig. 1: Workflow to localize broken limbs using YOLO v7.

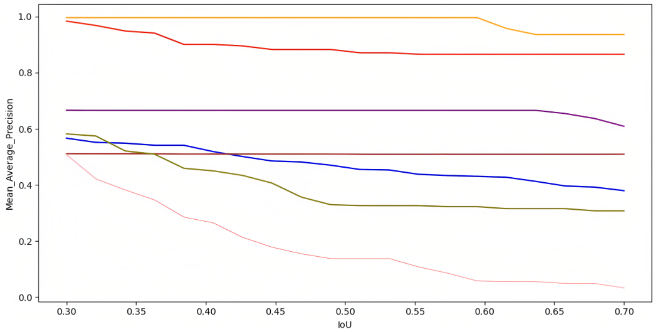

Fig. 2: mAP vs IoU curve, It is clear that mAP is highest at value of 0.3 IoU.

TABLE I: The table presents performance metrics, including Precision, Recall, mAP, Accuracy, F1-score, and Optimal Epochs all at IoU = 0.3, for a complete set of CT-scan images.

	Precision	Recall	mAP	Accuracy	F1-Score	Optimal epoch
RLL	0.99	0.98	0.99	0.98	0.98	1250
RUL	0.70	0.75	0.77	0.62	0.75	1750
LLL	1.00	1.00	0.99	1.00	1.00	750
LUL	0.64	0.75	0.51	0.52	0.69	1750
RLUL	0.73	0.76	0.67	0.51	0.67	1600
RLLL	0.68	0.67	0.66	0.41	0.57	1500
C	0.66	0.72	0.62	0.43	0.58	1250

RLL: Right Lower Limb, **RUL**: Right Upper Limb, **LLL**: Left Lower Limb, **LUL**: Left Upper Limb, **RLUL**: Right and Left Upper Limb, **LRLL**: Right and Left Lower Limb, **C**: Combined.

was randomly partitioned into training, validation, and testing sets, comprising 70%, 20%, and 10% of the data, respectively. However, the dataset was imbalanced as there were more fractures in the right limb than in the left. To address this, we trained the YOLO v7 model on separate datasets for each limb to ensure that the model can detect fractures in both limbs equally. We then combined the datasets for both limbs and trained the model again to detect fractures in both the upper and lower limbs. Finally, we trained the model using all datasets with separate labels to detect fractures in all four fracture sites, ensuring that the model can detect fractures accurately irrespective of the fracture site. To ensure reproducibility, we have made our code publicly available on GitHub at https://github.com/2ai-lab/yolov7.

IV. Results and discussion

We assessed our model's performance using standard evaluation metrics, such as True Positive, False Positive, Intersection over Union (IoU), Precision, Mean Average Precision, Accuracy, Recall, and F1 score. We conducted Monte Carlo simulation of mAP with different IoU values and found that the maximum mAP was achieved at an IoU of 0.3 which is illustrated in Fig. 2. Therefore, we computed all metrics using an IoU of 0.3, and the results are presented in Table I.

Our model demonstrated strong performance in detecting lower limb fractures, achieving precision and recall scores of 99.3% and 98%, respectively, for the right side, and 100% for both precision and recall on the left side. For upper limb fractures, the model achieved precision scores of 70% and 64% and recall scores of 75% and 75% for the right and left sides, respectively, along with accuracy scores of 62% and 52% and F1-scores of 75% and 69%. Combining all limbs resulted in a precision score of 66.8%, a recall score of 72%, an accuracy score of 43%, and an F1-score of 57%. When we combined the upper limbs of both right and left sides, we achieved a precision score of 73%, a recall score of 76%, an accuracy score of 51%, and an F1-score of 67%. Similarly, when we combined the lower limbs of both right and left sides, we achieved a precision score of 68%, a recall score of 67%, an accuracy score of 51%, and an F1-score of 57%.

V. Conclusion and future works

In this paper, we have presented a YOLO v7-based deep learning model for localizing and detecting fractures in CT scan images. The proposed model achieved high accuracy and performed well in detecting fractures in both upper and lower limbs. We have also demonstrated the impact of CT scan image quality and quantity on the model's performance, and provided insights on how to optimize the model's training for best results. Our work has significant implications in the field of medical imaging and can potentially improve the diagnosis and treatment of bone fractures. Future works includes a generic AI model to detect other fractures and injuries that integrates existing medical imaging software, and to conduct clinical trials.

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