Use of Keypoint-RCNN and YOLOv7 for Capturing Biomechanics and Barbell Trajectory in Weightlifting

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***Abstract*—Weightlifting is a demanding sport requiring power, flexibility, and the correct technique. The snatch and the clean and jerk involve the fast lifting of weight to an overhead position. Incorrect technique or posture may lead to inefficient lifts or even injury. This paper presents a new framework for biomechanics analysis and barbell trajectory tracking in weightlifting by leveraging the capabilities of Keypoint-RCNN and YOLOv7 deep learning models. The proposed framework extracts skeletal information from weightlifting video sequences using a pre-trained Keypoint-RCNN model for human pose estimation and a custom YOLOv7 model to detect and track barbell trajectories. The Keypoint-RCNN model estimates human pose without manual annotation or specialised apparatus, while the YOLOv7 model provides real-time, non-intrusive barbell tracking. The efficacy of barbell trajectory tracking with YOLOv7 on a public weightlifting dataset of 973 images (70-30 train-test ratio) was evaluated, obtaining high precision (0.9214), recall (0.9678), and mAP@0.5 of 0.9792 and mAP@0.5:0.95 of 0.7765, indicating the applicability of this model to weight training applications. The proposed framework presents a cost-effective, user-friendly, and easily accessible alternative to conventional motion capture and analysis systems, making it accessible for lifters of all skill levels and training environments.**

***Index Terms*—Weightlifting, Biomechanics, Barbell trajectory, Keypoint-RCNN, YOLOv7, Human pose estimation**

I. Introduction

The snatch, clean and jerk are the two primary competitive lifts in weightlifting, which is a physically demanding and generally difficult sport to master. The snatch is a single, continuous motion in which a barbell is lifted from the ground to the overhead position in a single motion. It requires the coordination of multiple muscle groups, precise synchronisation, and exceptional skill. Mastering the snatch technique is crucial for maximising performance and minimising injury risk due to its complexity.

Analysis methods such as marker-based motion capture systems [1], force platforms [2], and inertial motion capture analysis [3] are utilised in the conventional biomechanical analysis. Although these techniques provide valuable insights into the mechanics of weightlifting, they are time-consuming, invasive, and require specialised apparatus, which limits their practical application in training environments. In recent years, there has been a significant transition in research towards markerless motion capture systems [1]. This shift can be attributed to the numerous advantages of markerless systems over traditional marker-based methods, such as reduced setup time, enhanced usability, and the non-invasive nature of the system [4].

Rapid innovations in deep learning have led to the development of new methods for analysing human motion that have the potential to overcome the limitations of conventional approaches. Keypoint-RCNN [5] is a deep learning model based on Region-based Convolutional Neural Networks (RCNNs) that has demonstrated promising performance in diverse human pose estimation tasks. Without manual annotation or specialised apparatus, the model could potentially be used to capture the biomechanics of a weightlifter performing the snatch. In addition to analysing human motion, it is essential to monitor the path of the barbell during the snatch in order to comprehend lift efficiency and identify potential improvement areas. The use of YOLOv7 [6] to monitor the position and movement of the barbell during the lift can provide athletes and trainers with valuable information.

This paper presents the preliminary study of utilising Keypoint-RCNN and YOLOv7 to capture the biomechanics of weightlifters and monitor the path of the barbell during the snatch lift. By providing objective quantitative data, the combination of Keypoint-RCNN and YOLOv7 for weightlifting analysis can provide improved aid in coaching, injury prevention, and increase athlete performance. These techniques have the potential to vastly improve the accessibility and utility of biomechanical analysis in weightlifting and other sports by providing non-invasive, inexpensive, and user-friendly solutions.

II. Background

Weightlifting is a popular sport and exercise that targets specific muscle groups through the raising of weights in specific methods. It is a common component of strength training and numerous fitness routines. Weightlifting requires proper form and technique to prevent injury and maximise performance. Traditional motion capture systems are inaccessible to many athletes and fitness devotees because they are costly, require specialised apparatus, and are operated by highly trained technicians. Therefore, more accessible and affordable methods are required to capture the biomechanics and trajectory of the bar in weightlifting. For this purpose, the use of deep learning models such as Keypoint-RCNN and YOLOv7 presents a promising alternative. Keypoint-RCNN and YOLOv7 have tremendous potential for biomechanical

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analysis, tracking of barbell trajectories, and identification of technical flaws in the snatch and clean and jerk in the context of weightlifting. Provided with objective and quantitative data on an athlete's movement patterns, instructors and athletes effectively create individualised training programme which targets specific weaknesses, optimise technique, and reduce the risk of injury.

A. Keypoint-RCNN and Human Pose Estimation

Human pose estimation is a crucial computer vision task in detecting and localising the positions of key body joints in images and videos, outputing beneficial insights into the human motion and biomechanics [7], [8]. In sports such as weightlifting, it is essential to accurately estimate body posture to comprehend an athlete's technique, optimise performance, and prevent injury [9].

Traditional approaches to human pose estimation rely on marker-based motion capture systems requiring reflective markers be placed on body joints and specialised cameras to track their movement [1]. Although these systems can provide accurate and detailed information about body movement, they are invasive, time-consuming, and costly to setup, which limits their practical application in training environments.

Human pose estimation models such as Keypoint-RCNN [5] have emerged as non-invasive, efficient, and accurate alternatives to conventional motion capture systems with the advent of deep learning techniques. Keypoint-RCNN is a deep learning model for human pose estimation based on Regional Convolutional Neural Network (RCNN) architecture. The model is capable of locating and localising human joints in images and videos, enabling the extraction of biomechanical variables such as joint angles, velocities, and accelerations without the need for manual annotation or specialised apparatus.

The application of Keypoint-RCNN and other deep learning models to the estimation of human pose in sports as weightlifting has the potential to enable accurate, real-time analysis of athlete movements without the need for manual annotation or specialised apparatus [10]. This allows coaches and athletes to acquire valuable biomechanical information during training, allowing for more effective training, and decreased injury risk.

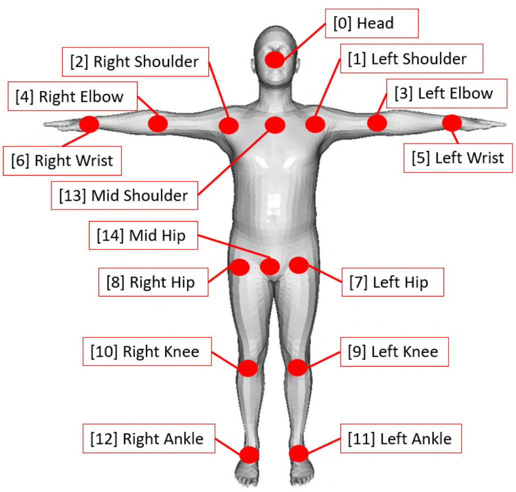
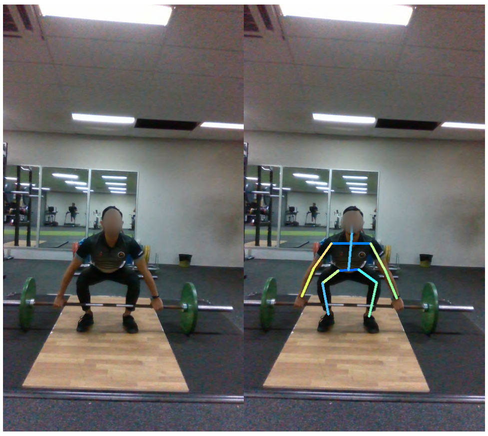


Fig. 1. Joints output from Keypoint RCNN.



(a) (b)

Fig. 2. (a) Original image, (b) Skeletal output from Keypoint RCNN.

B. YOLOv7 on Barbell Tracking

The lifting style of the barbell during weightlifting is essential for comprehending weightlifting efficiency, identifying potential improvement areas, and averting injury [11]. The path and trajectories of the barbell during weightlifting can provide athletes and instructors with insightful information regarding the technique and biomechanics of the athlete [12].

Object detection and tracking models such as YOLOv7 have emerged as promising alternatives for tracking barbell trajectories in weightlifting, thanks to advancements in deep learning and computer vision. These models offer a real-time, non-invasive solution that requires neither specialised apparatus nor manual annotation. In addition, the models can be readily integrated into a video analysis software or a mobile application [13], making them accessible to all levels of athletes and coaches.

In the context of weightlifting, YOLOv7 can be optimised for the detection and monitoring of barbells. The model may then be used to analyse weightlifting footage, locate the barbell in each frame, and visualise its course. This information is crucial for maximising the effectiveness of the lifting technique, pinpointing areas in which further development is necessary, and lowering the risk of injury.

TABLE I
JOINTS SELECTED TO VISUALISE THE JOINT ANGLES IN THIS STUDY.

Joint Set	Starting Joint	Reference Joint	Ending Joint
J1	1 - Left Shoulder	3 - Left Elbow	5 - Left Writst
J2	2 - Right Shoulder	4 - Right Elbow	6 - Right Wrist
J3	0 - Head	13 - Mid Shoulder	1 - Left Shoulder
J4	0 - Head	13 - Mid Shoulder	2 - Right Shoulder
J5	13 - Mid Shoulder	14 - Mid Hip	7 - Left Hip
J6	13 - Mid Shoulder	14 - Mid Hip	8 - Right Hip
J7	2 - Right Shoulder	13 - Mid Shoulder	1 - Left Shoulder
J8	8 - Right Hip	14 - Mid Hip	7 - Left Hip
J9	8 - Right Hip	10 - Right Knee	12 - Right Ankle
J10	7 - Left Hip	9 - Left Knee	11 - Left Ankle

III. Methodology

This research examines two prominent deep learning models, Keypoint-RCNN and YOLOv7, and their application to capturing weightlifting biomechanics and barbell trajectories. The following provide an overview of the methodology in utilising the two models.

A. Data Collection and Preprocessing

An Intel Realsense D435 camera that captures 1080×1920 RGB video at 30 frames per second was used to capture the lifting sessions. Image normalisation is applied, and the video is then processed to extract frames to pipe into the deep learning models. The data is processed using Intel NUC X15 Laptop Kit with Intel Core i7 and RTX3070.

B. Human Pose Estimation

The Keypoint-RCNN model is a pretrained model trained on COCO (Common Objects in Context) dataset [14], containing over 330,000 images and over 2.5 million object instances with 80 different object categories. The pretrained model is then applied to the frames extracted from recorded weightlifting sessions to generate 2D keypoints for each lifter's body joints. This yields 17 skeletal keypoints per frame, of which 13 are utilised (excluding the eyes and hearing) for the analysis shown in Fig. 1. The biomechanical variables involves selecting three joints; starting joint, measured joint, and ending joint and is referred as joint set (J) in this study. A total of ten joint sets were considered in this study are listed in Table I. The skeletal output of a weightlifter is shown in Fig. 2.

C. Barbell Trajectory Tracking

YOLOv7 [6] is a state-of-the-art object detection and localisation model using a single-stage model architecture. YOLOv7 is an upgraded version to the YOLO series with improved accuracy and speed. In addition to analysing human motion and human posture, tracking of the barbell during a weightlifting movement is essential for understanding lifting efficiency and identifying training development opportunities. The YOLOv7 model was trained on the weightlifting images from Roboflow Universe [15] to detect and monitor the position of the barbell throughout the entire lift. The training and testing dataset for the YOLOv7 barbell tracking model consists of 973 images. The data set is divided 70% for training (681 images) and 30% for testing (292 images) to ensure adequate data distribution for model training and performance evaluation. The hyperparameters used for training the model is summarised in Table II.

The model is configured to output a green bounding box encompassing the detected barbell and to calculate the box's centre point. The centre point is marked with a red dot during the lift and a blue dot during the descent, producing a dot track representing the barbell's trajectory. This can provide objective feedback to athletes and instructors regarding the path, velocity, and acceleration of the barbell which is crucial in performing a clean lift while preventing potential injuries due to incorrect method.

IV. Results and Discussion

Joint angles were computed for pairs of keypoints as listed in Table I. The joint angles results can be seen in Figure 3. The joints profile were subsequently employed to assess the

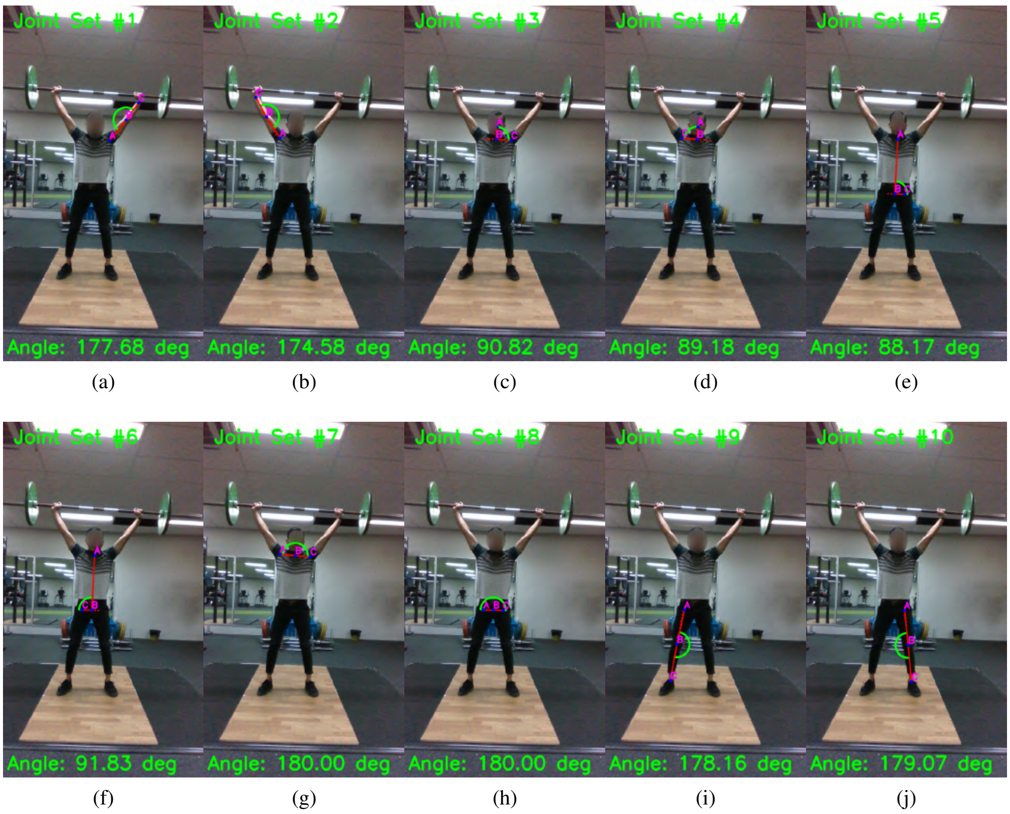


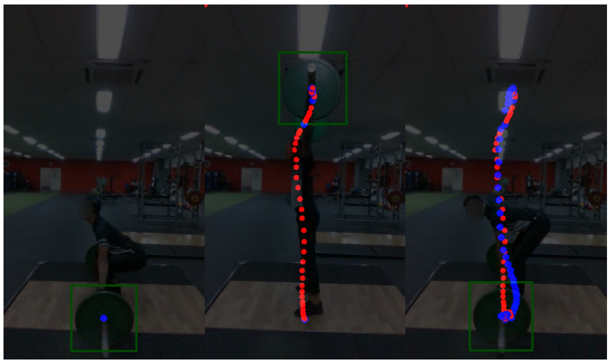
Fig. 3. Results of the pose estimation based on the specified joint profile.

(a) (b)

Fig. 4. Test predictions of barbell using YOLOv7 in (a) simple background and (b) complex background.

(a) (b) (c)

Fig. 5. Side view of the barbell lift at different stages: (a) beginning of lift, (b) full extension, and (c) end of lift, illustrating the barbell's trajectory throughout the lift.



(a) (b) (c)

Fig. 6. Color coded barbell tracking from YOLOv7. (a) Barbell bounding box, (b) Red dots represent lift trajectory, (c) Blue dots represent fall trajectory.

TABLE II
HYPERPARAMETERS USED FOR YOLOV7 TRAINING ON BARBELL TRACKING.

Hyperparameter	Value
Learning rate	0.01
Momentum	0.937
Weight decay	0.0005
Warmup epochs	3.0
Object confidence	0.7
IoU threshold	0.2
Translation	0.2
Scaling	0.5
Horizontal flipping	0.5
Mosaic augmentation	1.0

posture of the weightlifter over the lift session. The captured image of a weightlifting session shown in Fig. 2a, with the corresponding skeletal output from Keypoint RCNN model as shown in Fig. 2b. The pose estimation model successfully estimated joint keypoints on the human body as observed, demonstrating the benefit of the Keypoint-RCNN model in markerless human joint keypoints extraction in weightlifting.

Based on the selected joint sets in Table I, each of the respective joint angles from the pose estimation result are presented in Fig. 3. With ten joints set, their resultant angles, and angle overlay of joint keypoints on the human body is illustrated. Such information can be valuable for coaches and athletes to identify and correct lifting technique and posture issues. The side view of a recorded barbell lift is shown in Fig. 5 with a green bounding box which tracks the barbell. The color-coded barbell tracking results obtained from YOLOv7 model are illustrated in Fig. 6. This figure demonstrates the model's ability to track the barbell's trajectory throughout the lift. The lift trajectory is represented by red dots as shown in Fig. 6b, whereas the fall trajectory is represented by the blue dots in Fig. 6c. These visualisations gives visual aids to coaches and athletes in assessing the efficiency of their lift and making adjustments as needed.

The barbell tracking results of the YOLOv7 model as

TABLE III
YOLOv7 TEST RESULT ON 292 IMAGES.

Precision	Recall	mAP@0.5	mAP@{0.5:0.95}
0.9214	0.9678	0.9792	0.7765

shown in Table III demonstrate high performance with a precision of 0.9214, recall of 0.9678, mAP@0.5 of 0.9792, and mAP@{0.5:0.95} of 0.7765. These values indicate that the model is capable of identifying and tracking the barbell during weightlifting with precision. Overall, the potential of the proposed framework for barbell trajectory tracking in both simple and complex backgrounds are emphasised by Fig. 4a and Fig. 4b respectively.

V. Conclusion

This paper provides the potential use of Keypoint-RCNN and YOLOv7 for biomechanic analysis and barbell trajectory tracking in weightlifting respectively. This preliminary study presents a new method for visualising biomechanics and barbell trajectories in weightlifting. The results from barbell trajectory tracking with a precision of 0.9214 and a recall of 0.9678, demonstrate the model's potential for real-time analysis and feedback in weight training and injury prevention. In addition, high mAP@0.5 values of 0.9792 and mAP@0.5:95 values of 0.7765 indicate the effectiveness of the barbell tracking system. The combination of Keypoint-RCNN and YOLOv7 models in this framework offers a user-friendly and economical alternative solution to the conventional motion capture systems for real-time analysis and feedback in weight lifting sessions and injury prevention. These technologies are particularly attractive for real-world training environments due to their non-intrusive characteristics, which can be easily integrated into coaching and performance analytic workflows. The ability to provide immediate, objective feedback on an athlete's movement patterns can significantly enhance the effectiveness of training interventions. As for future work, an efficient algorithm such as Faster R-CNN, SSD, and EfficientDet is to applied to explore a real-time application in sport analysis.

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